Amazon SageMaker: Developer Guide
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What Is Amazon SageMaker?

Amazon SageMaker is a fully managed machine learning service. With SageMaker, data scientists and developers can quickly and easily build and train machine learning models, and then directly deploy them into a production-ready hosted environment. It provides an integrated Jupyter authoring notebook instance for easy access to your data sources for exploration and analysis, so you don't have to manage servers. It also provides common machine learning algorithms that are optimized to run efficiently against extremely large data in a distributed environment. With native support for bring-your-own-algorithms and frameworks, SageMaker offers flexible distributed training options that adjust to your specific workflows. Deploy a model into a secure and scalable environment by launching it with a few clicks from SageMaker Studio or the SageMaker console. Training and hosting are billed by minutes of usage, with no minimum fees and no upfront commitments.

This guide includes information and tutorials on SageMaker features. For additional information, see Amazon SageMaker developer resources.

Topics

- Amazon SageMaker Features (p. 1)
- Amazon SageMaker Pricing (p. 3)
- Are You a First-time User of Amazon SageMaker? (p. 3)

Amazon SageMaker Features

Amazon SageMaker includes the following features:

SageMaker Studio (p. 117)

An integrated machine learning environment where you can build, train, deploy, and analyze your models all in the same application.

SageMaker Canvas (p. 213)

An auto ML service that gives people with no coding experience the ability to build models and make predictions with them.

SageMaker Ground Truth Plus (p. 677)

A turnkey data labeling feature to create high-quality training datasets without having to build labeling applications and manage the labeling workforce on your own.

SageMaker Studio Lab (p. 90)

A free service that gives customers access to AWS compute resources in an environment based on open-source JupyterLab.

SageMaker Training Compiler (p. 2575)

Train deep learning models faster on scalable GPU instances managed by SageMaker.

SageMaker Studio Universal Notebook (p. 984)

Easily discover, connect to, create, terminate and manage Amazon EMR clusters in single account and cross account configurations directly from SageMaker Studio.
SageMaker Serverless Endpoints (p. 2923)

A serverless endpoint option for hosting your ML model. Automatically scales in capacity to serve your endpoint traffic. Removes the need to select instance types or manage scaling policies on an endpoint.

SageMaker Inference Recommender (p. 2712)

Get recommendations on inference instance types and configurations (e.g. instance count, container parameters and model optimizations) to use your ML models and workloads.

SageMaker Model Registry (p. 2982)

Versioning, artifact and lineage tracking, approval workflow, and cross account support for deployment of your machine learning models.

SageMaker Projects (p. 3281)

Create end-to-end ML solutions with CI/CD by using SageMaker projects.

SageMaker Model Building Pipelines (p. 3203)

Create and manage machine learning pipelines integrated directly with SageMaker jobs.

SageMaker ML Lineage Tracking (p. 3309)

Track the lineage of machine learning workflows.

SageMaker Data Wrangler (p. 815)

Import, analyze, prepare, and featurize data in SageMaker Studio. You can integrate Data Wrangler into your machine learning workflows to simplify and streamline data pre-processing and feature engineering using little to no coding. You can also add your own Python scripts and transformations to customize your data prep workflow.

SageMaker Feature Store (p. 1036)

A centralized store for features and associated metadata so features can be easily discovered and reused. You can create two types of stores, an Online or Offline store. The Online Store can be used for low latency, real-time inference use cases and the Offline Store can be used for training and batch inference.

SageMaker JumpStart (p. 45)

Learn about SageMaker features and capabilities through curated 1-click solutions, example notebooks, and pretrained models that you can deploy. You can also fine-tune the models and deploy them.

SageMaker Clarify (p. 6)

Improve your machine learning models by detecting potential bias and help explain the predictions that models make.

SageMaker Edge Manager (p. 3013)

Optimize custom models for edge devices, create and manage fleets and run models with an efficient runtime.

SageMaker Ground Truth (p. 370)

High-quality training datasets by using workers along with machine learning to create labeled datasets.

Amazon Augmented AI (p. 3390)

Build the workflows required for human review of ML predictions. Amazon A2I brings human review to all developers, removing the undifferentiated heavy lifting associated with building human review systems or managing large numbers of human reviewers.
SageMaker Studio Notebooks (p. 129)

The next generation of SageMaker notebooks that include AWS IAM Identity Center (successor to AWS Single Sign-On) (IAM Identity Center) integration, fast start-up times, and single-click sharing.

SageMaker Experiments (p. 2231)

Experiment management and tracking. You can use the tracked data to reconstruct an experiment, incrementally build on experiments conducted by peers, and trace model lineage for compliance and audit verifications.

SageMaker Debugger (p. 2258)

Inspect training parameters and data throughout the training process. Automatically detect and alert users to commonly occurring errors such as parameter values getting too large or small.

SageMaker Autopilot (p. 318)

Users without machine learning knowledge can quickly build classification and regression models.

SageMaker Model Monitor (p. 2853)

Monitor and analyze models in production (endpoints) to detect data drift and deviations in model quality.

SageMaker Neo (p. 3063)

Train machine learning models once, then run anywhere in the cloud and at the edge.

SageMaker Elastic Inference (p. 3129)

Speed up the throughput and decrease the latency of getting real-time inferences.

Reinforcement Learning (p. 2225)

Maximize the long-term reward that an agent receives as a result of its actions.

Preprocessing (p. 1022)

Analyze and preprocess data, tackle feature engineering, and evaluate models.

Batch Transform (p. 2955)

Preprocess datasets, run inference when you don't need a persistent endpoint, and associate input records with inferences to assist the interpretation of results.

Amazon SageMaker Pricing

As with other AWS products, there are no contracts or minimum commitments for using Amazon SageMaker. For more information about the cost of using SageMaker, see SageMaker Pricing.

Are You a First-time User of Amazon SageMaker?

If you are a first-time user of SageMaker, we recommend that you do the following:

1. Read How Amazon SageMaker Works (p. 4) – This section provides an overview of SageMaker, explains key concepts, and describes the core components involved in building AI solutions with SageMaker. We recommend that you read this topic in the order presented.

2. Set Up Amazon SageMaker Prerequisites (p. 33) – This section explains how to set up your AWS account.
3. Amazon SageMaker Autopilot simplifies the machine learning experience by automating machine learning tasks. If you are new to SageMaker, it provides the easiest learning path. It also serves as an excellent ML learning tool that provides visibility into the code with notebooks generated for each of the automated ML tasks. For an introduction to its capabilities, see Automate model development with Amazon SageMaker Autopilot (p. 318). To get started building, training, and deploying machine learning models, Autopilot provides:
   - Samples: Explore modeling with Amazon SageMaker Autopilot (p. 319)
   - Videos: Use Autopilot to automate and explore the machine learning process (p. 320)
   - Tutorials: Get started with Amazon SageMaker Autopilot (p. 321)

4. Get Started with Amazon SageMaker (p. 33) – This section walks you through training your first model using SageMaker Studio, or the SageMaker console and the SageMaker API. You use training algorithms provided by SageMaker.

5. Explore other topics – Depending on your needs, do the following:
   - Submit Python code to train with deep learning frameworks – In SageMaker, you can use your own training scripts to train models. For information, see Use Machine Learning Frameworks, Python, and R with Amazon SageMaker (p. 13).
   - Use SageMaker directly from Apache Spark – For information, see Use Apache Spark with Amazon SageMaker (p. 14).
   - Use SageMaker to train and deploy your own custom algorithms – Package your custom algorithms with Docker so you can train and/or deploy them in SageMaker. To learn how SageMaker interacts with Docker containers, and for the SageMaker requirements for Docker images, see Using Docker containers with SageMaker (p. 3149).

6. View the API Reference – This section describes the SageMaker API operations.

How Amazon SageMaker Works

SageMaker is a fully managed service that enables you to quickly and easily integrate machine learning-based models into your applications. This section provides an overview of machine learning and explains how SageMaker works. If you are a first-time user of SageMaker, we recommend that you read the following sections in order:

1. Machine Learning with Amazon SageMaker (p. 4)
2. Explore, Analyze, and Process Data (p. 6)
3. Train a Model with Amazon SageMaker (p. 9)
4. Deploy a Model in Amazon SageMaker (p. 11)
5. Use Machine Learning Frameworks, Python, and R with Amazon SageMaker (p. 13)
6. Get Started with Amazon SageMaker (p. 33)

Machine Learning with Amazon SageMaker

This section describes a typical machine learning workflow and summarizes how you accomplish those tasks with Amazon SageMaker.

In machine learning, you “teach” a computer to make predictions, or inferences. First, you use an algorithm and example data to train a model. Then you integrate your model into your application to generate inferences in real time and at scale. In a production environment, a model typically learns from millions of example data items and produces inferences in hundreds to less than 20 milliseconds.

The following diagram illustrates the typical workflow for creating a machine learning model:
As the diagram illustrates, you typically perform the following activities:

1. **Generate example data**—To train a model, you need example data. The type of data that you need depends on the business problem that you want the model to solve (the inferences that you want the model to generate). For example, suppose that you want to create a model to predict a number given an input image of a handwritten digit. To train such a model, you need example images of handwritten numbers.

   Data scientists often spend a lot of time exploring and preprocessing, or "wrangling," example data before using it for model training. To preprocess data, you typically do the following:
   a. **Fetch the data**—You might have in-house example data repositories, or you might use datasets that are publicly available. Typically, you pull the dataset or datasets into a single repository.
   b. **Clean the data**—To improve model training, inspect the data and clean it as needed. For example, if your data has a country name attribute with values United States and US, you might want to edit the data to be consistent.
   c. **Prepare or transform the data**—To improve performance, you might perform additional data transformations. For example, you might choose to combine attributes. If your model predicts the conditions that require de-icing an aircraft, instead of using temperature and humidity attributes separately, you might combine those attributes into a new attribute to get a better model.

   In SageMaker, you preprocess example data in a Jupyter notebook on your notebook instance. You use your notebook to fetch your dataset, explore it, and prepare it for model training. For more information, see *Explore, Analyze, and Process Data* (p. 6). For more information about preparing data in AWS Marketplace, see *data preparation*.

2. **Train a model**—Model training includes both training and evaluating the model, as follows:
   - **Training the model**—To train a model, you need an algorithm or a pre-trained base model. The algorithm you choose depends on a number of factors. For a quick, out-of-the-box solution, you might be able to use one of the algorithms that SageMaker provides. For a list of algorithms provided by SageMaker and related considerations, see *Use Amazon SageMaker Built-in Algorithms or Pre-trained Models* (p. 1096). For a UI-based training solution that provides algorithms and models, see *SageMaker JumpStart* (p. 45).
You also need compute resources for training. Depending on the size of your training dataset and how quickly you need the results, you can use resources ranging from a single general-purpose instance to a distributed cluster of GPU instances. For more information, see Train a Model with Amazon SageMaker (p. 9).

- **Evaluating the model**—After you've trained your model, you evaluate it to determine whether the accuracy of the inferences is acceptable. In SageMaker, you use either the AWS SDK for Python (Boto) or the high-level Python library that SageMaker provides to send requests to the model for inferences.

You use a Jupyter notebook in your SageMaker notebook instance to train and evaluate your model.

3. **Deploy the model**—You traditionally re-engineer a model before you integrate it with your application and deploy it. With SageMaker hosting services, you can deploy your model independently, decoupling it from your application code. For more information, see Deploy Models for Inference (p. 2711).

Machine learning is a continuous cycle. After deploying a model, you monitor the inferences, collect "ground truth," and evaluate the model to identify drift. You then increase the accuracy of your inferences by updating your training data to include the newly collected ground truth. You do this by retraining the model with the new dataset. As more and more example data becomes available, you continue retraining your model to increase accuracy.

**Explore, Analyze, and Process Data**

Before using a dataset to train a model, data scientists typically explore, analyze, and preprocess it.

Amazon SageMaker Processing enables running jobs to preprocess and postprocess data, perform feature engineering, and evaluate models on SageMaker easily and at scale. When combined with the other critical machine learning tasks provided by SageMaker, such as training and hosting, Processing provides you with the benefits of a fully managed machine learning environment, including all the security and compliance support built into SageMaker. With Processing, you have the flexibility to use the built-in data processing containers or to bring your own containers and submit custom jobs to run on managed infrastructure. After you submit a job, SageMaker launches the compute instances, processes and analyzes the input data, and releases the resources upon completion. For more information, see Process Data (p. 1022).

- For information about how to run your own data processing scripts, see Data Processing with scikit-learn (p. 1024).
- For information about how to build your own processing container to run scripts, see Build Your Own Processing Container (Advanced Scenario) (p. 1031).
- For information about how to perform exploratory data analysis (EDA) with a visual no-code interface, see Prepare ML Data with Amazon SageMaker Data Wrangler (p. 815).

**What Is Fairness and Model Explainability for Machine Learning Predictions?**

Amazon SageMaker Clarify helps improve your machine learning (ML) models by detecting potential bias and helping explain the predictions that models make. It helps you identify various types of bias.
in pretraining data and in posttraining that can emerge during model training or when the model is in production. SageMaker Clarify helps explain how these models make predictions using a feature attribution approach. It also monitors inferences models make in production for bias or feature attribution drift. The fairness and explainability functionality provided by SageMaker Clarify provides components that help AWS customers build less biased and more understandable machine learning models. It also provides tools to help you generate model governance reports that you can use to inform risk and compliance teams, and external regulators.

Machine learning models and data-driven systems are being increasingly used to help make decisions across domains such as financial services, healthcare, education, and human resources. Machine learning applications provide benefits such as improved accuracy, increased productivity, and cost savings to help meet regulatory requirements, improve business decisions, and provide better insights into data science procedures.

- **Regulatory** – In many situations, it is important to understand why an ML model made a specific prediction and also whether the prediction it made was impacted by any bias, either during training or at inference. Recently, policymakers, regulators, and advocates have raised awareness about the ethical and policy challenges posed by ML and data-driven systems. In particular, they have expressed concerns about the potentially discriminatory impact of such systems (for example, inadvertently encoding of bias into automated decisions).

- **Business** – The adoption of AI systems in regulated domains requires trust, which can be built by providing reliable explanations of the behavior of trained models and how the deployed models make predictions. Model explainability may be particularly important to certain industries with reliability, safety, and compliance requirements, such as financial services, human resources, healthcare, and automated transportation. To take a common financial example, lending applications that incorporate the use of ML models might need to provide explanations about how those models made certain predictions to internal teams of loan officers, customer service representatives, and forecasters, in addition to end users/customers.

- **Data Science** – Data scientists and ML engineers need tools to generate the insights required to debug and improve ML models through better feature engineering, to determine whether a model is making inferences based on noisy or irrelevant features, and to understand the limitations of their models and failure modes their models may encounter.

For a blog that shows how to architect and build a complete machine learning use case involving fraudulent automobile claims that integrates SageMaker Clarify into a SageMaker pipeline, see the [Architect and build the full machine learning lifecycle with AWS: An end-to-end Amazon SageMaker demo](#). This blog discusses how to assess pre and post training bias, how to mitigate the bias, and how the data features impact the prediction. There are links to the relevant code for each task in the ML lifecycle, including the creation of an automated workflow that integrates the fairness and explainability functionality of SageMaker Clarify into a SageMaker Pipeline.

### Best Practices for Evaluating Fairness and Explainability in the ML Lifecycle

**Fairness as a Process** – The notions of bias and fairness are highly dependent on the application. Further, the choice of the attributes for which bias is to be measured, as well as the choice of the bias metrics, may need to be guided by social, legal, and other non-technical considerations. Building consensus and achieving collaboration across key stakeholders (such as product, policy, legal, engineering, and AI/ML teams, as well as end users and communities) is a prerequisite for the successful adoption of fairness-aware ML approaches in practice.

**Fairness and Explainability by Design in the ML Lifecycle** – You should consider fairness and explainability during each stage of the ML lifecycle: problem formation, dataset construction, algorithm selection, model training process, testing process, deployment, and monitoring/feedback. It is important
to have the right tools to do this analysis. To encourage engaging with these considerations, here are a few example questions we recommend you ask during each of these stages.

Sample Notebooks

Amazon SageMaker Clarify provides the following sample notebooks:

- **Explainability and bias detection with Amazon SageMaker Clarify** – Use SageMaker Clarify to create a processing job for the detecting bias and explaining model predictions with feature attributions.

- **Monitoring bias drift and feature attribution drift Amazon SageMaker Clarify** – Use Amazon SageMaker Model Monitor to monitor bias drift and feature attribution drift over time.

- **Fairness and Explainability with SageMaker Clarify (Bring Your Own Container)** – This sample notebook introduces key terms and concepts needed to understand SageMaker Clarify, and it walks you through an end-to-end data science workflow demonstrating how to build your own model and container that can work seamlessly with your Clarify jobs, use the model and SageMaker Clarify to measure bias, explain the importance of the various input features on the model's decision and then access the reports through SageMaker Studio if you have an instance set up.

- **Fairness and Explainability with SageMaker Clarify - Spark Distributed Processing** – This sample notebook walks you through key terms and concepts needed to understand SageMaker Clarify, measures the pre-training bias of a dataset and post-training bias of a model, explains the importance of the various input features on the model's decision, and accesses the reports through SageMaker Studio if you have an instance set up.

- **Mitigate Bias, Train another unbiased Model and Put in the Model Registry** – This notebook describes how to detect bias using SageMaker Clarify, mitigate it with **Synthetic Minority Over-sampling Technique (SMOTE)**, train another model, then put it in the Model Registry along with all the lineage of the artifacts created along the way: data, code and model metadata. This notebook forms part of a series that shows how to integrate SageMaker Clarify into a SageMaker Pipeline that is described in the Architect and build the full machine learning lifecycle with AWS blog.

These notebooks have been verified to run in Amazon SageMaker Studio only. If you need instructions on how to open a notebook in Amazon SageMaker Studio, see [Create or Open an Amazon SageMaker Studio Notebook](p. 133). If you’re prompted to choose a kernel, choose **Python 3 (Data Science)**.

Guide to the SageMaker Clarify Documentation

Bias can occur and be measured in the data at each stage of the machine learning lifecycle: before training a model and after model training. SageMaker Clarify can provide feature attribution...
explanations of model predictions for trained models and for models deployed to production, where models can be monitored for any drift from their baseline explanatory attributions. Clarify calculates baselines when needed. The documentation for SageMaker Clarify is embedded throughout the larger SageMaker documentation set at the relevant ML stages as follows:

- For further information on detecting bias in preprocessing data before it's used to train a model, see [Detect Pretraining Data Bias](#).
- For further information on detecting posttraining data and model bias, see [Detect Posttraining Data and Model Bias with Amazon SageMaker Clarify](#).
- For further information on the model-agnostic feature attribution approach to explain model predictions after training, see [Amazon SageMaker Clarify Model Explainability](#).
- For further information on monitoring for bias in production model inferences due to the drift of data away from the baseline used to train the model, see [Monitor Bias Drift for Models in Production](#).
- For further information on monitoring for the drift of features' contributions away from the baseline that was established during model training, see [Monitor Feature Attribution Drift for Models in Production](#).

## Train a Model with Amazon SageMaker

The following diagram shows how you train and deploy a model with Amazon SageMaker:
The area labeled SageMaker highlights the two components of SageMaker: model training and model deployment.

To train a model in SageMaker, you create a training job. The training job includes the following information:

• The URL of the Amazon Simple Storage Service (Amazon S3) bucket where you've stored the training data.
• The compute resources that you want SageMaker to use for model training. Compute resources are ML compute instances that are managed by SageMaker.
• The URL of the S3 bucket where you want to store the output of the job.
• The Amazon Elastic Container Registry path where the training code is stored. For more information, see Docker Registry Paths and Example Code (p. 1105).

You have the following options for a training algorithm:

• Use an algorithm provided by SageMaker—SageMaker provides dozens of built-in training algorithms and hundreds of pre-trained models. If one of these meets your needs, it's a great out-
of-the-box solution for quick model training. For a list of algorithms provided by SageMaker, see Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096). To try an exercise that uses an algorithm provided by SageMaker, see Get Started with Amazon SageMaker (p. 33). You can also use SageMaker JumpStart (p. 45) to use algorithms and models through the Studio UI.

- **Use SageMaker Debugger**—to inspect training parameters and data throughout the training process when working with the TensorFlow, PyTorch, and Apache MXNet learning frameworks or the XGBoost algorithm. Debugger automatically detects and alerts users to commonly occurring errors such as parameter values getting too large or small. For more information about using Debugger, see Debug and Profile Training Jobs Using Amazon SageMaker Debugger (p. 2258). Debugger sample notebooks are available at Amazon SageMaker Debugger Samples.

- **Use Apache Spark with SageMaker**—SageMaker provides a library that you can use in Apache Spark to train models with SageMaker. Using the library provided by SageMaker is similar to using Apache Spark MLLib. For more information, see Use Apache Spark with Amazon SageMaker (p. 14).

- **Submit custom code to train with deep learning frameworks**—You can submit custom Python code that uses TensorFlow, PyTorch, or Apache MXNet for model training. For more information, see Use TensorFlow with Amazon SageMaker (p. 30), Use PyTorch with Amazon SageMaker (p. 26), and Use Apache MXNet with Amazon SageMaker (p. 14).

- **Use your own custom algorithms**—Put your code together as a Docker image and specify the registry path of the image in a SageMaker CreateTrainingJob API call. For more information, see Using Docker containers with SageMaker (p. 3149).

- **Use an algorithm that you subscribe to from AWS Marketplace**—For information, see Find and Subscribe to Algorithms and Model Packages on AWS Marketplace (p. 3492).

After you create the training job, SageMaker launches the ML compute instances and uses the training code and the training dataset to train the model. It saves the resulting model artifacts and other output in the S3 bucket you specified for that purpose.

You can create a training job with the SageMaker console or the API. For information about creating a training job with the API, see the CreateTrainingJob API.

When you create a training job with the API, SageMaker replicates the entire dataset on ML compute instances by default. To make SageMaker replicate a subset of the data on each ML compute instance, you must set the S3DataDistributionType field to ShardedByS3Key. You can set this field using the low-level SDK. For more information, see S3DataDistributionType in S3DataSource.

**Important**

To prevent your algorithm container from contending for memory, we reserve memory for our SageMaker critical system processes on your ML compute instances and therefore you cannot expect to see all the memory for your instance type.

### Deploy a Model in Amazon SageMaker

After you train your machine learning model, you can deploy it using Amazon SageMaker to get predictions in any of the following ways, depending on your use case:

- For persistent, real-time endpoints that make one prediction at a time, use SageMaker real-time hosting services. See Real-time inference (p. 2744).

- Workloads that have idle periods between traffic spurts and can tolerate cold starts, use Serverless Inference. See Serverless Inference (p. 2923).

- Requests with large payload sizes up to 1GB, long processing times, and near-real-time latency requirements, use Amazon SageMaker Asynchronous Inference. See Asynchronous inference (p. 2939).

- To get predictions for an entire dataset, use SageMaker batch transform. See Use Batch Transform (p. 2955).
Validating a Machine Learning Model

After training a model, evaluate it to determine whether its performance and accuracy enable you to achieve your business goals. You might generate multiple models using different methods and evaluate each. For example, you could apply different business rules for each model, and then apply various measures to determine each model's suitability. You might consider whether your model needs to be more sensitive than specific (or vice versa).

You can evaluate your model using historical data (offline) or live data:

- **Offline testing**—Use historical, not live, data to send requests to the model for inferences.

  Deploy your trained model to an alpha endpoint, and use historical data to send inference requests to it. To send the requests, use a Jupyter notebook in your Amazon SageMaker notebook instance and either the AWS SDK for Python (Boto) or the high-level Python library provided by SageMaker.

- **Online testing with live data**—SageMaker supports A/B testing for models in production by using production variants. Production variants are models that use the same inference code and are deployed on the same SageMaker endpoint. You configure the production variants so that a small portion of the live traffic goes to the model that you want to validate. For example, you might choose to send 10% of the traffic to a model variant for evaluation. After you are satisfied with the model's performance, you can route 100% traffic to the updated model. For an example of testing models in production, see Safely update models in production (p. 2819).

For more information, see articles and books about how to evaluate models, for example, Evaluating Machine Learning Models.

Options for offline model evaluation include:

- **Validating using a holdout set**—Machine learning practitioners often set aside a part of the data as a "holdout set." They don't use this data for model training.

  With this approach, you evaluate how well your model provides inferences on the holdout set. You then assess how effectively the model generalizes what it learned in the initial training, as opposed to using model memory. This approach to validation gives you an idea of how often the model is able to infer the correct answer.

In some ways, this approach is similar to teaching elementary school students. First, you provide them with a set of examples to learn, and then test their ability to generalize from their learning. With homework and tests, you pose problems that were not included in the initial learning and determine...
whether they are able to generalize effectively. Students with perfect memories could memorize the problems, instead of learning the rules.

Typically, the holdout dataset is of 20-30% of the training data.

- **k-fold validation**—In this validation approach, you split the example dataset into k parts. You treat each of these parts as a holdout set for k training runs, and use the other k-1 parts as the training set for that run. You produce k models using a similar process, and aggregate the models to generate your final model. The value k is typically in the range of 5-10.

### Monitoring a Model in Production

After you deploy a model into your production environment, use Amazon SageMaker model monitor to continuously monitor the quality of your machine learning models in real time. Amazon SageMaker model monitor enables you to set up an automated alert triggering system when there are deviations in the model quality, such as data drift and anomalies. Amazon CloudWatch Logs collects log files of monitoring the model status and notifies when the quality of your model hits certain thresholds that you preset. CloudWatch stores the log files to an Amazon S3 bucket you specify. Early and pro-active detection of model deviations through AWS model monitor products enables you to take prompt actions to maintain and improve the quality of your deployed model.

For more information about SageMaker model monitoring products, see Monitor models for data and model quality, bias, and explainability (p. 2853).

To start your machine learning journey with SageMaker, sign up for an AWS account at Set Up SageMaker.

### Use Machine Learning Frameworks, Python, and R with Amazon SageMaker

You can use Python and R natively in Amazon SageMaker notebook kernels. There are also kernels that support specific frameworks. A very popular way to get started with SageMaker is to use the Amazon SageMaker Python SDK. It provides open source Python APIs and containers that make it easy to train and deploy models in SageMaker, as well as examples for use with several different machine learning and deep learning frameworks.

For information about using specific frameworks or how to use R in SageMaker, see the following topics.

**Languages SDKs and user guides:**

- Amazon SageMaker Python SDK
- R (p. 26)
- API Reference Guide for Amazon SageMaker (p. 3693)

**Machine learning and deep learning frameworks guides:**

- Apache MXNet (p. 14)
- Apache Spark (p. 14)
- Chainer (p. 23)
- Hugging Face (p. 24)
Use Apache MXNet with Amazon SageMaker

You can use SageMaker to train and deploy a model using custom MXNet code. The Amazon SageMaker Python SDK MXNet estimators and models and the SageMaker open-source MXNet container make writing a MXNet script and running it in SageMaker easier.

What do you want to do?

I want to train a custom MXNet model in SageMaker.

For a sample Jupyter notebook, see the MXNet example notebooks in the Amazon SageMaker Examples GitHub repository.

For documentation, see Train a Model with MXNet.

I have an MXNet model that I trained in SageMaker, and I want to deploy it to a hosted endpoint.

For more information, see Deploy MXNet models.

I have an MXNet model that I trained outside of SageMaker, and I want to deploy it to a SageMaker endpoint

For more information, see Deploy Endpoints from Model Data.

I want to see the API documentation for Amazon SageMaker Python SDK MXNet classes.

For more information, see MXNet Classes.

I want to find the SageMaker MXNet container repository.

For more information, see SageMaker MXNet Container GitHub repository.

I want to find information about MXNet versions supported by AWS Deep Learning Containers.

For more information, see Available Deep Learning Container Images.

For general information about writing MXNet script mode training scripts and using MXNet script mode estimators and models with SageMaker, see Using MXNet with the SageMaker Python SDK.

Use Apache Spark with Amazon SageMaker

This section provides information for developers who want to use Apache Spark for preprocessing data and Amazon SageMaker for model training and hosting. For information about supported versions of Apache Spark, see the Getting SageMaker Spark page in the SageMaker Spark GitHub repository.

SageMaker provides an Apache Spark library, in both Python and Scala, that you can use to easily train models in SageMaker using org.apache.spark.sql.DataFrame data frames in your Spark clusters. After model training, you can also host the model using SageMaker hosting services.

The SageMaker Spark library, com.amazonaws.services.sagemaker.sparksdk, provides the following classes, among others:

• SageMakerEstimator—Extends the org.apache.spark.ml.Estimator interface. You can use this estimator for model training in SageMaker.
Amazon SageMaker Developer Guide
Apache Spark


With SageMaker Studio, you can easily connect to an Amazon EMR cluster. For more information, see Prepare data at Scale with Studio Notebooks.

Download the SageMaker Spark Library

You have the following options for downloading the Spark library provided by SageMaker:

- You can download the source code for both PySpark and Scala libraries from the SageMaker Spark GitHub repository.
- For the Python Spark library, you have the following additional options:
  - Use pip install:

    ```bash
    pip install sagemaker_pyspark
    ```
  - In a notebook instance, create a new notebook that uses either the Sparkmagic (PySpark) or the Sparkmagic (PySpark3) kernel and connect to a remote Amazon EMR cluster.

    **Note**
    The EMR cluster must be configured with an IAM role that has the AmazonSageMakerFullAccess policy attached. For information about configuring roles for an EMR cluster, see Configure IAM Roles for Amazon EMR Permissions to AWS Services in the Amazon EMR Management Guide.

- You can get the Scala library from Maven. Add the Spark library to your project by adding the following dependency to your pom.xml file:

```xml
<dependency>
    <groupId>com.amazonaws</groupId>
    <artifactId>sagemaker-spark_2.11</artifactId>
    <version>spark_2.2.0-1.0</version>
</dependency>
```

Integrate Your Apache Spark Application with SageMaker

The following is high-level summary of the steps for integrating your Apache Spark application with SageMaker.

1. Continue data preprocessing using the Apache Spark library that you are familiar with. Your dataset remains a DataFrame in your Spark cluster. Load your data into a DataFrame and preprocess it so that you have a features column with org.apache.spark.ml.linalg.Vector of Doubles, and an optional label column with values of Double type.

2. Use the estimator in the SageMaker Spark library to train your model. For example, if you choose the k-means algorithm provided by SageMaker for model training, you call the KMeansSageMakerEstimator.fit method.

   Provide your DataFrame as input. The estimator returns a SageMakerModel object.

   **Note**
   SageMakerModel extends the org.apache.spark.ml.Model.
The fit method does the following:

a. Converts the input DataFrame to the protobuf format by selecting the features and label columns from the input DataFrame and uploading the protobuf data to an Amazon S3 bucket. The protobuf format is efficient for model training in SageMaker.

b. Starts model training in SageMaker by sending a SageMaker CreateTrainingJob request. After model training has completed, SageMaker saves the model artifacts to an S3 bucket.

SageMaker assumes the IAM role that you specified for model training to perform tasks on your behalf. For example, it uses the role to read training data from an S3 bucket and to write model artifacts to a bucket.

c. Creates and returns a SageMakerModel object. The constructor does the following tasks, which are related to deploying your model to SageMaker.

   i. Sends a CreateModel request to SageMaker.
   
   ii. Sends a CreateEndpointConfig request to SageMaker.
   
   iii. Sends a CreateEndpoint request to SageMaker, which then launches the specified resources, and hosts the model on them.

3. You can get inferences from your model hosted in SageMaker with the SageMakerModel.transform method.

   Provide an input DataFrame with features as input. The transform method transforms it to a DataFrame containing inferences. Internally, the transform method sends a request to the InvokeEndpoint SageMaker API to get inferences. The transform method appends the inferences to the input DataFrame.

Example 1: Use Amazon SageMaker for Training and Inference with Apache Spark

Topics
- Use Custom Algorithms for Model Training and Hosting on Amazon SageMaker with Apache Spark (p. 20)
- Use the SageMakerEstimator in a Spark Pipeline (p. 21)

Amazon SageMaker provides an Apache Spark library (in both Python and Scala) that you can use to integrate your Apache Spark applications with SageMaker. For example, you might use Apache Spark for data preprocessing and SageMaker for model training and hosting. For more information, see Use Apache Spark with Amazon SageMaker (p. 14). This section provides example code that uses the Apache Spark Scala library provided by SageMaker to train a model in SageMaker using DataFrames in your Spark cluster. The example also hosts the resulting model artifacts using SageMaker hosting services. Specifically, this example does the following:

- Uses the KMeansSageMakerEstimator to fit (or train) a model on data

Because the example uses the k-means algorithm provided by SageMaker to train a model, you use the KMeansSageMakerEstimator. You train the model using images of handwritten single-digit numbers (from the MNIST dataset). You provide the images as an input DataFrame. For your convenience, SageMaker provides this dataset in an S3 bucket.
In response, the estimator returns a `SageMakerModel` object.

- Obtains inferences using the trained `SageMakerModel`

To get inferences from a model hosted in SageMaker, you call the `SageMakerModel.transform` method. You pass a `DataFrame` as input. The method transforms the input `DataFrame` to another `DataFrame` containing inferences obtained from the model.

For a given input image of a handwritten single-digit number, the inference identifies a cluster that the image belongs to. For more information, see K-Means Algorithm (p. 2151).

This is the example code:

```scala
import org.apache.spark.sql.SparkSession
import com.amazonaws.services.sagemaker.sparksdk.IAMRole
import com.amazonaws.services.sagemaker.sparksdk.algorithms
import com.amazonaws.services.sagemaker.sparksdk.algorithms.KMeansSageMakerEstimator
val spark = SparkSession.builder.getOrCreate
// load mnist data as a dataframe from libsvm
val region = "us-east-1"
val trainingData = spark.read.format("libsvm")
  .option("numFeatures", "784")
  .load(s"s3://sagemaker-sample-data-$region/spark/mnist/train/")
val testData = spark.read.format("libsvm")
  .option("numFeatures", "784")
  .load(s"s3://sagemaker-sample-data-$region/spark/mnist/test/")
val roleArn = "arn:aws:iam::<account-id>:role/rolename"
val estimator = new KMeansSageMakerEstimator(
  sagemakerRole = IAMRole(roleArn),
  trainingInstanceType = "ml.p2.xlarge",
  trainingInstanceCount = 1,
  endpointInstanceType = "ml.c4.xlarge",
  endpointInitialInstanceCount = 1)
  .setK(10).setFeatureDim(784)
// train
val model = estimator.fit(trainingData)
val transformedData = model.transform(testData)
transformedData.show
```

The code does the following:

- Loads the MNIST dataset from an S3 bucket provided by SageMaker (awsai-sparksdk-dataset) into a Spark DataFrame (`mnistTrainingDataFrame`):

```scala
// Get a Spark session.
val spark = SparkSession.builder.getOrCreate
// load mnist data as a dataframe from libsvm
```
val region = "us-east-1"
val trainingData = spark.read.format("libsvm")
                   .option("numFeatures", "784")
                   .load(s"s3://sagemaker-sample-data-$region/spark/mnist/train/")
val testData = spark.read.format("libsvm")
              .option("numFeatures", "784")
              .load(s"s3://sagemaker-sample-data-$region/spark/mnist/test/")
val roleArn = "arn:aws:iam::account-id:role/rolename"

trainingData.show()

The show method displays the first 20 rows in the data frame:

```
+-----+--------------------+
|label|            features|
+-----+--------------------+
|  5.0|[784,[152,153,154...|
|  0.0|[784,[127,128,129...|
|  4.0|[784,[160,161,162...|
|  1.0|[784,[158,159,160...|
|  9.0|[784,[208,209,210...|
|  2.0|[784,[155,156,157...|
|  1.0|[784,[124,125,126...|
|  5.0|[784,[151,152,155...|
|  1.0|[784,[152,153,154...|
|  4.0|[784,[134,135,161...|
|  3.0|[784,[123,124,125...|
|  5.0|[784,[216,217,218...|
|  3.0|[784,[143,144,145...|
|  6.0|[784,[72,73,74,99...|
|  1.0|[784,[151,152,153...|
|  7.0|[784,[211,212,213...|
|  2.0|[784,[151,152,153...|
|  8.0|[784,[159,160,161...|
|  6.0|[784,[100,101,102...|
|  9.0|[784,[209,210,211...|
+-----+--------------------+
```

only showing top 20 rows

In each row:

- The label column identifies the image's label. For example, if the image of the handwritten number is the digit 5, the label value is 5.
- The features column stores a vector (org.apache.spark.ml.linalg.Vector) of Double values. These are the 784 features of the handwritten number. (Each handwritten number is a 28 x 28-pixel image, making 784 features.)

- Creates a SageMaker estimator (KMeansSageMakerEstimator)

    The fit method of this estimator uses the k-means algorithm provided by SageMaker to train models using an input DataFrame. In response, it returns a SageMakerModel object that you can use to get inferences.

    **Note**
    The KMeansSageMakerEstimator extends the SageMaker SageMakerEstimator, which extends the Apache Spark Estimator.

val estimator = new KMeansSageMakerEstimator(
    sagemakerRole = IAMRole(roleArn),
    trainingInstanceType = "ml.p2.xlarge",
)
The constructor parameters provide information that is used for training a model and deploying it on SageMaker:

- `trainingInstanceType` and `trainingInstanceCount`—Identify the type and number of ML compute instances to use for model training.

- `endpointInstanceType`—Identifies the ML compute instance type to use when hosting the model in SageMaker. By default, one ML compute instance is assumed.

- `endpointInitialInstanceCount`—Identifies the number of ML compute instances initially backing the endpoint hosting the model in SageMaker.

- `sagemakerRole`—SageMaker assumes this IAM role to perform tasks on your behalf. For example, for model training, it reads data from S3 and writes training results (model artifacts) to S3.

  **Note**
  This example implicitly creates a SageMaker client. To create this client, you must provide your credentials. The API uses these credentials to authenticate requests to SageMaker. For example, it uses the credentials to authenticate requests to create a training job and API calls for deploying the model using SageMaker hosting services.

- After the `KMeansSageMakerEstimator` object has been created, you set the following parameters, are used in model training:
  - The number of clusters that the k-means algorithm should create during model training. You specify 10 clusters, one for each digit, 0 through 9.
  - Identifies that each input image has 784 features (each handwritten number is a 28 x 28-pixel image, making 784 features).

- Calls the estimator `fit` method

```scala
// train
val model = estimator.fit(trainingData)
```

You pass the input `DataFrame` as a parameter. The model does all the work of training the model and deploying it to SageMaker. For more information see, [Integrate Your Apache Spark Application with SageMaker](p. 15). In response, you get a `SageMakerModel` object, which you can use to get inferences from your model deployed in SageMaker.

You provide only the input `DataFrame`. You don't need to specify the registry path to the k-means algorithm used for model training because the `KMeansSageMakerEstimator` knows it.

- Calls the `SageMakerModel.transform` method to get inferences from the model deployed in SageMaker.
The `transform` method takes a DataFrame as input, transforms it, and returns another DataFrame containing inferences obtained from the model.

```scala
val transformedData = model.transform(testData)
transformedData.show
```

For simplicity, we use the same DataFrame as input to the `transform` method that we used for model training in this example. The `transform` method does the following:

- Serializes the `features` column in the input DataFrame to protobuf and sends it to the SageMaker endpoint for inference.
- Deserializes the protobuf response into the two additional columns (`distance_to_cluster` and `closest_cluster`) in the transformed DataFrame.

The `show` method gets inferences to the first 20 rows in the input DataFrame:

<table>
<thead>
<tr>
<th>label</th>
<th>features</th>
<th>distance_to_cluster</th>
<th>closest_cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td>5.0</td>
<td>(784, [152, 153, 154..., 1767.897705078125, 4.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.0</td>
<td>(784, [127, 128, 129..., 1392.157470703125, 5.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.0</td>
<td>(784, [160, 161, 162..., 1671.571169921875, 9.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.0</td>
<td>(784, [159, 159, 160..., 1182.6082763671875, 6.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9.0</td>
<td>(784, [208, 209, 210..., 1590.4002685546875, 0.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.0</td>
<td>(784, [155, 156, 157..., 1713.988037109375, 1.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.0</td>
<td>(784, [124, 125, 126..., 1246.3016357421875, 2.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.0</td>
<td>(784, [151, 152, 153..., 1753.229248046875, 4.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.0</td>
<td>(784, [152, 153, 154..., 978.8394165039062, 2.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.0</td>
<td>(784, [154, 155, 161..., 1623.176513671875, 3.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.0</td>
<td>(784, [123, 124, 125..., 1533.863525390625, 4.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.0</td>
<td>(784, [216, 217, 218..., 1469.357177734375, 6.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.0</td>
<td>(784, [143, 144, 145..., 1736.765869140625, 4.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.0</td>
<td>(784, [72, 73, 74, 99..., 1473.69384765625, 8.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.0</td>
<td>(784, [151, 152, 153..., 944.88720703125, 2.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7.0</td>
<td>(784, [211, 212, 213..., 1285.9071044921875, 3.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.0</td>
<td>(784, [151, 152, 153..., 1635.0125732421875, 1.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8.0</td>
<td>(784, [159, 160, 161..., 1436.3162841796875, 6.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.0</td>
<td>(784, [100, 101, 102..., 1499.7366943359375, 7.0]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9.0</td>
<td>(784, [209, 210, 211..., 1364.631958078125, 6.0]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

You can interpret the data, as follows:

- A handwritten number with the label 5 belongs to cluster 4 (`closest_cluster`).
- A handwritten number with the label 0 belongs to cluster 5.
- A handwritten number with the label 4 belongs to cluster 9.
- A handwritten number with the label 1 belongs to cluster 6.

For more information on how to run these examples, see [https://github.com/aws/sagemaker-spark/blob/master/README.md](https://github.com/aws/sagemaker-spark/blob/master/README.md) on GitHub.

**Use Custom Algorithms for Model Training and Hosting on Amazon SageMaker with Apache Spark**

In Example 1: Use Amazon SageMaker for Training and Inference with Apache Spark (p. 16), you use the `kMeansSageMakerEstimator` because the example uses the k-means algorithm provided by Amazon SageMaker for model training. You might choose to use your own custom algorithm for model training.
training instead. Assuming that you have already created a Docker image, you can create your own SageMakerEstimator and specify the Amazon Elastic Container Registry path for your custom image.

The following example shows how to create a KMeansSageMakerEstimator from the SageMakerEstimator. In the new estimator, you explicitly specify the Docker registry path to your training and inference code images.

```scala
import com.amazonaws.services.sagemaker.sparksdk.IAMRole
import com.amazonaws.services.sagemaker.sparksdk.SageMakerEstimator
import com.amazonaws.services.sagemaker.sparksdk.transformation.serializers.ProtobufRequestRowSerializer
import com.amazonaws.services.sagemaker.sparksdk.transformation.deserializers.KMeansProtobufResponseRowDeserializer

val estimator = new SageMakerEstimator(
  trainingImage = "811284229777.dkr.ecr.us-east-1.amazonaws.com/kmeans:1",
  modelImage = "811284229777.dkr.ecr.us-east-1.amazonaws.com/kmeans:1",
  requestRowSerializer = new ProtobufRequestRowSerializer(),
  responseRowDeserializer = new KMeansProtobufResponseRowDeserializer(),
  hyperParameters = Map("k" -> "10", "feature_dim" -> "784"),
  sagemakerRole = IAMRole(roleArn),
  trainingInstanceType = "ml.p2.xlarge",
  trainingInstanceCount = 1,
  endpointInstanceType = "ml.c4.xlarge",
  endpointInitialInstanceCount = 1,
  trainingSparkDataFormat = "sagemaker")
```

In the code, the parameters in the SageMakerEstimator constructor include:

- **trainingImage** — Identifies the Docker registry path to the training image containing your custom code.
- **modelImage** — Identifies the Docker registry path to the image containing inference code.
- **requestRowSerializer** — Implements `com.amazonaws.services.sagemaker.sparksdk.transformation.RequestRowSerializer`. This parameter serializes rows in the input DataFrame to send them to the model hosted in SageMaker for inference.
- **responseRowDeserializer** — Implements `com.amazonaws.services.sagemaker.sparksdk.transformation.ResponseRowDeserializer`. This parameter deserializes responses from the model, hosted in SageMaker, back into a DataFrame.
- **trainingSparkDataFormat** — Specifies the data format that Spark uses when uploading training data from a DataFrame to S3. For example, "sagemaker" for protobuf format, "csv" for comma-separated values, and "libsvm" for LibSVM format.

You can implement your own RequestRowSerializer and ResponseRowDeserializer to serialize and deserialize rows from a data format that your inference code supports, such as .libsvm or .csv.

**Use the SageMakerEstimator in a Spark Pipeline**

You can use `org.apache.spark.ml.Estimator` estimators and `org.apache.spark.ml.Model` models, and SageMakerEstimator estimators and SageMakerModel models in `org.apache.spark.ml.Pipeline` pipelines, as shown in the following example:

```scala
import org.apache.spark.ml.Pipeline
import org.apache.spark.ml.feature.PCA
```
import org.apache.spark.sql.SparkSession
import com.amazonaws.services.sagemaker.sparksdk.IAMRole
import com.amazonaws.services.sagemaker.sparksdk.algorithms
import com.amazonaws.services.sagemaker.sparksdk.algorithms.KMeansSageMakerEstimator

val spark = SparkSession.builder.getOrCreate

// load mnist data as a dataframe from libsvm
val region = "us-east-1"
val trainingData = spark.read.format("libsvm")
  .option("numFeatures", "784")
  .load(s"s3://sagemaker-sample-data-$region/spark/mnist/train/")
val testData = spark.read.format("libsvm")
  .option("numFeatures", "784")
  .load(s"s3://sagemaker-sample-data-$region/spark/mnist/test/")

// substitute your SageMaker IAM role here
val roleArn = "arn:aws:iam::<account-id>:role/rolename"

val pcaEstimator = new PCA()
  .setInputCol("features")
  .setOutputCol("projectedFeatures")
  .setK(50)

val kMeansSageMakerEstimator = new KMeansSageMakerEstimator(
  sagemakerRole = IAMRole(integTestingRole),
  requestRowSerializer =
    new ProtobufRequestRowSerializer(featuresColumnName = "projectedFeatures"),
  trainingSparkDataFormatOptions = Map("featuresColumnName" -> "projectedFeatures"),
  trainingInstanceType = "ml.p2.xlarge",
  trainingInstanceCount = 1,
  endpointInstanceType = "ml.c4.xlarge",
  endpointInitialInstanceCount = 1)
  .setK(10).setFeatureDim(50)

val pipeline = new Pipeline().setStages(Array(pcaEstimator, kMeansSageMakerEstimator))

// train
val pipelineModel = pipeline.fit(trainingData)
val transformedData = pipelineModel.transform(testData)
transformedData.show()

The parameter trainingSparkDataFormatOptions configures Spark to serialize to protobuf the "projectedFeatures" column for model training. Additionally, Spark serializes to protobuf the "label" column by default. Because we want to make inferences using the "projectedFeatures" column, we pass the column name into the ProtobufRequestRowSerializer.

The following example shows a transformed DataFrame:

+-----+--------------------+--------------------+-------------------+---------------+
|label|            features|   projectedFeatures|distance_to_cluster|closest_cluster|
+-----+--------------------+--------------------+-------------------+---------------+
|  5.0| [784,[152,153,154...|[880.731433034386...|     1500.470703125|            0.0|
|  0.0| [784,[127,128,129...|1168.51722024166...|  1386.24682617875|            9.0|
|  4.0| [784,[160,161,162...|1704.51722024166...|   1277.07368394375|            3.0|
|  1.0| [784,[158,159,160...|[-42.328192193771...|  1277.07368394375|            5.0|
|  9.0| [784,[208,209,210...|[-42.328192193771...|  1277.07368394375|            5.0|
|  2.0| [784,[155,156,157...|941.267714528850...|  1496.157958984375|            8.0|
|  1.0| [784,[124,125,126...|30.2848596410594...|  1327.6766357421875|            5.0|
|  3.0| [784,[151,152,153...|1270.14374062052...|  1570.7674560546875|            0.0|
|  1.0| [784,[152,153,154...|[-112.10792566485...|  1037.568359375|            5.0|
SDK examples: Use Amazon SageMaker with Apache Spark

The following list is a subset of available examples. Visit the examples website to see more.

- sagemaker-spark: a Spark library for SageMaker
- SageMaker PySpark K-Means Clustering MNIST Example
- Distributed Data Processing using Apache Spark and SageMaker Processing

**Note**
To run the notebooks on a notebook instance, see Example Notebooks (p. 306). To run the notebooks on Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133).

Use Chainer with Amazon SageMaker

You can use SageMaker to train and deploy a model using custom Chainer code. The SageMaker Python SDK Chainer estimators and models and the SageMaker open-source Chainer container make writing a Chainer script and running it in SageMaker easier.

**What do you want to do?**

I want to train a custom Chainer model in SageMaker.

For a sample Jupyter notebook, see the Chainer example notebooks in the Amazon SageMaker Examples GitHub repository.

For documentation, see Train a Model with Chainer.

I have a Chainer model that I trained in SageMaker, and I want to deploy it to a hosted endpoint.

For more information, see Deploy Chainer models.

I have a Chainer model that I trained outside of SageMaker, and I want to deploy it to a SageMaker endpoint

For more information, see Deploy Endpoints from Model Data.

I want to see the API documentation for Amazon SageMaker Python SDK Chainer classes.

For more information, see Chainer Classes.

I want to find information about SageMaker Chainer containers.

For more information, see the SageMaker Chainer Container GitHub repository.

For information about supported Chainer versions, and for general information about writing Chainer training scripts and using Chainer estimators and models with SageMaker, see Using Chainer with the SageMaker Python SDK.
Use Hugging Face with Amazon SageMaker

Amazon SageMaker enables customers to train, fine-tune, and run inference using Hugging Face models for Natural Language Processing (NLP) on SageMaker. You can use Hugging Face for both training and inference. This functionality is available through the development of Hugging Face AWS Deep Learning Containers. These containers include Hugging Face Transformers, Tokenizers and the Datasets library, which allows you to use these resources for your training and inference jobs. For a list of the available Deep Learning Containers images, see Available Deep Learning Containers Images. These Deep Learning Containers images are maintained and regularly updated with security patches.

To use the Hugging Face Deep Learning Containers with the SageMaker Python SDK for training, see the Hugging Face SageMaker Estimator. With the Hugging Face Estimator, you can use the Hugging Face models as you would any other SageMaker Estimator. However, using the SageMaker Python SDK is optional. You can also orchestrate your use of the Hugging Face Deep Learning Containers with the AWS CLI and AWS SDK for Python (Boto3).

For more information on Hugging Face and the models available in it, see the Hugging Face documentation.

Training

To run training, you can use any of the thousands of models available in Hugging Face and fine-tune them for your specific use case with additional training. With SageMaker, you can use standard training or take advantage of SageMaker Distributed Data and Model Parallel training. As with other SageMaker training jobs using custom code, you can capture your own metrics by passing a metrics definition to the SageMaker Python SDK as shown in Defining Training Metrics (SageMaker Python SDK). The captured metrics are then accessible via CloudWatch and as a Pandas DataFrame via the TrainingJobAnalytics method. Once your model is trained and fine-tuned, you can use it like any other model to run inference jobs.

How to run training with the Hugging Face Estimator

You can implement the Hugging Face Estimator for training jobs using the SageMaker Python SDK. The SageMaker Python SDK is an open source library for training and deploying machine learning models on SageMaker. For more information on the Hugging Face Estimator, see the SageMaker Python SDK documentation.

With the SageMaker Python SDK, you can run training jobs using the Hugging Face Estimator in the following environments:

- **SageMaker Studio**: Amazon SageMaker Studio is the first fully integrated development environment (IDE) for machine learning (ML). SageMaker Studio provides a single, web-based visual interface where you can perform all ML development steps required to prepare, build, train and tune, deploy and manage models. For information on using Jupyter Notebooks in Studio, see Use Amazon SageMaker Studio Notebooks.

- **SageMaker Notebook Instances**: An Amazon SageMaker notebook instance is a machine learning (ML) compute instance running the Jupyter Notebook App. This app lets you run Jupyter Notebooks in your notebook instance to prepare and process data, write code to train models, deploy models to SageMaker hosting, and test or validate your models without SageMaker Studio features like Debugger, Model Monitoring, and a web-based IDE.

- **Locally**: If you have connectivity to AWS and have appropriate SageMaker permissions, you can use the SageMaker Python SDK locally to launch remote training and inference jobs for Hugging Face in SageMaker on AWS. This works on your local machine, as well as other AWS services with a connected SageMaker Python SDK and appropriate permissions.
Inference

For inference, you can use your trained Hugging Face model or one of the pretrained Hugging Face models to deploy an inference job with SageMaker. With this collaboration, you only need one line of code to deploy both your trained models and pretrained models with SageMaker. You can also run inference jobs without having to write any custom inference code. With custom inference code, you can customize the inference logic by providing your own Python script.

How to deploy an inference job using the Hugging Face Deep Learning Containers

You have two options for running inference with SageMaker. You can run inference using a model that you trained, or deploy a pretrained Hugging Face model.

- **Run inference with your trained model**: You have two options for running inference with your own trained model. You can run inference with a model that you trained using an existing Hugging Face model with the SageMaker Hugging Face Deep Learning Containers, or you can bring your own existing Hugging Face model and deploy it using SageMaker. When you run inference with a model that you trained with the SageMaker Hugging Face Estimator, you can deploy the model immediately after training completes or you can upload the trained model to an Amazon S3 bucket and ingest it when running inference later. If you bring your own existing Hugging Face model, you must upload the trained model to an Amazon S3 bucket and ingest that bucket when running inference as shown in Deploy your Hugging Face Transformers for inference example.

- **Run inference with a pretrained Hugging Face model**: You can use one of the thousands of pretrained Hugging Face models to run your inference jobs with no additional training needed. To run inference, you select the pretrained model from the list of Hugging Face models, as outlined in Deploy pre-trained Hugging Face Transformers for inference example.

What do you want to do?

The following Jupyter Notebooks in the Hugging Face notebooks repository illustrate how to use the Hugging Face Deep Learning Containers with SageMaker in various use cases.

I want to train and deploy a text classification model using Hugging Face in SageMaker with PyTorch.

For a sample Jupyter Notebook, see the PyTorch Getting Started Demo.

I want to train and deploy a text classification model using Hugging Face in SageMaker with TensorFlow.

For a sample Jupyter Notebook, see the TensorFlow Getting Started example.

I want to run distributed training with data parallelism using Hugging Face and SageMaker Distributed.

For a sample Jupyter Notebook, see the Distributed Training example.

I want to run distributed training with model parallelism using Hugging Face and SageMaker Distributed.

For a sample Jupyter Notebook, see the Model Parallelism example.

I want to use a spot instance to train and deploy a model using Hugging Face in SageMaker.

For a sample Jupyter Notebook, see the Spot Instances example.

I want to capture custom metrics and use SageMaker Checkpointing when training a text classification model using Hugging Face in SageMaker.

For a sample Jupyter Notebook, see the Training with Custom Metrics example.

I want to train a distributed question-answering TensorFlow model using Hugging Face in SageMaker.

For a sample Jupyter Notebook, see the Distributed TensorFlow Training example.
I want to train a distributed summarization model using Hugging Face in SageMaker.

For a sample Jupyter Notebook, see the Distributed Summarization Training example.

I want to train an image classification model using Hugging Face in SageMaker.

For a sample Jupyter Notebook, see the Vision Transformer Training example.

I want to deploy my trained Hugging Face model in SageMaker.

For a sample Jupyter Notebook, see the Deploy your Hugging Face Transformers for inference example.

I want to deploy a pre-trained Hugging Face model in SageMaker.

For a sample Jupyter Notebook, see the Deploy pre-trained Hugging Face Transformers for inference example.

**Use PyTorch with Amazon SageMaker**

You can use Amazon SageMaker to train and deploy a model using custom PyTorch code. The SageMaker Python SDK PyTorch estimators and models and the SageMaker open-source PyTorch container make writing a PyTorch script and running it in SageMaker easier.

What do you want to do?

I want to train a custom PyTorch model in SageMaker.

For a sample Jupyter notebook, see the PyTorch example notebook in the Amazon SageMaker Examples GitHub repository.

For documentation, see Train a Model with PyTorch.

I have a PyTorch model that I trained in SageMaker, and I want to deploy it to a hosted endpoint.

For more information, see Deploy PyTorch models.

I have a PyTorch model that I trained outside of SageMaker, and I want to deploy it to a SageMaker endpoint.

For more information, see Deploy Endpoints from Model Data.

I want to see the API documentation for Amazon SageMaker Python SDK PyTorch classes.

For more information, see PyTorch Classes.

I want to find the SageMaker PyTorch container repository.

For more information, see SageMaker PyTorch Container GitHub repository.

I want to find information about PyTorch versions supported by AWS Deep Learning Containers.

For more information, see Available Deep Learning Container Images.

For general information about writing PyTorch training scripts and using PyTorch estimators and models with SageMaker, see Using PyTorch with the SageMaker Python SDK.

**R User Guide to Amazon SageMaker**

This document will walk you through ways of leveraging Amazon SageMaker features using R. This guide introduces SageMaker's built-in R kernel, how to get started with R on SageMaker, and finally several example notebooks.
The examples are organized in three levels, Beginner, Intermediate, and Advanced. They start from Getting Started with R on SageMaker, continue to end-to-end machine learning with R on SageMaker, and then finish with more advanced topics such as SageMaker Processing with R script, and Bring-Your-Own (BYO) R algorithm to SageMaker.

For information on how to bring your own custom R image to Studio, see Bring your own SageMaker image (p. 152). For a similar blog article, see Bringing your own R environment to Amazon SageMaker Studio.

RStudio Support in SageMaker

Amazon SageMaker supports RStudio as a fully-managed integrated development environment (IDE) integrated with Amazon SageMaker Domain. With RStudio integration, you can launch an RStudio environment in the Domain to run your RStudio workflows on SageMaker resources. For more information, see RStudio on Amazon SageMaker (p. 182).

R Kernel in SageMaker

SageMaker notebook instances support R using a pre-installed R kernel. Also, the R kernel has the reticulate library, an R to Python interface, so you can use the features of SageMaker Python SDK from within an R script.

- reticulatelibrary: provides an R interface to the Amazon SageMaker Python SDK. The reticulate package translates between R and Python objects.

Get Started with R in SageMaker

- Create a Notebook Instance using the t2.medium instance type and default storage size. You can pick a faster instance and more storage if you plan to continue using the instance for more advanced examples, or create a bigger instance later.
- Wait until the status of the notebook is In Service, and then click Open Jupyter.

- Create a new notebook with R kernel from the list of available environments.
• When the new notebook is created, you should see an R logo in the upper right corner of the notebook environment, and also R as the kernel under that logo. This indicates that SageMaker has successfully launched the R kernel for this notebook.

• Alternatively, when you are in a Jupyter notebook, you can use Kernel menu, and then select R from Change Kernel option.

Example Notebooks

Prerequisites

Getting Started with R on SageMaker: This sample notebook describes how you can develop R scripts using Amazon SageMaker’s R kernel. In this notebook you set up your SageMaker environment and permissions, download the abalone dataset from the UCI Machine Learning Repository, do some basic processing and visualization on the data, then save the data as .csv format to S3.

Beginner Level

SageMaker Batch Transform using R Kernel: This sample Notebook describes how to conduct a batch transform job using SageMaker’s Transformer API and the XGBoost algorithm. The notebook also uses the Abalone dataset.

Intermediate Level

Hyperparameter Optimization for XGBoost in R: This sample notebook extends the previous beginner notebooks that use the abalone dataset and XGBoost. It describes how to do model tuning with hyperparameter optimization. You will also learn how to use batch transform for batching predictions, as well as how to create a model endpoint to make real-time predictions.

Amazon SageMaker Processing with R: SageMaker Processing lets you preprocess, post-process and run model evaluation workloads. This example shows you how to create an R script to orchestrate a Processing job.

Advanced Level
**Train and Deploy Your Own R Algorithm in SageMaker:** Do you already have an R algorithm, and you want to bring it into SageMaker to tune, train, or deploy it? This example walks you through how to customize SageMaker containers with custom R packages, all the way to using a hosted endpoint for inference on your R-origin model.

### Use Scikit-learn with Amazon SageMaker

You can use Amazon SageMaker to train and deploy a model using custom Scikit-learn code. The SageMaker Python SDK Scikit-learn estimators and models and the SageMaker open-source Scikit-learn containers make writing a Scikit-learn script and running it in SageMaker easier.

#### Requirements

Scikit-learn 1.0 has the following dependencies.

<table>
<thead>
<tr>
<th>Dependency</th>
<th>Minimum version</th>
</tr>
</thead>
<tbody>
<tr>
<td>Python</td>
<td>3.7</td>
</tr>
<tr>
<td>NumPy</td>
<td>1.14.6</td>
</tr>
<tr>
<td>SciPy</td>
<td>1.1.0</td>
</tr>
<tr>
<td>joblib</td>
<td>0.11</td>
</tr>
<tr>
<td>threadpoolctl</td>
<td>2.0.0</td>
</tr>
</tbody>
</table>

The SageMaker Scikit-learn container supports the following Scikit-learn versions.

<table>
<thead>
<tr>
<th>Supported Scikit-learn version</th>
<th>Minimum Python version</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.0-1</td>
<td>3.7</td>
</tr>
<tr>
<td>0.23-1</td>
<td>3.6</td>
</tr>
<tr>
<td>0.20.0</td>
<td>2.7 or 3.4</td>
</tr>
</tbody>
</table>

For general information about writing Scikit-learn training scripts and using Scikit-learn estimators and models with SageMaker, see [Using Scikit-learn with the SageMaker Python SDK](#).

### What do you want to do?

**Note**

Matplotlib v2.2.3 or newer is required to run the SageMaker Scikit-learn example notebooks.

I want to use Scikit-learn for data processing, feature engineering, or model evaluation in SageMaker.


For documentation, see [ReadTheDocs](#).

I want to train a custom Scikit-learn model in SageMaker.

I have a Scikit-learn model that I trained in SageMaker, and I want to deploy it to a hosted endpoint. For more information, see Deploy Scikit-learn models.

I have a Scikit-learn model that I trained outside of SageMaker, and I want to deploy it to a SageMaker endpoint. For more information, see Deploy Endpoints from Model Data.

I want to see the API documentation for Amazon SageMaker Python SDK Scikit-learn classes. For more information, see Scikit-learn Classes.

I want to see information about SageMaker Scikit-learn containers. For more information, see SageMaker Scikit-learn Container GitHub repository.

Use SparkML Serving with Amazon SageMaker

The Amazon SageMaker Python SDK SparkML Serving model and predictor and the Amazon SageMaker open-source SparkML Serving container support deploying Apache Spark ML pipelines serialized with MLeeap in SageMaker to get inferences.

For information about using the SparkML Serving container to deploy models to SageMaker, see SageMaker Spark ML Container GitHub repository. For information about the Amazon SageMaker Python SDK SparkML Serving model and predictors, see the SparkML Serving Model and Predictor API documentation.

Use TensorFlow with Amazon SageMaker


Use TensorFlow Version 1.11 and Later

For TensorFlow versions 1.11 and later, the Amazon SageMaker Python SDK supports script mode training scripts.

What do you want to do?

I want to train a custom TensorFlow model in SageMaker.

For a sample Jupyter notebook, see TensorFlow script mode training and serving.

For documentation, see Train a Model with TensorFlow.

I have a TensorFlow model that I trained in SageMaker, and I want to deploy it to a hosted endpoint.

For more information, see Deploy TensorFlow Serving models.

I have a TensorFlow model that I trained outside of SageMaker, and I want to deploy it to a SageMaker endpoint.

For more information, see Deploying directly from model artifacts.

I want to see the API documentation for Amazon SageMaker Python SDK TensorFlow classes.

For more information, see TensorFlow Estimator.
I want to find the SageMaker TensorFlow container repository.

For more information, see SageMaker TensorFlow Container GitHub repository.

I want to find information about TensorFlow versions supported by AWS Deep Learning Containers.

For more information, see Available Deep Learning Container Images.

For general information about writing TensorFlow script mode training scripts and using TensorFlow script mode estimators and models with SageMaker, see Using TensorFlow with the SageMaker Python SDK.

Use TensorFlow Legacy Mode for Versions 1.11 and Earlier

The Amazon SageMaker Python SDK provides a legacy mode that supports TensorFlow versions 1.11 and earlier. Use legacy mode TensorFlow training scripts to run TensorFlow jobs in SageMaker if:

• You have existing legacy mode scripts that you do not want to convert to script mode.
• You want to use a TensorFlow version earlier than 1.11.

For information about writing legacy mode TensorFlow scripts to use with the SageMaker Python SDK, see TensorFlow SageMaker Estimators and Models.

Use Triton Inference Server with Amazon SageMaker

SageMaker enables customers to deploy a model using custom code with NVIDIA Triton Inference Server. This functionality is available through the development of Triton Inference Server Containers. These containers include NVIDIA Triton Inference Server, support for common ML frameworks, and useful environment variables that let you optimize performance on SageMaker. For a list of all available Deep Learning Containers images, see Available Deep Learning Containers Images. Deep Learning Containers images are maintained and regularly updated with security patches.

You can use the Triton Inference Server Container with SageMaker Python SDK as you would any other container in your SageMaker models. However, using the SageMaker Python SDK is optional. You can use Triton Inference Server Containers with the AWS CLI and AWS SDK for Python (Boto3).

For more information on NVIDIA Triton Inference Server see the Triton documentation.

Inference

Note

The Triton Python backend uses shared memory (SHMEM) to connect your code to Triton. SageMaker Inference provides up to half of the instance memory as SHMEM so you can use an instance with more memory for larger SHMEM size.

For inference, you can use your trained ML models with Triton Inference Server to deploy an inference job with SageMaker.

Some of the key features of Triton Inference Server Container are:

• Support for multiple frameworks: Triton can be used to deploy models from all major ML frameworks. Triton supports TensorFlow GraphDef and SavedModel, ONNX, PyTorch TorchScript, TensorRT, and custom Python/C++ model formats.
• Model pipelines: Triton model ensemble represents a pipeline of one model with pre/post processing logic and the connection of input and output tensors between them. A single inference request to an ensemble triggers the execution of the entire pipeline.
• **Concurrent model execution**: Multiple instances of the same model can run simultaneously on the same GPU or on multiple GPUs.

• **Dynamic batching**: For models that support batching, Triton has multiple built-in scheduling and batching algorithms that combine individual inference requests together to improve inference throughput. These scheduling and batching decisions are transparent to the client requesting inference.

• **Diverse CPU and GPU support**: The models can be executed on CPUs or GPUs for maximum flexibility and to support heterogeneous computing requirements.

**What do you want to do?**

I want to deploy my trained PyTorch model in SageMaker.

For a sample Jupyter Notebook, see the [Deploy your PyTorch Resnet50 model with Triton Inference Server example](#).

I want to deploy my trained Hugging Face model in SageMaker.

For a sample Jupyter Notebook, see the [Deploy your PyTorch BERT model with Triton Inference Server example](#).

**Supported Regions and Quotas**

For the AWS Regions supported by Amazon SageMaker and the Amazon Elastic Compute Cloud (Amazon EC2) instance types that are available in each Region, see [Amazon SageMaker Pricing](#).

For a list of the SageMaker service endpoints for each Region, see [Amazon SageMaker endpoints and quotas in the AWS General Reference](#).

Amazon SageMaker Pipelines is available in all the AWS Regions supported by AWS except the AWS GovCloud (US) Regions. SageMaker Projects is available in the AWS regions where CodePipeline is available. For more information about CodePipeline region availability, see the [AWS Regional Services List](#).

The following SageMaker features aren’t available in the Asia Pacific (Osaka) Region:

• Amazon SageMaker Autopilot
• Clarify
• SageMaker Edge Manager
• Ground Truth
• Amazon SageMaker Inference Recommender
• Amazon SageMaker Model Monitor
• Reinforcement learning
• RStudio on Amazon SageMaker

**Quotas**

The **Service Quotas console** provides information about your service quotas. You can use the Service Quotas console to view your default service quotas or to request quota increases. To request a quota increase for adjustable quotas, see [Requesting a quota increase](#).

You can set up a quota request template for your AWS Organization that automatically requests quota increases during account creation. For more information, see [Using Service Quotas request templates](#).
Get Started with Amazon SageMaker

Before you can use Amazon SageMaker, you must sign up for an AWS account and create an IAM admin user by following the steps in Set Up Amazon SageMaker Prerequisites (p. 33).

Amazon SageMaker Studio Lab does not require an AWS account or IAM integration.

After you complete these tasks, continue to one of the following topics, depending on your use case.

- **Onboard to Amazon SageMaker Domain (p. 35):** Follow these steps to create a Domain, which gives you access to Amazon SageMaker Studio and RStudio on Amazon SageMaker. For more information about Domains, see Amazon SageMaker Machine Learning Environments (p. 115).
- **SageMaker JumpStart (p. 45):** Follow these steps to start working with SageMaker JumpStart and learn about SageMaker features and capabilities through curated one-click solutions, example notebooks, and pretrained models that you can deploy. To use SageMaker JumpStart, which is a feature of Amazon SageMaker Studio, you must first onboard to an Amazon SageMaker Domain.
- **Get Started with Amazon SageMaker Notebook Instances (p. 73):** Follow these steps to train and deploy Machine Learning (ML) models using SageMaker notebook instances. SageMaker notebook instances help create the environment by initiating Jupyter servers on Amazon Elastic Compute Cloud (Amazon EC2) and providing preconfigured kernels. For more information, see Use Amazon SageMaker Notebook Instances (p. 291).
- **Amazon SageMaker Studio Lab (p. 90):** Follow these steps to start working with Amazon SageMaker Studio Lab. Studio Lab is a free service that gives you access to AWS compute resources, in an environment based on open-source JupyterLab, without requiring an AWS account.

Topics

- Set Up Amazon SageMaker Prerequisites (p. 33)
- Onboard to Amazon SageMaker Domain (p. 35)
- SageMaker JumpStart (p. 45)
- Get Started with Amazon SageMaker Notebook Instances (p. 73)
- Amazon SageMaker Studio Lab (p. 90)

Set Up Amazon SageMaker Prerequisites

In this section, you sign up for an AWS account and create an AWS Identity and Access Management (IAM) admin user.

If you’re new to SageMaker, we recommend that you read How Amazon SageMaker Works (p. 4).

Topics

- Create an AWS Account (p. 33)
- Create an IAM Administrator User and Group (p. 34)

Create an AWS Account

In this section, you sign up for an AWS account. If you already have an AWS account, skip this step.

When you sign up for Amazon Web Services (AWS), your AWS account is automatically signed up for all AWS services, including SageMaker. You are charged only for the services that you use.
To create an AWS account
2. Follow the online instructions.

Part of the sign-up procedure involves receiving a phone call and entering a verification code on the phone keypad.

When you sign up for an AWS account, an AWS account root user is created. The root user has access to all AWS services and resources in the account. As a security best practice, assign administrative access to an administrative user, and use only the root user to perform tasks that require root user access.

Write down your AWS account ID because you'll need it for the next task.

Create an IAM Administrator User and Group

When you create an AWS account, you get a single sign-in identity that has complete access to all of the AWS services and resources in the account. This identity is called the AWS account root user. Signing in to the AWS console using the email address and password that you used to create the account gives you complete access to all of the AWS resources in your account.

We strongly recommend that you not use the root user for everyday tasks, even the administrative ones. Instead, adhere to the Create Individual IAM Users, an AWS Identity and Access Management (IAM) administrator user. Then securely lock away the root user credentials and use them to perform only a few account and service management tasks.

To create an administrator user
1. Create an administrator user in your AWS account. For instructions, see Creating Your First IAM User and Administrators Group in the IAM User Guide.

   Note
   We assume that you use administrator user credentials for the exercises and procedures in this guide. If you choose to create and use another IAM user, grant that user minimum permissions. For more information, see Authenticating with Identities (p. 3501).

2. Ensure that your administrator user has the AmazonSageMakerFullAccess policy, as well as a policy with the following content needed to create a SageMaker domain. For more information about creating IAM policies, see Creating IAM policies.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [
                "sagemaker:*"
            ],
            "Resource": [
                "arn:aws:sagemaker:*:*:domain/*",
                "arn:aws:sagemaker:*:*:user-profile/*",
                "arn:aws:sagemaker:*:*:app/*",
                "arn:aws:sagemaker:*:*:flow-definition/*"
            ]
        },
        {
            "Effect": "Allow",
            "Action": [
                "iam:GetRole",
                "iam:PassRole"
            ],
            "Resource": [
                "arn:aws:iam:::role/*",
                "arn:aws:iam:::instance-profile/*"
            ]
        }
    ]
}
```
Onboard to Amazon SageMaker Domain

An Amazon SageMaker Domain consists of an associated Amazon Elastic File System (Amazon EFS) volume; a list of authorized users; and a variety of security, application, policy, and Amazon Virtual Private Cloud (Amazon VPC) configurations. To use Amazon SageMaker Studio, Amazon SageMaker Studio Notebooks, and RStudio, you must complete the Amazon SageMaker Domain onboarding process using the SageMaker console. For more information about Amazon SageMaker Domains, see Amazon SageMaker Machine Learning Environments (p. 115).

When onboarding, you can choose to use either AWS IAM Identity Center (successor to AWS Single Sign-On) (IAM Identity Center) or AWS Identity and Access Management (IAM) for authentication methods. When you use IAM authentication, you can choose either the Quick setup or the Standard setup procedure. RStudio setup is only available when using the Standard setup procedure.

Note
If you onboard using IAM authentication and want to switch to authentication using IAM Identity Center later, you must delete the Domain that you created. Then, you need to manually re-import all notebooks and other user data that you created. For more information, see Delete an Amazon SageMaker Domain (p. 43).

The simplest way to create an Amazon SageMaker Domain is to follow the Quick setup procedure. Quick setup uses the same default settings as the Standard setup procedures. These settings include shareable notebooks and public internet access. For more control, including the option of using authentication using IAM Identity Center and RStudio, use the Standard setup procedures.

Authentication using IAM Identity Center

To use authentication using IAM Identity Center with Amazon SageMaker Studio and RStudio, you must onboard to an AWS Organizations organization.

Note
The AWS Organizations account must be in the same AWS Region as Amazon SageMaker Studio and RStudio.

Authentication using IAM Identity Center provides the following benefits over IAM authentication:

• Members given access to Studio have a unique sign-in URL that directly opens Studio, and they sign in with their IAM Identity Center credentials. When you use IAM authentication, you must sign in through the SageMaker console.
• Organizations manage their members in IAM Identity Center instead of the Domain. You can assign multiple members access to the Domain at the same time. When you use IAM authentication, you must add and manage members manually, one at time, using the Domain Control Panel.

Topics
• Onboard to Amazon SageMaker Domain Using Quick setup (p. 36)
• Onboard to Amazon SageMaker Domain Using IAM Identity Center (p. 37)
• Onboard to Amazon SageMaker Domain Using IAM (p. 40)
Onboard to Amazon SageMaker Domain Using Quick setup

This topic describes how to onboard to Amazon SageMaker Domain using the Quick setup procedure, which uses AWS Identity and Access Management (IAM) authentication. For information on how to onboard using the standard IAM procedure, see Onboard Using IAM (p. 40).

RStudio support is not currently available when onboarding using the Quick setup procedure.

For information on how to onboard using AWS IAM Identity Center (successor to AWS Single Sign-On) (IAM Identity Center), see Onboard Using IAM Identity Center (p. 37).

To onboard to the Domain using Quick setup

1. Open the SageMaker console.
2. Choose Control Panel at the top left of the page.
4. Under User profile, for Name keep the default name or create a new name. The name can be up to 63 characters. Valid characters: A-Z, a-z, 0-9, and - (hyphen).
5. For Default execution role, choose an option from the role selector. This is the default role that is assigned to the Amazon SageMaker Domain user profile.

   If you choose Enter a custom IAM role ARN, the role must have at a minimum, an attached trust policy that grants SageMaker permission to assume the role. For more information, see SageMaker Roles (p. 3536).

   If you choose Create a new role, the Create an IAM role dialog opens:
   - For S3 buckets you specify, specify additional S3 buckets that users of your notebooks can access. If you don't want to add access to more buckets, choose None.
   - Choose Create role. SageMaker creates a new IAM AmazonSageMaker-ExecutionPolicy role with the AmazonSageMakerFullAccess policy attached.
6. Choose Submit.
7. From the pop-up window, select a Amazon Virtual Private Cloud (Amazon VPC) and subnet to use.
8. Choose Save and continue.

   Note
   If you receive an error message that you need to create a VPC, see Choose a VPC (p. 42).

   When Status is Ready, the user name that you specified is enabled and chosen. The Add user and Delete user buttons, and the Launch app link are also enabled.

   When Studio opens, you can start using it.

Now that you've onboarded to SageMaker Studio, use the following steps to access Studio later.

To access Studio after you onboard

1. Open the SageMaker console.
2. Choose Control Panel at the top left of the page.
3. On the Control Panel, choose your user name and then choose Launch app. Select Studio.

To add more users
1. On the Control Panel, choose Add user.
2. Repeat steps 4 and 5 from the first procedure, “To onboard to Amazon SageMaker Domain using Quick setup.”
3. Choose Submit.

For information about using SageMaker Studio, see SageMaker Studio (p. 117).

Onboard to Amazon SageMaker Domain Using IAM Identity Center

This topic describes how to onboard to Amazon SageMaker Domain using authentication using IAM Identity Center. For information on how to onboard using AWS Identity and Access Management (IAM) authentication, see Onboard Using Quick setup (p. 36) or Onboard Using IAM (p. 40).

To onboard to Domain using IAM Identity Center
1. Open the SageMaker console.
2. Choose Control Panel at the top left of the page.
4. Select Configure.

Step 1: General settings
1. For Authentication, choose AWS IAM Identity Center (successor to AWS Single Sign-On).
2. If you don't have a group in IAM Identity Center in the same Region as your SageMaker Domain, you must create a group in IAM Identity Center in the same Region as your SageMaker Domain before proceeding. To continue to onboard without IAM Identity Center, choose the AWS Identity and Access Management (IAM) authentication method or the Quick setup procedure, which also uses IAM.

For information about setting up IAM Identity Center for use with Domain, see Set Up IAM Identity Center for use with Amazon SageMaker Domain (p. 39).
3. Under Permission, for IAM role, choose an option from the role selector.

If you choose Enter a custom IAM role ARN, the role must have at a minimum, an attached trust policy that grants SageMaker permission to assume the role. For more information, see SageMaker Roles (p. 3536).

If you choose Create a new role, the Create an IAM role dialog opens:

   a. For S3 buckets you specify, specify additional S3 buckets that users of your notebooks can access. If you don't want to add access to more buckets, choose None.
   b. Choose Create role. SageMaker creates a new IAM AmazonSageMaker-ExecutionPolicy role with the AmazonSageMakerFullAccess policy attached.

4. Under Network and storage, specify the following:
   • Your VPC information – For more information, see Choose a VPC (p. 42).
(Optional) **Encryption key** – SageMaker uses an AWS KMS key to encrypt your Amazon Elastic File System (Amazon EFS) and Amazon Elastic Block Store (Amazon EBS) file systems. By default, it uses an AWS managed key. To use a customer managed key, enter its key ID or Amazon Resource Name (ARN). For more information, see Protect Data at Rest Using Encryption (p. 3496).

**Note**
Encryption in transit is only available for Amazon SageMaker Studio.

5. Select **Next**.

**Step 2: Studio settings**

1. Under **Default JupyterLab version**, select a JupyterLab version from the dropdown to use as the default for your domain. For information on selecting a JupyterLab version, see JupyterLab Versioning (p. 120).

2. Under **Notebook Sharing Configuration**, accept the default notebook sharing configuration or customize the options.

3. Under **SageMaker Projects and JumpStart**, accept the default Project and JumpStart settings, or customize whether administrators and users can create projects and use JumpStart. For more information, see SageMaker Studio Permissions Required to Use Projects (p. 3286).

4. Select **Next**.

**Step 3: RStudio settings**

1. Under **RStudio Workbench**, verify that your RStudio license is automatically detected. For more information about getting an RStudio license and activating it with SageMaker, see RStudio license (p. 183).

2. Select an instance type to launch your RStudio Server on. For more information, see RStudioServerPro instance type (p. 186).

3. Under **Permission**, create your role or select an existing role. The role must have the following permissions policy. This policy allows the RStudioServerPro app to access necessary resources and allows Amazon SageMaker to automatically launch an RStudioServerPro app when the existing RStudioServerPro app is in a Deleted or Failed status. For information about adding permissions to a role, see Modifying a role permissions policy (console).

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "VisualEditor0",
      "Effect": "Allow",
      "Action": [
        "license-manager:ExtendLicenseConsumption",
        "license-manager:ListReceivedLicenses",
        "license-manager:GetLicense",
        "license-manager:CheckoutLicense",
        "license-manager:CheckInLicense",
        "logs:CreateLogDelivery",
        "logs:CreateLogGroup",
        "logs:CreateLogStream",
        "logs:DeleteLogDelivery",
        "logs:Describe*",
        "logs:GetLogDelivery",
        "logs:GetLogEvents",
        "logs:GetLogGroup",
        "logs:GetLogStream",
        "logs:GetLogTag",
        "logs:GetLogTrace",
        "logs:ListLogDeliveries",
        "logs:ListLogGroups",
        "logs:ListLogStreams",
        "logs:TagLogDelivery",
        "logs:TagLogGroup",
        "logs:PutLogEvents",
        "logs:UpdateLogDelivery"
      ]
    }
  ]
}
```
4. Under **RStudio Connect**, add the URL for your RStudio Connect server. RStudio Connect is a publishing platform for Shiny applications, R Markdown reports, dashboards, plots, and more. When you onboard to RStudio on SageMaker, an RStudio Connect server is not created. For more information, see **RStudio Connect URL** (p. 186).

5. Under **RStudio Package Manager**, add the URL for your RStudio Package Manager. SageMaker creates a default package repository for the Package Manager when you onboard RStudio. For more information about RStudio Package Manager, see **RStudio Package Manager** (p. 187).

6. Select **Submit**.

**To access the Domain after onboarding**

After you are given access to the Domain, you are sent an email inviting you to create a password and use IAM Identity Center. The email also contains the URL to sign in to the Domain. For more information about signing in and session duration, see **How to sign in to the user portal**.

After you activate your account, go to the Domain URL, sign in, and wait for your user profile to be created. On subsequent visits, you only need to wait for the Studio or RStudio app to load.

Bookmark the URL. The URL is also available in the **Control Panel**.

For information about using SageMaker Studio, see **SageMaker Studio** (p. 117).

For information about using RStudio, see **RStudio on Amazon SageMaker** (p. 182).

**Set Up IAM Identity Center for use with Amazon SageMaker Domain**

To use authentication in IAM Identity Center, you must belong to an AWS Organizations. If you don't belong to an AWS Organizations, you can create one following the steps in **Tutorial: Creating and configuring an organization**.

After you have created your organization and user, you can create a SageMaker Studio user profile for that user in IAM Identity Center as follows.

1. **From the Amazon SageMaker Console**: – You can use the Amazon SageMaker Console to create a user profile for the user in IAM Identity Center. If the user in IAM Identity Center hasn’t already been associated with Studio, it is automatically associated.

2. **Using the AWS CLI or AWS CloudFormation** – A user in IAM Identity Center assigned to Studio can create a Studio user profile using the SageMaker console, AWS CLI or AWS CloudFormation.
   - The user in IAM Identity Center, or a group in IAM Identity Center containing that user, must first be assigned to the Studio application from the IAM Identity Center Console. For more information about application assignment, see **Assign user access**.
   - A user profile can then be created for the user in IAM Identity Center with the AWS CLI or AWS CloudFormation.

**Note**

To simplify administration of access permissions, we recommend assigning groups in IAM Identity Center to the SageMaker Studio application instead of assigning users in IAM Identity Center. Groups allow permissions to be granted or denied to multiple users at once.
A user can be moved out of a group or to a different group if needed. When assigning user access to applications, IAM Identity Center does not currently support users being added to nested groups. If a user is added to a nested group, they may receive a “You do not have any applications” error message during sign-in. Assignments must be made to the immediate group the user is a member of.

Return to the Control Panel to continue to onboard using authentication using IAM Identity Center.

Onboard to Amazon SageMaker Domain Using IAM

This topic describes how to onboard to Amazon SageMaker Domain using the standard setup procedure for AWS Identity and Access Management (IAM) authentication. To onboard faster using IAM, see Onboard Using Quick setup (p. 36).

For information on how to onboard using AWS IAM Identity Center (successor to AWS Single Sign-On) (IAM Identity Center), see Onboard Using IAM Identity Center (p. 37).

To onboard to Domain using IAM

1. Open the SageMaker console.
2. Choose Control Panel at the top left of the page.
4. Select Configure.

Step 1: General settings

1. For Authentication, choose AWS Identity and Access Management (IAM).
2. Under Permission, for IAM role, choose an option from the role selector.
   If you choose Enter a custom IAM role ARN, the role must have at a minimum, an attached trust policy that grants SageMaker permission to assume the role. For more information, see SageMaker Roles (p. 3536).
   If you choose Create a new role, the Create an IAM role dialog opens:
   a. For S3 buckets you specify, specify additional S3 buckets that users of your notebooks can access. If you don't want to add access to more buckets, choose None.
   b. Choose Create role. SageMaker creates a new IAM AmazonSageMaker-ExecutionPolicy role with the AmazonSageMakerFullAccess policy attached.
3. Under Network and storage, specify the following:
   • Your VPC information – For more information, see Choose a VPC (p. 42).
   • (Optional) Storage encryption key – SageMaker uses an AWS KMS key to encrypt your Amazon Elastic File System (Amazon EFS) and Amazon Elastic Block Store (Amazon EBS) file systems. By default, it uses an AWS managed key. To use a customer managed key, enter its key ID or Amazon Resource Name (ARN). For more information, see Protect Data at Rest Using Encryption (p. 3496).
     Note
     Encryption in transit is only available for Amazon SageMaker Studio.
4. Select Next.

Step 2: Studio settings

1. Under Default JupyterLab version, select a JupyterLab version from the dropdown to use as the default for your domain. For information on selecting a JupyterLab version, see JupyterLab Versioning (p. 120).
2. Under **Notebook Sharing Configuration**, accept the default notebook sharing configuration or customize the options.

3. Under **SageMaker Projects and JumpStart**, accept the default Project and JumpStart settings or customize whether administrators and user can create projects and use Jumpstart. For more information, see [SageMaker Studio Permissions Required to Use Projects](p. 3286).

4. Select **Next**.

**Step 3: RStudio settings**

1. Under **RStudio Workbench**, verify that your RStudio license is automatically detected. For more information about getting an RStudio license and activating it with SageMaker, see [RStudio license](p. 183).

2. Select an instance type to launch your RStudio Server on. For more information, see [RStudioServerPro instance type](p. 186).

3. Under **Permission**, create your role or select an existing role. The role must have the following permissions policy. This policy allows the RStudioServerPro app to access necessary resources and allows Amazon SageMaker to automatically launch an RStudioServerPro app when the existing RStudioServerPro app is in a Deleted or Failed status. For information on adding permissions to a role, see [Modifying a role permissions policy (console)].

4. Under **RStudio Connect**, add the URL for your RStudio Connect Server. RStudio Connect is a publishing platform for Shiny applications, R Markdown reports, dashboards, plots, and more. When you onboard to RStudio on Amazon SageMaker, an RStudio Connect server is not created. You must create an RStudio Connect server on an EC2 instance to use Connect with Amazon SageMaker. For more information, see [RStudio Connect URL](p. 186).

5. Under **RStudio Package Manager**, add the URL for your RStudio Package Manager. SageMaker creates a default package repository for the Package Manager when you onboard RStudio. For more information about RStudio Package Manager, see [RStudio Package Manager](p. 187).

6. Select **Submit**.
Choose a VPC

This topic provides detailed information about choosing an Amazon Virtual Private Cloud (VPC) when you onboard to Amazon SageMaker Domain. For more information about onboarding to SageMaker Domain, see Onboard to Amazon SageMaker Domain (p. 35).

By default, SageMaker Domain uses two VPCs. One VPC is managed by Amazon SageMaker and provides direct internet access. You specify the other VPC, which provides encrypted traffic between the Domain and your Amazon Elastic File System (EFS) volume.

You can change this behavior so that SageMaker sends all traffic over your specified VPC. When you choose this option, you must provide the subnets, security groups, and interface endpoints that are necessary to communicate with the SageMaker API and SageMaker runtime, and various AWS services, such as Amazon Simple Storage Service (Amazon S3) and Amazon CloudWatch, that are used by Studio and your Studio notebooks.

When you onboard to SageMaker Domain, you tell SageMaker to send all traffic over your VPC by setting the network access type to VPC only.

To specify the VPC information

When you specify the VPC entities (that is, the VPC, subnet, or security group) in the following procedure, one of three options is presented based on the number of entities you have in the current AWS Region. The behavior is as follows:

- One entity – SageMaker uses that entity. This can't be changed.
- Multiple entities – You must choose the entities from the dropdown list.
- No entities – You must create one or more entities in order to use Domain. Choose Create <entity> to open the VPC console in a new browser tab. After you create the entities, return to the Domain Get started page to continue the onboarding process.

This procedure is part of the Amazon SageMaker Domain onboarding process when you choose Standard setup. Your VPC information is specified under the Network section.

1. Choose the VPC.
2. Choose one or more subnets. If you don't choose any subnets, SageMaker uses all the subnets in the VPC.
3. Select the network access type.
   - Public internet only – Non-EFS traffic goes through a SageMaker managed VPC, which allows internet access. Traffic between the domain and your Amazon EFS volume is through the specified VPC.
• **VPC only** – All SageMaker traffic is through the specified VPC and subnets. Internet access is disabled by default.

4. Choose the security groups. If you chose **Public internet only**, this step is optional. If you chose **VPC only**, this step is required.

   **Note**
   For the maximum number of allowed security groups, see [UserSettings](#).

For VPC requirements in **VPC only** mode, see [Connect SageMaker Studio Notebooks in a VPC to External Resources](#p. 3631).

---

# Delete an Amazon SageMaker Domain

A domain consists of a list of authorized users, configuration settings, and an Amazon Elastic File System (Amazon EFS) volume, which contains data for the users, including notebooks, resources, and artifacts. A user can have multiple applications (apps) which support the reading and execution experience of the user’s notebooks, terminals, and consoles.

You can delete your domain using one of the following:

- AWS console
- AWS Command Line Interface (AWS CLI)
- SageMaker SDK

The following sections give information on the requirements to delete a domain, as well as how to delete the domain.

**Topics**

- Requirements (p. 43)
- EFS files (p. 44)
- Delete a Amazon SageMaker Domain (Console) (p. 44)
- Delete a Amazon SageMaker Domain (CLI) (p. 44)

**Requirements**

You must satisfy the following requirements to delete a domain.

- You must have admin permission to delete a Domain.
- You can only delete an app whose status is InService, which is displayed as **Ready** in the domain. An app whose status is Failed doesn't need to be deleted to delete the containing domain. In the domain, an attempt to delete an app in the failed state results in an error.
- To delete a domain, the domain cannot contain any user profiles. To delete a user profile, the profile cannot contain any non-failed apps.

When you delete these resources, the following occurs:

- **App** – The data (files and notebooks) in a user’s home directory is saved. Unsaved notebook data is lost.
- **User profile** – The user is no longer able to sign in to the Domain and loses access to their home directory, but the data is not deleted. An admin can retrieve the data from the Amazon EFS volume where it is stored under the user’s AWS account.
- You must delete the domain if you want to switch authentication modes from IAM to IAM Identity Center.
EFS files

Your files are kept in an Amazon EFS volume as a backup. This backup includes the files in the mounted directory, which is `/home/sagemaker-user` for Jupyter and `/root` for your kernel. When you delete files from these mounted directories, the kernel or app may move the deleted files into a hidden trash folder. If the trash folder is inside the mounted directory, those files are copied into the Amazon EFS volume and will incur charges. To avoid these Amazon EFS charges, you must identify and clean the trash folder location. The trash folder location for default apps and kernels is `~/.local/`. This may vary depending on the Linux distribution used for custom apps or kernels. For more information about the Amazon EFS volume, see Manage Your EFS Storage Volume in SageMaker Studio (p. 178).

When you use the AWS console to delete the domain, the Amazon EFS volume is detached but not deleted. The same behavior occurs by default when you use the AWS CLI or the SDK to delete the domain. However, when you use the AWS CLI or the SDK, you can set the RetentionPolicy to `HomeEfsFileSystem=Delete` to delete the EFS volume along with the domain.

Delete a Amazon SageMaker Domain (Console)

To delete a domain

1. Open the SageMaker console.
2. Choose Control Panel on the left side of the page.
3. Repeat the following steps for each user in the User name list.
   a. Choose the user.
   b. On the User Details page, for each non-failed app in the Apps list, choose Action.
   c. From the dropdown list, choose Delete.
   d. On the Delete app dialog, choose Yes, delete app, type delete in the confirmation field, and then choose Delete.
   e. When the Status for all apps show as Deleted, choose Edit.
   f. From the Edit User page, choose Delete user.
   g. On the Delete user dialog, choose Yes, delete user, type delete in the confirmation field, and then choose Delete.

   **Important**
   When a user is deleted, they lose access to the Amazon EFS volume that contains their data, including notebooks and other artifacts. The data is not deleted and can be accessed by an administrator.

4. When all users are deleted, choose the domain settings icon (Commit).
5. From the General settings page, choose Delete Domain.
6. On the Delete Domain dialog, choose Yes, delete Domain, type delete in the confirmation field, and then choose Delete.

Delete a Amazon SageMaker Domain (CLI)

To delete a domain

1. Retrieve the list of domains in your account.

   ```bash
   aws --region Region sagemaker list-domains
   ```
2. Retrieve the list of applications for the domain to be deleted.

```bash
aws --region Region sagemaker list-apps \
    --domain-id-equals DomainId
```

3. Delete each application in the list.

```bash
aws --region Region sagemaker delete-app \
    --domain-id DomainId \n    --app-name AppName \n    --app-type AppType \n    --user-profile-name UserProfileName
```

4. Retrieve the list of user profiles in the domain.

```bash
aws --region Region sagemaker list-user-profiles \
    --domain-id-equals DomainId
```

5. Delete each user profile in the list.

```bash
aws --region Region sagemaker delete-user-profile \
    --domain-id DomainId \n    --user-profile-name UserProfileName
```

6. Delete the domain. To also delete the Amazon EFS volume, specify HomeEfsFileSystem=Delete.

```bash
aws --region Region sagemaker delete-domain \
    --domain-id DomainId \n    --retention-policy HomeEfsFileSystem=Retain
```

## SageMaker JumpStart

SageMaker JumpStart provides pre-trained, open-source models for a wide range of problem types to help you get started with machine learning. You can incrementally train and tune these models before deployment. JumpStart also provides solution-templates that set up infrastructure for common use cases, and executable example notebooks for machine learning with SageMaker.

You can access the pre-trained models, solution templates, and examples through the JumpStart landing page in Amazon SageMaker Studio. The following steps show how to access JumpStart models and solutions using Amazon SageMaker Studio.

You can also access the models using the SageMaker Python SDK. For information about how to use JumpStart models programmatically via API, see [Use SageMaker JumpStart Algorithms with Pretrained Models](#).

### Open and use JumpStart

The following sections give information on how to open and use JumpStart from the Amazon SageMaker Studio UI.

#### Open JumpStart

In Amazon SageMaker Studio, open JumpStart by using one of the following:

- The JumpStart launcher in the Get Started section.
Open and use JumpStart

- The JumpStart icon ( ) in the left sidebar.
- The Browse JumpStart button in the launched assets pane.

Important
Before downloading or using third-party content: You are responsible for reviewing and complying with any applicable license terms and making sure that they are acceptable for your use case.

Use JumpStart

From the SageMaker JumpStart landing page, you can browse for solutions, models, notebooks, and other resources. You can also view your currently launched solutions, endpoints, and training jobs. Using the JumpStart search bar, you can search for topics of interest.
You can find JumpStart resources by using search, or by browsing each category that follows the search panel:

- **Featured** – The latest or most used solutions, models, and examples.
- **Solutions** – In one step, launch comprehensive machine learning solutions that tie SageMaker to other AWS services. Select **Explore All Solutions** to view all available solutions.
- **Models** – Find a model that fits your needs from the collection of text, vision, and tabular models. You can filter the collection by problem types, data types, and frameworks. Then, deploy and refine pre-trained models for image classification and object detection in one step. Select **Explore All Models** to view all available models.
- **Resources** – Use example notebooks, blogs, and video tutorials to learn and head start your problem types.
  - **Example notebooks** – Run example notebooks that use SageMaker features like Spot Instance training and experiments over a large variety of model types and use cases.
  - **Blogs** – Read details and solutions from machine learning experts.
  - **Video tutorials** – Watch video tutorials for SageMaker features and machine learning use cases from machine learning experts.
Solution Templates

SageMaker JumpStart provides one-click, end-to-end solutions for many common machine learning use cases. Explore the following use cases for more information on available solution templates.

- Demand forecasting (p. 48)
- Credit rating prediction (p. 49)
- Fraud detection (p. 49)
- Computer vision (p. 50)
- Extract and analyze data from documents (p. 50)
- Predictive maintenance (p. 51)
- Churn prediction (p. 51)
- Personalized recommendations (p. 52)
- Reinforcement learning (p. 52)
- Healthcare and life sciences (p. 52)
- Financial pricing (p. 53)

Choose the solution template that best fits your use case from the JumpStart landing page. When you choose a solution template, JumpStart shows a description of the solution and a Launch button. When you select Launch, JumpStart creates all of the resources that you need to run the solution, including training and model hosting instances. For more information on launching a JumpStart solution, see the section called “Launch a Solution” (p. 53).

After launching the solution, you can explore solution features and any generated artifacts in JumpStart. Select Open Notebook to use provided notebooks and explore the solution’s features. When artifacts are generated during launch or after running the provided notebooks, they’re listed in the Generated Artifacts table. You can delete individual artifacts with the trash icon (Trash). You can delete all of the solution’s resources by choosing Delete solution resources.

Demand forecasting

Demand forecasting uses historical time series data in order to make future estimations in relation to customer demand over a specific period and streamline the supply-demand decision-making process across businesses.

Demand forecasting use cases include predicting ticket sales in the transportation industry, stock prices, number of hospital visits, number of customer representatives to hire for multiple locations in the next month, product sales across multiple regions in the next quarter, cloud server usage for the next day for a video streaming service, electricity consumption for multiple regions over the next week, number of IoT devices and sensors such as energy consumption, and more.

Time series data is categorized as univariate and multi-variate. For example, the total electricity consumption for a single household is a univariate time series over a period of time. When multiple univariate time series are stacked on each other, it’s called a multi-variate time series. For example, the total electricity consumption of 10 different (but correlated) households in a single neighborhood make up a multi-variate time series dataset.
<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand forecasting</td>
<td>Demand forecasting for multivariate time series data using three state-of-the-art time series forecasting algorithms: LSTNet, Prophet, and SageMaker DeepAR.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Credit rating prediction</td>
<td>Use JumpStart's credit rating prediction solutions to predict corporate credit ratings or to explain credit prediction decisions made by machine learning models. Compared to traditional credit rating modeling methods, machine learning models can automate and improve the accuracy of credit prediction.</td>
<td></td>
</tr>
<tr>
<td>Corporate credit rating prediction</td>
<td>Multimodal (long text and tabular) machine learning for quality credit predictions using AWS AutoGluon Tabular.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Graph-based credit scoring</td>
<td>Predict corporate credit ratings using tabular data and a corporate network by training a Graph Neural Network GraphSAGE and AWS AutoGluon Tabular model.</td>
<td>Find in Amazon SageMaker Studio.</td>
</tr>
<tr>
<td>Explain credit decisions</td>
<td>Predict credit default in credit applications and provide explanations using LightGBM and SHAP (SHapley Additive exPlanations).</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Fraud detection</td>
<td>Many businesses lose billions annually to fraud. Machine learning based fraud detection models can help systematically identify likely fraudulent activities from a tremendous amount of data. The following solutions use transaction and user identity datasets to identify fraudulent transactions.</td>
<td></td>
</tr>
<tr>
<td>Detect malicious users and transactions</td>
<td>Automatically detect potentially fraudulent activity in transactions using SageMaker XGBoost with the over-sampling technique Synthetic Minority Over-sampling (SMOTE).</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Fraud detection in financial transactions using deep graph library</td>
<td>Detect fraud in financial transactions by training a graph convolutional network with</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Solution name</td>
<td>Description</td>
<td>Get started</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------</td>
</tr>
<tr>
<td>Get started</td>
<td>the deep graph library and a SageMaker XGBoost model.</td>
<td></td>
</tr>
<tr>
<td>Financial payment classification</td>
<td>Classify financial payments based on transaction information using SageMaker XGBoost. Use this solution template as an intermediate step in fraud detection, personalization, or anomaly detection.</td>
<td>Find in Amazon SageMaker Studio.</td>
</tr>
</tbody>
</table>

### Computer vision

With the rise of business use cases such as autonomous vehicles, smart video surveillance, healthcare monitoring and various object counting tasks, fast and accurate object detection systems are rising in demand. These systems involve not only recognizing and classifying every object in an image, but localizing each one by drawing the appropriate bounding box around it. In the last decade, the rapid advances of deep learning techniques greatly accelerated the momentum of object detection.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Visual product defect detection</td>
<td>Identify defective regions in product images either by training an object detection model from scratch or fine-tuning pretrained SageMaker models.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Handwriting recognition</td>
<td>Recognize handwritten text in images by training an object detection model and handwriting recognition model. Label your own data using SageMaker Ground Truth.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Object detection for bird species</td>
<td>Identify birds species in a scene using a SageMaker object detection model.</td>
<td>Find in Amazon SageMaker Studio.</td>
</tr>
</tbody>
</table>

### Extract and analyze data from documents

JumpStart provides solutions for you to uncover valuable insights and connections in business-critical documents. Use cases include text classification, document summarization, handwriting recognition, relationship extraction, question and answering, and filling in missing values in tabular records.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Privacy for sentiment classification</td>
<td>Anonymize text to better preserve user privacy in sentiment classification.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Solution name</td>
<td>Description</td>
<td>Get started</td>
</tr>
<tr>
<td>---------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-------------</td>
</tr>
<tr>
<td>Document understanding</td>
<td>Document summarization, entity, and relationship extraction using the transformers library in PyTorch.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Handwriting recognition</td>
<td>Recognize handwritten text in images by training an object detection model and handwriting recognition model. Label your own data using SageMaker Ground Truth.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Filling in missing values in tabular records</td>
<td>Fill missing values in tabular records by training a SageMaker AutoPilot model.</td>
<td>GitHub »</td>
</tr>
</tbody>
</table>

### Predictive maintenance

Predictive maintenance aims to optimize the balance between corrective and preventative maintenance by facilitating the timely replacement of components. The following solutions use sensor data from industrial assets to predict machine failures, unplanned downtime, and repair costs.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predictive maintenance for vehicle fleets</td>
<td>Predict vehicle fleet failures using vehicle sensor and maintenance information with a convolutional neural network model.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Predictive maintenance for manufacturing</td>
<td>Predict the remaining useful life for each sensor by training a stacked Bidirectional LSTM neural network model using historical sensor readings.</td>
<td>GitHub »</td>
</tr>
</tbody>
</table>

### Churn prediction

Customer churn, or rate of attrition, is a costly problem faced by a wide range of companies. In an effort to reduce churn, companies can identify customers that are likely to leave their service in order to focus their efforts on customer retention. Use a JumpStart churn prediction solution to analyze data sources such as user behavior and customer support chat logs to identify customers that are at a high risk of cancelling a subscription or service.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Churn prediction with text</td>
<td>Predict churn using numerical, categorical, and textual features with BERT encoder and RandomForestClassifier.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Solution name</td>
<td>Description</td>
<td>Get started</td>
</tr>
<tr>
<td>---------------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>------------------------------</td>
</tr>
<tr>
<td>Churn prediction for mobile phone customers</td>
<td>Identify unhappy mobile phone customers using SageMaker XGBoost.</td>
<td>Find in Amazon SageMaker Studio.</td>
</tr>
</tbody>
</table>

**Personalized recommendations**

You can use JumpStart solutions to analyze customer identity graphs or user sessions to better understand and predict customer behavior. Use the following solutions for personalized recommendations to model customer identity across multiple devices or to determine the likelihood of a customer making a purchase.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Entity resolution in identity graphs with deep graph library</td>
<td>Perform cross-device entity linking for online advertising by training a graph convolutional network with deep graph library.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Purchase modeling</td>
<td>Predict whether a customer will make a purchase by training a SageMaker XGBoost model.</td>
<td>GitHub »</td>
</tr>
</tbody>
</table>

**Reinforcement learning**

Reinforcement learning (RL) is a type of learning that is based on interaction with the environment. This type of learning is used by an agent that must learn behavior through trial-and-error interactions with a dynamic environment in which the goal is to maximize the long-term rewards that the agent receives as a result of its actions. Rewards are maximized by trading off exploring actions that have uncertain rewards with exploiting actions that have known rewards.

RL is well-suited for solving large, complex problems, such as supply chain management, HVAC systems, industrial robotics, game artificial intelligence, dialog systems, and autonomous vehicles.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reinforcement learning for Battlesnake AI competitions</td>
<td>Provide a reinforcement learning workflow for training and inference with the BattleSnake AI competitions.</td>
<td>GitHub »</td>
</tr>
<tr>
<td>Distributed reinforcement learning for Procgen challenge</td>
<td>Distributed reinforcement learning starter kit for NeurIPS 2020 Procgen Reinforcement learning challenge.</td>
<td>GitHub »</td>
</tr>
</tbody>
</table>

**Healthcare and life sciences**

Clinicians and researchers can use JumpStart solutions to analyze medical imagery, genomic information, and clinical health records.
<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lung cancer survival prediction</td>
<td>Predict non-small cell lung cancer patient survival status with 3-dimensional lung computerized tomography (CT) scans, genomic data, and clinical health records using SageMaker XGBoost.</td>
<td>GitHub »</td>
</tr>
</tbody>
</table>

### Financial pricing

Many businesses dynamically adjust pricing on a regular basis in order to maximize their returns. Use the following JumpStart solutions for price optimization, dynamic pricing, option pricing, or portfolio optimization use cases.

<table>
<thead>
<tr>
<th>Solution name</th>
<th>Description</th>
<th>Get started</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price optimization</td>
<td>Estimate price elasticity using Double Machine Learning (ML) for causal inference and the Prophet forecasting procedure. Use these estimates to optimize daily prices.</td>
<td>Find in Amazon SageMaker Studio.</td>
</tr>
</tbody>
</table>

### Launch a Solution

On the page for each solution, JumpStart shows a description of the solution and a Launch button. To launch a solution, select Launch. JumpStart then creates all of the resources needed to run the solution. This includes training and model hosting instances. After you choose a solution, the Launch Solution pane opens.

### Advanced parameters

The solution that you select may have advanced parameters that you can select. Choose Advanced Parameters to specify the AWS Identity and Access Management role for the solution.

Solutions are able to launch resources across 9 AWS services that interact with each other. For the solution to work as expected, newly created components from one service must be able to act on newly created components from another service. We recommend that you use the default IAM role to ensure that all needed permissions are added. For more information about IAM roles, see Identity and Access Management for Amazon SageMaker (p. 3500).

### Default IAM role

If you select this option, the default IAM roles that are required by this solution are used. Each solution requires different resources. The following list describes the default roles that are used for the solutions based on the service needed. For a description of the permissions required for each service, see AWS Managed Policies for SageMaker projects and JumpStart (p. 3593).

- **API Gateway** – AmazonSageMakerServiceCatalogProductsApiGatewayRole
- **CloudFormation** – AmazonSageMakerServiceCatalogProductsCloudformationRole
- **CodeBuild** – AmazonSageMakerServiceCatalogProductsCodeBuildRole
- **CodePipeline** – AmazonSageMakerServiceCatalogProductsCodePipelineRole
Models

JumpStart supports models across fifteen of the most popular problem types. Of the supported problem types, Vision and NLP-related types total thirteen. There are eight problem types that support
incremental training and fine-tuning. For more information about incremental training and hyperparameter tuning, see SageMaker Automatic Model Tuning. JumpStart also supports four popular algorithms for tabular data modeling.

You can search and browse models from the JumpStart landing page in Studio. When you select a model, the model detail page provides information about the model, and you can train and deploy your model in a few steps. The description section describes what you can do with the model, the expected types of inputs and outputs, and the data type needed for fine-tuning your model.

You can also programmatically utilize models with the SageMaker Python SDK.

The list of problem types and links to their example Jupyter notebooks are summarized in the following table. For a complete list of JumpStart models, see JumpStart Available Model Table.

<table>
<thead>
<tr>
<th>Problem types</th>
<th>Supports inference with pre-trained models</th>
<th>Trainable on a custom dataset</th>
<th>Supported frameworks</th>
<th>Example Notebooks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image classification</td>
<td>Yes</td>
<td>Yes</td>
<td>PyTorch, TensorFlow</td>
<td>Introduction to JumpStart - Image Classification</td>
</tr>
<tr>
<td>Object detection</td>
<td>Yes</td>
<td>Yes</td>
<td>PyTorch, TensorFlow, MXNet</td>
<td>Introduction to JumpStart - Object Detection</td>
</tr>
<tr>
<td>Semantic segmentation</td>
<td>Yes</td>
<td>Yes</td>
<td>MXNet</td>
<td>Introduction to JumpStart - Semantic Segmentation</td>
</tr>
<tr>
<td>Instance segmentation</td>
<td>Yes</td>
<td>Yes</td>
<td>MXNet</td>
<td>Introduction to JumpStart - Instance Segmentation</td>
</tr>
<tr>
<td>Image embedding</td>
<td>Yes</td>
<td>No</td>
<td>TensorFlow, MXNet</td>
<td>Introduction to JumpStart - Image Embedding</td>
</tr>
<tr>
<td>Text classification</td>
<td>Yes</td>
<td>Yes</td>
<td>TensorFlow</td>
<td>Introduction to JumpStart - Text Classification</td>
</tr>
<tr>
<td>Sentence pair classification</td>
<td>Yes</td>
<td>Yes</td>
<td>TensorFlow, Hugging Face</td>
<td>Introduction to JumpStart - Sentence Pair Classification</td>
</tr>
<tr>
<td>Question answering</td>
<td>Yes</td>
<td>Yes</td>
<td>PyTorch, Hugging Face</td>
<td>Introduction to JumpStart – Question Answering</td>
</tr>
<tr>
<td>Named entity recognition</td>
<td>Yes</td>
<td>No</td>
<td>Hugging Face</td>
<td>Introduction to JumpStart - Named Entity Recognition</td>
</tr>
<tr>
<td>Problem types</td>
<td>Supports inference with pre-trained models</td>
<td>Trainable on a custom dataset</td>
<td>Supported frameworks</td>
<td>Example Notebooks</td>
</tr>
<tr>
<td>---------------------------</td>
<td>--------------------------------------------</td>
<td>-------------------------------</td>
<td>----------------------</td>
<td>-------------------------------------------------------</td>
</tr>
<tr>
<td>Text summarization</td>
<td>Yes</td>
<td>No</td>
<td>Hugging Face</td>
<td>Introduction to JumpStart - Text Summarization</td>
</tr>
<tr>
<td>Text generation</td>
<td>Yes</td>
<td>No</td>
<td>Hugging Face</td>
<td>Introduction to JumpStart - Text Generation</td>
</tr>
<tr>
<td>Machine translation</td>
<td>Yes</td>
<td>No</td>
<td>Hugging Face</td>
<td>Introduction to JumpStart - Machine Translation</td>
</tr>
<tr>
<td>Text embedding</td>
<td>Yes</td>
<td>No</td>
<td>TensorFlow, MXNet</td>
<td>Introduction to JumpStart - Text Embedding</td>
</tr>
<tr>
<td>Tabular classification</td>
<td>Yes</td>
<td>Yes</td>
<td>LightGBM, CatBoost, XGBoost, AutoGluon-Tabular, TabTransformer, Linear Learner</td>
<td>Introduction to JumpStart - Tabular Classification - LightGBM, CatBoost</td>
</tr>
</tbody>
</table>
## Problem types

<table>
<thead>
<tr>
<th>Supports inference with pre-trained models</th>
<th>Trainable on a custom dataset</th>
<th>Supported frameworks</th>
<th>Example Notebooks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabular regression</td>
<td>Yes</td>
<td>Yes</td>
<td>LightGBM, CatBoost, XGBoost, AutoGluon-Tabular, TabTransformer, Linear Learner</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td></td>
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<td></td>
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<td></td>
</tr>
</tbody>
</table>

## Deploy a Model

When you deploy a model from JumpStart, SageMaker hosts the model and deploys an endpoint that you can use for inference. JumpStart also provides an example notebook that you can use to access the model after it's deployed.

### Model deployment configuration

After you choose a model, the **Deploy Model** pane opens. Choose **Deployment Configuration** to configure your model deployment.
The default instance type for deploying a model depends on the model. The instance type is the hardware that the training job runs on. In the following example, the \texttt{ml.g4dn.xlarge} instance is the default for this particular BERT model.

You can also change the \textbf{Endpoint name}.
Choose **Security Settings** to specify the AWS Identity and Access Management (IAM) role, Amazon Virtual Private Cloud (Amazon VPC), and encryption keys for the model.
Deploy a pretrained model to an endpoint for inference. Deploying on SageMaker deploys the model on the specified compute instance and creates an internal API endpoint. Just like training, you will provide you an example notebook to access the model after it is deployed. Learn more.

Deployment Configuration

Security Settings

This model runs in network isolation. Learn more.

Specify the IAM role that Amazon SageMaker should use to deploy your model:

- Default IAM role
- Find IAM role
- Input IAM role

Amazon SageMaker will deploy your model using your Studio execution role.

Specify whether your model should connect to a virtual private cloud (VPC).

- No VPC
- Find VPC
- Input VPC

No VPC will be used to access your model container.

Specify the encryption keys to secure your data. Learn more.

- No encryption
- Find encryption keys
- Input encryption keys

Your data will not be fully encrypted. Learn more.
Model deployment security

When you deploy a model with JumpStart, you can specify an IAM role, Amazon VPC, and encryption keys for the model. If you don't specify any values for these entries: The default IAM role is your Studio runtime role; default encryption is used; no Amazon VPC is used.

IAM role

You can select an IAM role that is passed as part of training jobs and hosting jobs. SageMaker uses this role to access training data and model artifacts. If you don't select an IAM role, SageMaker deploys the model using your Studio runtime role. For more information about IAM roles, see Identity and Access Management for Amazon SageMaker (p. 3500).

The role that you pass must have access to the resources that the model needs, and must include all of the following.

- For training jobs: CreateTrainingJob API: Execution Role Permissions.
- For hosting jobs: CreateModel API: Execution Role Permissions.

Note

You can scope down the Amazon S3 permissions granted in each of the following roles. Do this by using the ARN of your Amazon Simple Storage Service (Amazon S3) bucket and the JumpStart Amazon S3 bucket.

```json
{  
    "Effect": "Allow",
    "Action": [
        "s3:GetObject",
        "s3:PutObject",
        "s3:ListMultipartUploadParts"
    ],
    "Resources": [
        "arn:aws:s3::<region>::bucket/jumpstart-cache-prod-<region>/**",
        "arn:aws:s3::<region>::bucket/*",
    ],
},
{  
    "Effect": "Allow",
    "Action": [
        "s3:ListBucket",
    ],
    "Resources": [
        "arn:aws:s3::<region>::bucket/jumpstart-cache-prod-<region>/",
        "arn:aws:s3::<region>::bucket/*",
    ]
}
```

Find IAM role

If you select this option, you must select an existing IAM role from the dropdown list.
Input IAM role

If you select this option, you must manually enter the ARN for an existing IAM role. If your Studio runtime role or Amazon VPC block the `iam: list*` call, you must use this option to use an existing IAM role.

Amazon VPC

All JumpStart models run in network isolation mode. After the model container is created, no more calls can be made. You can select an Amazon VPC that is passed as part of training jobs and hosting jobs. SageMaker uses this Amazon VPC to push and pull resources from your Amazon S3 bucket. This Amazon VPC is different from the Amazon VPC that limits access to the public internet from your Studio instance. For more information about the Studio Amazon VPC, see Connect SageMaker Studio Notebooks in a VPC to External Resources (p. 3631).

The Amazon VPC that you pass does not need access to the public internet, but it does need access to Amazon S3. The Amazon VPC endpoint for Amazon S3 must allow access to at least the following resources that the model needs.

```json
{
  "Effect": "Allow",
  "Action": [
    "s3:GetObject",
    "s3:PutObject",
  ]
}
```
If you do not select an Amazon VPC, no Amazon VPC is used.

Find VPC

If you select this option, you must select an existing Amazon VPC from the dropdown list. After you select an Amazon VPC, you must select a subnet and security group for your Amazon VPC. For more information about subnets and security groups, see Overview of VPCs and subnets.

Input VPC

If you select this option, you must manually select the subnet and security group that compose your Amazon VPC. If your Studio runtime role or Amazon VPC blocks the `ec2:list*` call, you must use this option to select the subnet and security group.
Encryption keys

You can select an AWS KMS key that is passed as part of training jobs and hosting jobs. SageMaker uses this key to encrypt the Amazon EBS volume for the container, and the repackaged model in Amazon S3 for hosting jobs and the output for training jobs. For more information about AWS KMS keys, see AWS KMS keys.

The key that you pass must trust the IAM role that you pass. If you do not specify an IAM role, the AWS KMS key must trust your Studio runtime role.

If you do not select an AWS KMS key, SageMaker provides default encryption for the data in the Amazon EBS volume and the Amazon S3 artifacts.

Find encryption keys

If you select this option, you must select existing AWS KMS keys from the dropdown list.
Input encryption keys

If you select this option, you must manually enter the AWS KMS keys. If your Studio execution role or Amazon VPC block the `kms:list*` call, you must use this option to select existing AWS KMS keys.
Fine-Tune a Model

Fine-tuning trains a pretrained model on a new dataset without training from scratch. This process, also known as transfer learning, can produce accurate models with smaller datasets and less training time.

Fine-Tuning data source

When you fine-tune a model, you can use the default dataset or choose your own data, which is located in an Amazon S3 bucket.

To browse the buckets available to you, choose **Find S3 bucket**. These buckets are limited by the permissions used to set up your Studio account. You can also specify an Amazon S3 URI by choosing **Enter Amazon S3 bucket location**.

**Tip**
To find out how to format the data in your bucket, choose **Learn more**. The description section for the model has detailed information about inputs and outputs.
For text models:

- The bucket must have a data.csv file.
- The first column must be a unique integer for the class label. For example: 1, 2, 3, 4, n
- The second column must be a string.
- The second column should have the corresponding text that matches the type and language for the model.

For vision models:

- The bucket must have as many subdirectories as the number of classes.
- Each subdirectory should contain images that belong to that class in .jpg format.

Note

The Amazon S3 bucket must be in the same AWS Region where you’re running SageMaker Studio because SageMaker doesn’t allow cross-Region requests.

Fine-Tuning deployment configuration

The p3 family is recommended as the fastest for deep learning training, and this is recommended for fine-tuning a model. The following chart shows the number of GPUs in each instance type. There are other available options that you can choose from, including p2 and g4 instance types.

<table>
<thead>
<tr>
<th>Instance type</th>
<th>GPUs</th>
</tr>
</thead>
<tbody>
<tr>
<td>p3.2xlarge</td>
<td>1</td>
</tr>
<tr>
<td>p3.8xlarge</td>
<td>4</td>
</tr>
<tr>
<td>p3.16xlarge</td>
<td>8</td>
</tr>
<tr>
<td>p3dn.24xlarge</td>
<td>8</td>
</tr>
</tbody>
</table>

Hyperparameters

You can customize the hyperparameters of the training job that are used to fine-tune the model.

If you use the default dataset for text models without changing the hyperparameters, you get a nearly identical model as a result. For vision models, the default dataset is different from the dataset used to train the pretrained models, so your model is different as a result.

You have the following hyperparameter options:

- **Epochs** – One epoch is one cycle through the entire dataset. Multiple intervals complete a batch, and multiple batches eventually complete an epoch. Multiple epochs are run until the accuracy of the model reaches an acceptable level, or when the error rate drops below an acceptable level.
- **Learning rate** – The amount that values should be changed between epochs. As the model is refined, its internal weights are being nudged and error rates are checked to see if the model improves. A typical learning rate is 0.1 or 0.01, where 0.01 is a much smaller adjustment and could cause the training to take a long time to converge, whereas 0.1 is much larger and can cause the training to overshoot. It is one of the primary hyperparameters that you might adjust for training your model. Note that for text models, a much smaller learning rate (5e-5 for BERT) can result in a more accurate model.
- **Batch size** – The number of records from the dataset that is to be selected for each interval to send to the GPUs for training.
In an image example, you might send out 32 images per GPU, so 32 would be your batch size. If you choose an instance type with more than one GPU, the batch is divided by the number of GPUs. Suggested batch size varies depending on the data and the model that you are using. For example, how you optimize for image data differs from how you handle language data.

In the instance type chart in the deployment configuration section, you can see the number of GPUs per instance type. Start with a standard recommended batch size (for example, 32 for a vision model). Then, multiply this by the number of GPUs in the instance type that you selected. For example, if you're using a p3.8xlarge, this would be 32(batch size) multiplied by 4 (GPUs), for a total of 128, as your batch size adjusts for the number of GPUs. For a text model like BERT, try starting with a batch size of 64, and then reduce as needed.

### Hyper-parameters

**Epochs**

3

**Learning Rate**

0.00002

**Batch Size**

8

[Reset to default]

**Training output**

When the fine-tuning process is complete, JumpStart provides information about the model: parent model, training job name, training job ARN, training time, and output path. The output path is where you can find your new model in an Amazon S3 bucket. The folder structure uses the model name that you provided and the model file is in an /output subfolder and it's always named model.tar.gz.

Example: s3://bucket/model-name/output/model.tar.gz
Amazon SageMaker JumpStart Industry: Financial

Use SageMaker JumpStart Industry: Financial solutions, models, and example notebooks to learn about SageMaker features and capabilities through curated one-step solutions and example notebooks of industry-focused machine learning (ML) problems. The notebooks also walk through how to use the SageMaker JumpStart Industry Python SDK to enhance industry text data and fine-tune pretrained models.

Topics
- Amazon SageMaker JumpStart Industry Python SDK (p. 69)
- Amazon SageMaker JumpStart Industry: Financial Solution (p. 69)
- Amazon SageMaker JumpStart Industry: Financial Models (p. 70)
- Amazon SageMaker JumpStart Industry: Financial Example Notebooks (p. 71)
- Amazon SageMaker JumpStart Industry: Financial Blog Posts (p. 72)
- Amazon SageMaker JumpStart Industry: Financial Related Research (p. 73)
- Amazon SageMaker JumpStart Industry: Financial Additional Resources (p. 73)

Amazon SageMaker JumpStart Industry Python SDK

SageMaker JumpStart provides processing tools for curating industry datasets and fine-tuning pretrained models through its client library called SageMaker JumpStart Industry Python SDK. For detailed API documentation of the SDK, and to learn more about processing and enhancing industry text datasets for improving the performance of state-of-the-art models on SageMaker JumpStart, see the SageMaker JumpStart Industry Python SDK open source documentation.

Amazon SageMaker JumpStart Industry: Financial Solution

SageMaker JumpStart Industry: Financial provides the following solution notebooks:

- **Corporate Credit Rating Prediction – Financial Services**

  This SageMaker JumpStart Industry: Financial solution provides a template for a text-enhanced corporate credit rating model. It shows how to take a model based on numeric features (in this case, Altman’s famous 5 financial ratios) combined with texts from SEC filings to achieve an improvement in the prediction of credit ratings. In addition to the 5 Altman ratios, you can add more variables as needed or set custom variables. This solution notebook shows how SageMaker JumpStart Industry Python SDK helps process NLP scoring of texts from SEC filings. Furthermore, the solution demonstrates how to train a model using the enhanced dataset to achieve a best-in-class model, deploy the model to a SageMaker endpoint for production, and receive improved predictions in real time.

- **Graph-Based Credit Scoring – Financial Services**

  Credit ratings are traditionally generated using models that use financial statement data and market data, which is tabular only (numeric and categorical). This solution constructs a network of firms using SEC filings and shows how to use the network of firm relationships with tabular data to generate accurate rating predictions. This solution demonstrates a methodology to use data on firm linkages to extend the traditionally tabular-based credit scoring models, which have been used by the ratings industry for decades, to the class of machine learning models on networks.

  **Note**
  The solution notebooks are for demonstration purposes only. They should not be relied on as financial or investment advice.
You can find these financial services solutions through the SageMaker JumpStart page in Studio.

**Note**
The SageMaker JumpStart Industry: Financial solutions, model cards, and example notebooks are hosted and runnable only through SageMaker Studio. Log in to the SageMaker console, and launch SageMaker Studio. For more information about how to find the solution card, see the previous topic at SageMaker JumpStart.

## Amazon SageMaker JumpStart Industry: Financial Models

SageMaker JumpStart Industry: Financial provides the following pretrained Robustly Optimized BERT approach (RoBERTa) models:

- RoBERTa-SEC-Base
- RoBERTa-SEC-WIKI-Base
- RoBERTa-SEC-Large
- RoBERTa-SEC-WIKI-Large

The RoBERTa-SEC-Base and RoBERTa-SEC-Large models are the text embedding models based on GluonNLP’s RoBERTa model and pre-trained on S&P 500 SEC 10-K/10-Q reports of the decade of the 2010’s (from 2010 to 2019). In addition to these, SageMaker JumpStart Industry: Financial provides two more RoBERTa variations, RoBERTa-SEC-WIKI-Base and RoBERTa-SEC-WIKI-Large, which are pretrained on the SEC filings and common texts of Wikipedia.

By deploying the model cards through SageMaker JumpStart, you’ll be able to access their corresponding notebooks. The paired notebooks will walk you through how the pretrained models can be fine-tuned for specific classification tasks on multimodal datasets, which are enhanced by the SageMaker JumpStart Industry Python SDK.

**Note**
The model notebooks are for demonstration purposes only. They should not be relied on as financial or investment advice.

The following screenshot shows the pretrained model cards provided through the SageMaker JumpStart page on Studio.
Note
The SageMaker JumpStart Industry: Financial solutions, model cards, and example notebooks are hosted and runnable only through SageMaker Studio. Log in to the SageMaker console, and launch SageMaker Studio. For more information about how to find the model cards, see the previous topic at SageMaker JumpStart.

Amazon SageMaker JumpStart Industry: Financial Example Notebooks

SageMaker JumpStart Industry: Financial provides the following hands-on examples of solving industry-focused ML problems:

- **SEC Filings Retrieval w/ Summarizer and Scoring** – This example introduces how to use the SageMaker JumpStart Industry Python SDK for processing the SEC filings, such as text summarization and scoring texts based on NLP score types and their corresponding word lists. To preview the content of this notebook, see Simple Construction of a Multimodal Dataset from SEC Filings and NLP Scores

- **ML on a TabText (Multimodal) Dataset** – This example shows how to merge different types of datasets into a single dataframe called TabText and perform multimodal ML. To preview the content of this notebook, see Machine Learning on a TabText Dataframe – An Example Based on the Paycheck Protection Program

- **Multi-category ML on SEC filings data** – This example shows how to train an AutoGluon NLP model over the multimodal (TabText) datasets curated from SEC filings for a multiclass classification task. Classify SEC 10K/Q Filings to Industry Codes Based on the MDNA Text Column
Note
The example notebooks are for demonstrative purposes only. They should not be relied on as financial or investment advice.

The following screenshot shows the example notebook cards provided through the SageMaker JumpStart page on Studio.

Note
The SageMaker JumpStart Industry: Financial solutions, model cards, and example notebooks are hosted and runnable only through SageMaker Studio. Log in to the SageMaker console, and launch SageMaker Studio. For more information about how to find the example notebooks, see the previous topic at SageMaker JumpStart.

To preview the content of the example notebooks, see Tutorials – Finance in the SageMaker JumpStart Industry Python SDK documentation.

Amazon SageMaker JumpStart Industry: Financial Blog Posts

For thorough applications of using SageMaker JumpStart Industry: Financial solutions, models, examples, and the SDK, see the following blog posts:

- Use pre-trained financial language models for transfer learning in Amazon SageMaker JumpStart
- Use SEC text for ratings classification using multimodal ML in Amazon SageMaker JumpStart
- Create a dashboard with SEC text for financial NLP in Amazon SageMaker JumpStart
- Build a corporate credit ratings classifier using graph machine learning in Amazon SageMaker JumpStart
Amazon SageMaker JumpStart Industry: Financial Related Research

For research related to SageMaker JumpStart Industry: Financial solutions, see the following papers:

- Context, Language Modeling, and Multimodal Data in Finance
- Multimodal Machine Learning for Credit Modeling
- On the Lack of Robust Interpretability of Neural Text Classifiers
- FinLex: An Effective Use of Word Embeddings for Financial Lexicon Generation

Amazon SageMaker JumpStart Industry: Financial Additional Resources

For additional documentation and tutorials, see the following resources:

- The SageMaker JumpStart Industry: Financial Python SDK
- SageMaker JumpStart Industry: Financial Python SDK Tutorials
- The SageMaker JumpStart Industry: Financial GitHub repository
- Getting started with Amazon SageMaker - Machine Learning Tutorials

Get Started with Amazon SageMaker Notebook Instances

One of the best ways for machine learning (ML) practitioners to use Amazon SageMaker is to train and deploy ML models using SageMaker notebook instances. The SageMaker notebook instances help create the environment by initiating Jupyter servers on Amazon Elastic Compute Cloud (Amazon EC2) and providing preconfigured kernels with the following packages: the Amazon SageMaker Python SDK, AWS SDK for Python (Boto3), AWS Command Line Interface (AWS CLI), Conda, Pandas, deep learning framework libraries, and other libraries for data science and machine learning.

Machine Learning with the SageMaker Python SDK

To train, validate, deploy, and evaluate an ML model in a SageMaker notebook instance, use the SageMaker Python SDK. The SageMaker Python SDK abstracts AWS SDK for Python (Boto3) and SageMaker API operations. It enables you to integrate with and orchestrate other AWS services, such as Amazon Simple Storage Service (Amazon S3) for saving data and model artifacts, Amazon Elastic Container Registry (ECR) for importing and servicing the ML models, Amazon Elastic Compute Cloud (Amazon EC2) for training and inference.

You can also take advantage of SageMaker features that help you deal with every stage of a complete ML cycle: data labeling, data preprocessing, model training, model deployment, evaluation on prediction performance, and monitoring the quality of model in production.

If you're a first-time SageMaker user, we recommend you to use the SageMaker Python SDK, following the end-to-end ML tutorial. To find the open source documentation, see the Amazon SageMaker Python SDK.

Tutorial Overview

This Get Started tutorial walks you through how to create a SageMaker notebook instance, open a Jupyter notebook with a preconfigured kernel with the Conda environment for machine learning, and
Step 1: Create an Amazon SageMaker Notebook Instance

An Amazon SageMaker notebook instance is a fully managed machine learning (ML) Amazon Elastic Compute Cloud (Amazon EC2) compute instance that runs the Jupyter Notebook App. You use the notebook instance to create and manage Jupyter notebooks for preprocessing data and to train and deploy machine learning models.

To create a SageMaker notebook instance

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Choose Notebook instances, and then choose Create notebook instance.
3. On the Create notebook instance page, provide the following information (if a field is not mentioned, leave the default values):
   a. For Notebook instance name, type a name for your notebook instance.
   b. For Notebook Instance type, choose ml.t2.medium. This is the least expensive instance type that notebook instances support, and it suffices for this exercise. If a ml.t2.medium instance type isn't available in your current AWS Region, choose ml.t3.medium.
   c. For Platform Identifier, choose a platform type to create the notebook instance on. This platform type dictates the Operating System and the JupyterLab version that your notebook instance is created with. For information about platform identifier type, see Amazon Linux 2 vs

Topics

- Step 1: Create an Amazon SageMaker Notebook Instance (p. 74)
- Step 2: Create a Jupyter Notebook (p. 76)
- Step 3: Download, Explore, and Transform a Dataset (p. 76)
- Step 4: Train a Model (p. 81)
- Step 5: Deploy the Model to Amazon EC2 (p. 85)
- Step 6: Evaluate the Model (p. 87)
- Step 7: Clean Up (p. 90)
d. For IAM role, choose Create a new role, and then choose Create role. This IAM role automatically gets permissions to access any S3 bucket that has sagemaker in the name. It gets these permissions through the AmazonSageMakerFullAccess policy, which SageMaker attaches to the role.

**Note**
If you want to grant the IAM role permission to access S3 buckets without sagemaker in the name, you need to attach the S3FullAccess policy or limit the permissions to specific S3 buckets to the IAM role. For more information and examples of adding bucket policies to the IAM role, see Bucket Policy Examples.

e. Choose Create notebook instance.

In a few minutes, SageMaker launches an ML compute instance—in this case, a notebook instance—and attaches a 5 GB of Amazon EBS storage volume to it. The notebook instance has a preconfigured Jupyter notebook server, SageMaker and AWS SDK libraries, and a set of Anaconda libraries.

For more information about creating a SageMaker notebook instance, see Create a Notebook Instance.

## (Optional) Change SageMaker Notebook Instance Settings

If you want to change the ML compute instance type or the size of the Amazon EBS storage of a SageMaker notebook instance that’s already created, you can edit the notebook instance settings.

**To change and update the SageMaker Notebook instance type and the EBS volume**

1. On the Notebook instances page in the SageMaker console, choose your notebook instance.
2. Choose Actions, choose Stop, and then wait until the notebook instance fully stops.
3. After the notebook instance status changes to Stopped, choose Actions, and then choose Update settings.
   a. For Notebook instance type, choose a different ML instance type.
   b. For Volume size in GB, type a different integer to specify a new EBS volume size.

**Note**
EBS storage volumes are encrypted, so SageMaker can’t determine the amount of available free space on the volume. Because of this, you can increase the volume size when you update a notebook instance, but you can’t decrease the volume size. If you want to decrease the size of the ML storage volume in use, create a new notebook instance with the desired size.

4. At the bottom of the page, choose Update notebook instance.
5. When the update is complete, Start the notebook instance with the new settings.

For more information about updating SageMaker notebook instance settings, see Update a Notebook Instance.

## (Optional) Advanced Settings for SageMaker Notebook Instances

The following tutorial video shows how to set up and use SageMaker notebook instances through the SageMaker console with advanced options, such as SageMaker lifecycle configuration and importing GitHub repositories. (Length: 26:04)
Step 2: Create a Jupyter Notebook

To start scripting for training and deploying your model, create a Jupyter notebook in the SageMaker notebook instance. Using the Jupyter notebook, you can conduct machine learning (ML) experiments for training and inference while accessing the SageMaker features and the AWS infrastructure.

To create a Jupyter notebook

1. Open the notebook instance as follows:
   b. On the Notebook instances page, open your notebook instance by choosing either Open JupyterLab for the JupyterLab interface or Open Jupyter for the classic Jupyter view.

   Note
   If the notebook instance status shows Pending in the Status column, your notebook instance is still being created. The status will change to InService when the notebook instance is ready for use.

2. Create a notebook as follows:
   • If you opened the notebook in the JupyterLab view, on the File menu, choose New, and then choose Notebook. For Select Kernel, choose conda_python3. This preinstalled environment includes the default Anaconda installation and Python 3.
   • If you opened the notebook in the classic Jupyter view, on the Files tab, choose New, and then choose conda_python3. This preinstalled environment includes the default Anaconda installation and Python 3.

3. Save the notebooks as follows:
   • In the JupyterLab view, choose File, choose Save Notebook As..., and then rename the notebook.
   • In the Jupyter classic view, choose File, choose Save as..., and then rename the notebook.

Step 3: Download, Explore, and Transform a Dataset

In this step, you load the Adult Census dataset to your notebook instance using the SHAP (SHapley Additive exPlanations) Library, review the dataset, transform it, and upload it to Amazon S3. SHAP is a game theoretic approach to explain the output of any machine learning model. For more information about SHAP, see Welcome to the SHAP documentation.

To run the following example, paste the sample code into a cell in your notebook instance.

Load Adult Census Dataset Using SHAP

Using the SHAP library, import the Adult Census dataset as shown following:

```python
import shap
X, y = shap.datasets.adult()
X_display, y_display = shap.datasets.adult(display=True)
feature_names = list(X.columns)
feature_names
```

Note
If the current Jupyter kernel does not have the SHAP library, install it by running the following conda command:
If you're using JupyterLab, you must manually refresh the kernel after the installation and updates have completed. Run the following IPython script to shut down the kernel (the kernel will restart automatically):

```python
import IPython
IPython.Application.instance().kernel.do_shutdown(True)
```

The `feature_names` list object should return the following list of features:

```
['Age',
 'Workclass',
 'Education-Num',
 'Marital Status',
 'Occupation',
 'Relationship',
 'Race',
 'Sex',
 'Capital Gain',
 'Capital Loss',
 'Hours per week',
 'Country']
```

**Tip**
If you're starting with unlabeled data, you can use Amazon SageMaker Ground Truth to create a data labeling workflow in minutes. To learn more, see [Label Data](Label Data).

## Overview the Dataset

Run the following script to display the statistical overview of the dataset and histograms of the numeric features.

```python
display(X.describe())
hist = X.hist(bins=30, sharey=True, figsize=(20, 10))
```
Tip
If you want to use a dataset that needs to be cleaned and transformed, you can simplify and streamline data preprocessing and feature engineering using Amazon SageMaker Data Wrangler. To learn more, see Prepare ML Data with Amazon SageMaker Data Wrangler.

Split the Dataset into Train, Validation, and Test Datasets

Using Sklearn, split the dataset into a training set and a test set. The training set is used to train the model, while the test set is used to evaluate the performance of the final trained model. The dataset is randomly sorted with the fixed random seed: 80 percent of the dataset for training set and 20 percent of it for a test set.

```python
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
X_train_display = X_display.loc[X_train.index]
```

Split the training set to separate out a validation set. The validation set is used to evaluate the performance of the trained model while tuning the model's hyperparameters. 75 percent of the training set becomes the final training set, and the rest is the validation set.

```python
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.25, random_state=1)
X_train_display = X_display.loc[X_train.index]
X_val_display = X_display.loc[X_val.index]
```

Using the pandas package, explicitly align each dataset by concatenating the numeric features with the true labels.
import pandas as pd
train = pd.concat([pd.Series(y_train, index=X_train.index, name='Income>50K', dtype=int), X_train], axis=1)
validation = pd.concat([pd.Series(y_val, index=X_val.index, name='Income>50K', dtype=int), X_val], axis=1)
test = pd.concat([pd.Series(y_test, index=X_test.index, name='Income>50K', dtype=int), X_test], axis=1)

Check if the dataset is split and structured as expected:

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<td></td>
</tr>
</tbody>
</table>
Step 3: Download, Explore, and Transform Data

Convert the Train and Validation Datasets to CSV Files

Convert the train and validation dataframe objects to CSV files to match the input file format for the XGBoost algorithm.

```python
# Use 'csv' format to store the data
# The first column is expected to be the output column
train.to_csv('train.csv', index=False, header=False)
validation.to_csv('validation.csv', index=False, header=False)
```

Upload the Datasets to Amazon S3

Using the SageMaker and Boto3, upload the training and validation datasets to the default Amazon S3 bucket. The datasets in the S3 bucket will be used by a compute-optimized SageMaker instance on Amazon EC2 for training.

The following code sets up the default S3 bucket URI for your current SageMaker session, creates a new demo-sagemaker-xgboost-adult-income-prediction folder, and uploads the training and validation datasets to the data subfolder.

```python
import sagemaker, boto3, os
bucket = sagemaker.Session().default_bucket()
prefix = "demo-sagemaker-xgboost-adult-income-prediction"
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'data/train.csv')).upload_file('train.csv')
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'data/validation.csv')).upload_file('validation.csv')
```

Run the following AWS CLI to check if the CSV files are successfully uploaded to the S3 bucket.

```bash
! aws s3 ls {bucket}/{prefix}/data --recursive
```

This should return the following output:

```
2021-01-14 17:52:00    786285 demo-sagemaker-xgboost-adult-income-prediction/data/train.csv
2021-01-14 17:52:10    262122 demo-sagemaker-xgboost-adult-income-prediction/data/validation.csv
```
Step 4: Train a Model

The Amazon SageMaker Python SDK provides framework estimators and generic estimators to train your model while orchestrating the machine learning (ML) lifecycle accessing the SageMaker features for training and the AWS infrastructures, such as Amazon Elastic Container Registry (Amazon ECR), Amazon Elastic Compute Cloud (Amazon EC2), Amazon Simple Storage Service (Amazon S3). For more information about SageMaker built-in framework estimators, see Frameworks in the Amazon SageMaker Python SDK documentation. For more information about built-in algorithms, see Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096).

Topics
- Choose the Training Algorithm (p. 81)
- Create and Run a Training Job (p. 81)

Choose the Training Algorithm

To choose the right algorithm for your dataset, you typically need to evaluate different models to find the most suitable models to your data. For simplicity, the SageMaker XGBoost Algorithm built-in algorithm is used throughout this tutorial without the pre-evaluation of models.

Tip
If you want SageMaker to find an appropriate model for your tabular dataset, use Amazon SageMaker Autopilot that automates a machine learning solution. For more information, see Automate model development with Amazon SageMaker Autopilot (p. 318).

Create and Run a Training Job

After you figured out which model to use, start constructing a SageMaker estimator for training. This tutorial uses the XGBoost built-in algorithm for the SageMaker generic estimator.

To run a model training job

1. Import the Amazon SageMaker Python SDK and start by retrieving the basic information from your current SageMaker session.

   ```python
   import sagemaker
   region = sagemaker.Session().boto_region_name
   print("AWS Region: {0}".format(region))
   role = sagemaker.get_execution_role()
   print("RoleArn: {0}".format(role))
   ```

   This returns the following information:
   - region – The current AWS Region where the SageMaker notebook instance is running.
   - role – The IAM role used by the notebook instance.

   Note
   Check the SageMaker Python SDK version by running sagemaker.__version__. This tutorial is based on sagemaker>=2.20. If the SDK is outdated, install the latest version by running the following command:

   ```bash
   ! pip install -qU sagemaker
   ```
If you run this installation in your exiting SageMaker Studio or notebook instances, you need to manually refresh the kernel to finish applying the version update.

2. Create an XGBoost estimator using the `sagemaker.estimator.Estimator` class. In the following example code, the XGBoost estimator is named `xgb_model`.

```python
from sagemaker.debugger import Rule, rule_configs
from sagemaker.session import TrainingInput
s3_output_location='s3://{}/{}/{}'.format(bucket, prefix, 'xgboost_model')
container=sagemaker.image_uri.retrieve("xgboost", region, "1.2-1")
print(container)
xgb_model=sagemaker.estimator.Estimator(
    image_uri=container,
    role=role,
    instance_count=1,
    instance_type='ml.m4.xlarge',
    volume_size=5,
    output_path=s3_output_location,
    sagemaker_session=sagemaker.Session(),
    rules=[Rule.sagemaker(rule_configs.create_xgboost_report())]
)
```

To construct the SageMaker estimator, specify the following parameters:

- **image_uri** – Specify the training container image URI. In this example, the SageMaker XGBoost training container URI is specified using `sagemaker.image_uri.retrieve`.
- **role** – The AWS Identity and Access Management (IAM) role that SageMaker uses to perform tasks on your behalf (for example, reading training results, call model artifacts from Amazon S3, and writing training results to Amazon S3).
- **instance_count** and **instance_type** – The type and number of Amazon EC2 ML compute instances to use for model training. For this training exercise, you use a single `ml.m4.xlarge` instance, which has 4 CPUs, 16 GB of memory, an Amazon Elastic Block Store (Amazon EBS) storage, and a high network performance. For more information about EC2 compute instance types, see Amazon EC2 Instance Types. For more information about billing, see Amazon SageMaker pricing.
- **volume_size** – The size, in GB, of the EBS storage volume to attach to the training instance. This must be large enough to store training data if you use File mode (File mode is on by default).
- **output_path** – The path to the S3 bucket where SageMaker stores the model artifact and training results.
- **sagemaker_session** – The session object that manages interactions with SageMaker API operations and other AWS service that the training job uses.
- **rules** – Specify a list of SageMaker Debugger built-in rules. In this example, the `create_xgboost_report()` rule creates an XGBoost report that provides insights into the training progress and results. For more information, see SageMaker Debugger XGBoost Training Report (p. 2345).

**Tip**

If you want to run distributed training of large sized deep learning models, such as convolutional neural networks (CNN) and natural language processing (NLP) models, use SageMaker Distributed for data parallelism or model parallelism. For more information, see Amazon SageMaker Distributed Training Libraries (p. 2466).
3. Set the hyperparameters for the XGBoost algorithm by calling the `set_hyperparameters` method of the estimator. For a complete list of XGBoost hyperparameters, see XGBoost Hyperparameters (p. 2044).

```python
xgb_model.set_hyperparameters(
    max_depth = 5,
    eta = 0.2,
    gamma = 4,
    min_child_weight = 6,
    subsample = 0.7,
    objective = "binary:logistic",
    num_round = 1000
)
```

**Tip**
You can also tune the hyperparameters using the SageMaker hyperparameter optimization feature. For more information, see Perform Automatic Model Tuning with SageMaker (p. 2436).

4. Use the `TrainingInput` class to configure a data input flow for training. The following example code shows how to configure `TrainingInput` objects to use the training and validation datasets you uploaded to Amazon S3 in the Split the Dataset into Train, Validation, and Test Datasets (p. 78) section.

```python
from sagemaker.session import TrainingInput

train_input = TrainingInput(
    "s3://{}/{}".format(bucket, prefix, "data/train.csv"), content_type="csv"
)
validation_input = TrainingInput(
    "s3://{}/{}".format(bucket, prefix, "data/validation.csv"), content_type="csv"
)
```

5. To start model training, call the estimator's `fit` method with the training and validation datasets. By setting `wait=True`, the `fit` method displays progress logs and waits until training is complete.

```python
xgb_model.fit({"train": train_input, "validation": validation_input}, wait=True)
```

For more information about model training, see Train a Model with Amazon SageMaker (p. 9). This tutorial training job might take up to 10 minutes.

After the training job has done, you can download an XGBoost training report and a profiling report generated by SageMaker Debugger. The XGBoost training report offers you insights into the training progress and results, such as the loss function with respect to iteration, feature importance, confusion matrix, accuracy curves, and other statistical results of training. For example, you can find the following loss curve from the XGBoost training report which clearly indicates that there is an overfitting problem.
Run the following code to specify the S3 bucket URI where the Debugger training reports are generated and check if the reports exist.

```python
rule_output_path = xgb_model.output_path + "/" + xgb_model.latest_training_job.job_name + "/rule-output"
! aws s3 ls {rule_output_path} --recursive
```

Download the Debugger XGBoost training and profiling reports to the current workspace:

```bash
! aws s3 cp {rule_output_path} ./ --recursive
```

Run the following IPython script to get the file link of the XGBoost training report:

```python
from IPython.display import FileLink, FileLinks
display("Click link below to view the XGBoost Training report",
    FileLink("CreateXgboostReport/xgboost_report.html"))
```

The following IPython script returns the file link of the Debugger profiling report that shows summaries and details of the EC2 instance resource utilization, system bottleneck detection results, and python operation profiling results:

```python
profiler_report_name = [rule["RuleConfigurationName"]
    for rule in xgb_model.latest_training_job.rule_job_summary()
    if "Profiler" in rule["RuleConfigurationName"]][0]

display("Click link below to view the profiler report", FileLink(profiler_report_name + "/profiler-output/profiler-report.html"))
```
Tip
If the HTML reports do not render plots in the JupyterLab view, you must choose Trust HTML at the top of the reports.

To identify training issues, such as overfitting, vanishing gradients, and other problems that prevents your model from converging, use SageMaker Debugger and take automated actions while prototyping and training your ML models. For more information, see Debug and Profile Training Jobs Using Amazon SageMaker Debugger (p. 2258). To find a complete analysis of model parameters, see the Explainability with Amazon SageMaker Debugger example notebook.

You now have a trained XGBoost model. SageMaker stores the model artifact in your S3 bucket. To find the location of the model artifact, run the following code to print the model_data attribute of the xgb_model estimator:

```python
xgb_model.model_data
```

Tip
To measure biases that can occur during each stage of the ML lifecycle (data collection, model training and tuning, and monitoring of ML models deployed for prediction), use SageMaker Clarify. For more information, see Amazon SageMaker Clarify Model Explainability (p. 2652). For an end-to-end example of it, see the Fairness and Explainability with SageMaker Clarify example notebook.

Step 5: Deploy the Model to Amazon EC2

To get predictions, deploy your model to Amazon EC2 using Amazon SageMaker.

Topics
- Deploy the Model to SageMaker Hosting Services (p. 85)
- (Optional) Use SageMaker Predictor to Reuse the Hosted Endpoint (p. 86)
- (Optional) Make Prediction with Batch Transform (p. 86)

Deploy the Model to SageMaker Hosting Services

To host a model through Amazon EC2 using Amazon SageMaker, deploy the model that you trained in Create and Run a Training Job (p. 81) by calling the deploy method of the xgb_model estimator. When you call the deploy method, you must specify the number and type of EC2 ML instances that you want to use for hosting an endpoint.

```python
import sagemaker
from sagemaker.serializers import CSVSerializer
xgb_predictor=xgb_model.deploy(
    initial_instance_count=1,
    instance_type='ml.t2.medium',
    serializer=CSVSerializer()
)
```

- `initial_instance_count` (int) – The number of instances to deploy the model.
- `instance_type` (str) – The type of instances that you want to operate your deployed model.
- `serializer` (int) – Serialize input data of various formats (a NumPy array, list, file, or buffer) to a CSV-formatted string. We use this because the XGBoost algorithm accepts input files in CSV format.
The deploy method creates a deployable model, configures the SageMaker hosting services endpoint, and launches the endpoint to host the model. For more information, see the SageMaker generic Estimator's deploy class method in the Amazon SageMaker Python SDK. To retrieve the name of endpoint that's generated by the deploy method, run the following code:

```python
xgb_predictor.endpoint_name
```

This should return the endpoint name of the xgb_predictor. The format of the endpoint name is "sagemaker-xgboost-YYYY-MM-DD-HH-MM-SS-SSS". This endpoint stays active in the ML instance, and you can make instantaneous predictions at any time unless you shut it down later. Copy this endpoint name and save it to reuse and make real-time predictions elsewhere in SageMaker Studio or SageMaker notebook instances.

**Tip**

To learn more about compiling and optimizing your model for deployment to Amazon EC2 instances or edge devices, see Compile and Deploy Models with Neo.

**(Optional) Use SageMaker Predictor to Reuse the Hosted Endpoint**

After you deploy the model to an endpoint, you can set up a new SageMaker predictor by pairing the endpoint and continuously make real-time predictions in any other notebooks. The following example code shows how to use the SageMaker Predictor class to set up a new predictor object using the same endpoint. Re-use the endpoint name that you used for the xgb_predictor.

```python
import sagemaker
xgb_predictor_reuse = sagemaker.predictor.Predictor(
    endpoint_name="sagemaker-xgboost-YYYY-MM-DD-HH-MM-SS-SSS",
    sagemaker_session=sagemaker.Session(),
    serializer=sagemaker.serializers.CSVSerializer()
)
```

The xgb_predictor_reuse Predictor behaves exactly the same as the original xgb_predictor. For more information, see the SageMaker Predictor class in the Amazon SageMaker Python SDK.

**(Optional) Make Prediction with Batch Transform**

Instead of hosting an endpoint in production, you can run a one-time batch inference job to make predictions on a test dataset using the SageMaker batch transform. After your model training has completed, you can extend the estimator to a transformer object, which is based on the SageMaker Transformer class. The batch transformer reads in input data from a specified S3 bucket and makes predictions.

**To run a batch transform job**

1. Run the following code to convert the feature columns of the test dataset to a CSV file and uploads to the S3 bucket:

   ```python
   X_test.to_csv('test.csv', index=False, header=False)
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'test/test.csv')).upload_file('test.csv')
   ```

2. Specify S3 bucket URIs of input and output for the batch transform job as shown following:

   ```python
   # The location of the test dataset
   batch_input = 's3://{}/{}test'.format(bucket, prefix)
   ```
Step 6: Evaluate the Model

Now that you have trained and deployed a model using Amazon SageMaker, evaluate the model to ensure that it generates accurate predictions on new data. For model evaluation, use the test dataset that you created in Step 3: Download, Explore, and Transform a Dataset (p. 76).

Evaluate the Model Deployed to SageMaker Hosting Services

To evaluate the model and use it in production, invoke the endpoint with the test dataset and check whether the inferences you get returns a target accuracy you want to achieve.

To evaluate the model

1. Set up the following function to predict each line of the test set. In the following example code, the `rows` argument is to specify the number of lines to predict at a time. You can change the value of it to perform a batch inference that fully utilizes the instance's hardware resource.

```python
import numpy as np
def predict(data, rows=1000):
    split_array = np.array_split(data, int(data.shape[0] / float(rows) + 1))
    predictions = ''
    for array in split_array:
        predictions = ','.join([predictions, xgb_predictor.predict(array).decode('utf-8')])
```

# The location to store the results of the batch transform job
batch_output = 's3://{}//{}//batch-prediction'.format(bucket, prefix)

3. Create a transformer object specifying the minimal number of parameters: the `instance_count` and `instance_type` parameters to run the batch transform job, and the `output_path` to save prediction data as shown following:

```python
transformer = xgb_model.transformer(
    instance_count=1,
    instance_type='ml.m4.xlarge',
    output_path=batch_output
)
```

4. Initiate the batch transform job by executing the `transform()` method of the transformer object as shown following:

```python
transformer.transform(
    data=batch_input,
    data_type='S3Prefix',
    content_type='text/csv',
    split_type='Line'
)
transformer.wait()
```

5. When the batch transform job is complete, SageMaker creates the `test.csv.out` prediction data saved in the `batch_output` path, which should be in the following format: `s3://sagemaker-<region>-111122223333/demo-sagemaker-xgboost-adult-income-prediction/batch-prediction`. Run the following AWS CLI to download the output data of the batch transform job:

```
! aws s3 cp {batch_output} ./ --recursive
```

This should create the `test.csv.out` file under the current working directory. You'll be able to see the float values that are predicted based on the logistic regression of the XGBoost training job.

Step 6: Evaluate the Model

Now that you have trained and deployed a model using Amazon SageMaker, evaluate the model to ensure that it generates accurate predictions on new data. For model evaluation, use the test dataset that you created in Step 3: Download, Explore, and Transform a Dataset (p. 76).

Evaluate the Model Deployed to SageMaker Hosting Services

To evaluate the model and use it in production, invoke the endpoint with the test dataset and check whether the inferences you get returns a target accuracy you want to achieve.

To evaluate the model

1. Set up the following function to predict each line of the test set. In the following example code, the `rows` argument is to specify the number of lines to predict at a time. You can change the value of it to perform a batch inference that fully utilizes the instance's hardware resource.

```python
import numpy as np
def predict(data, rows=1000):
    split_array = np.array_split(data, int(data.shape[0] / float(rows) + 1))
    predictions = ''
    for array in split_array:
        predictions = ','.join([predictions, xgb_predictor.predict(array).decode('utf-8')])
```
Step 6: Evaluate the Model

2. Run the following code to make predictions of the test dataset and plot a histogram. You need to take only the feature columns of the test dataset, excluding the 0th column for the actual values.

```python
import matplotlib.pyplot as plt
predictions = predict(test.to_numpy()[:, 1:])
plt.hist(predictions)
plt.show()
```

3. The predicted values are float type. To determine True or False based on the float values, you need to set a cutoff value. As shown in the following example code, use the Scikit-learn library to return the output confusion metrics and classification report with a cutoff of 0.5.

```python
import sklearn
cutoff = 0.5
print(sklearn.metrics.confusion_matrix(test.iloc[:, 0], np.where(predictions > cutoff, 1, 0)))
print(sklearn.metrics.classification_report(test.iloc[:, 0], np.where(predictions > cutoff, 1, 0)))
```

This should return the following confusion matrix:

```
[[4670 356]
 [ 480 1007]]
```

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<th>recall</th>
<th>f1-score</th>
<th>support</th>
</tr>
</thead>
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<td>0.92</td>
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</tr>
<tr>
<td>1</td>
<td>0.74</td>
<td>0.68</td>
<td>0.71</td>
<td>1487</td>
</tr>
</tbody>
</table>

4. To find the best cutoff with the given test set, compute the log loss function of the logistic regression. The log loss function is defined as the negative log-likelihood of a logistic model that returns prediction probabilities for its ground truth labels. The following example code numerically and iteratively calculates the log loss values \(-y \log(p) + (1-y) \log(1-p)\), where y is the true label and p is a probability estimate of the corresponding test sample. It returns a log loss versus cutoff graph.

```python
import matplotlib.pyplot as plt
```
cutoffs = np.arange(0.01, 1, 0.01)
log_loss = []
for c in cutoffs:
    log_loss.append(
        sklearn.metrics.log_loss(test.iloc[:, 0], np.where(predictions > c, 1, 0))
    )
plt.figure(figsize=(15,10))
plt.plot(cutoffs, log_loss)
plt.xlabel("Cutoff")
plt.ylabel("Log loss")
plt.show()

This should return the following log loss curve.

5. Find the minimum points of the error curve using the NumPy `argmin` and `min` functions:

```python
print(
    'Log loss is minimized at a cutoff of ', cutoffs[np.argmin(log_loss)],
    ', and the log loss value at the minimum is ', np.min(log_loss)
)
```

This should return: Log loss is minimized at a cutoff of 0.53, and the log loss value at the minimum is 4.348539186773897.

Instead of computing and minimizing the log loss function, you can estimate a cost function as an alternative. For example, if you want to train a model to perform a binary classification for a business problem such as a customer churn prediction problem, you can set weights to the elements of confusion matrix and calculate the cost function accordingly.

You have now trained, deployed, and evaluated your first model in SageMaker.

**Tip**
To monitor model quality, data quality, and bias drift, use Amazon SageMaker Model Monitor and SageMaker Clarify. To learn more, see Amazon SageMaker Model Monitor, Monitor Data Quality, Monitor Model Quality, Monitor Bias Drift, and Monitor Feature Attribution Drift.
Tip
To get human review of low confidence ML predictions or a random sample of predictions, use Amazon Augmented AI human review workflows. For more information, see Using Amazon Augmented AI for Human Review.

Step 7: Clean Up

To avoid incurring unnecessary charges, use the AWS Management Console to delete the endpoints and resources that you created while running the exercises.

Note
Training jobs and logs cannot be deleted and are retained indefinitely.

Note
If you plan to explore other exercises in this guide, you might want to keep some of these resources, such as your notebook instance, S3 bucket, and IAM role.

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/ and delete the following resources:
   • The endpoint. Deleting the endpoint also deletes the ML compute instance or instances that support it.
     1. Under Inference, choose Endpoints.
     2. Choose the endpoint that you created in the example, choose Actions, and then choose Delete.
   • The endpoint configuration.
     1. Under Inference, choose Endpoint configurations.
     2. Choose the endpoint configuration that you created in the example, choose Actions, and then choose Delete.
   • The model.
     1. Under Inference, choose Models.
     2. Choose the model that you created in the example, choose Actions, and then choose Delete.
   • The notebook instance. Before deleting the notebook instance, stop it.
     1. Under Notebook, choose Notebook instances.
     2. Choose the notebook instance that you created in the example, choose Actions, and then choose Stop. The notebook instance takes several minutes to stop. When the Status changes to Stopped, move on to the next step.
     3. Choose Actions, and then choose Delete.
2. Open the Amazon S3 console at https://console.aws.amazon.com/s3/, and then delete the bucket that you created for storing model artifacts and the training dataset.
3. Open the Amazon CloudWatch console at https://console.aws.amazon.com/cloudwatch/, and then delete all of the log groups that have names starting with /aws/sagemaker/.

Amazon SageMaker Studio Lab

Amazon SageMaker Studio Lab is a free service that gives customers access to AWS compute resources, in an environment based on open-source JupyterLab. It is based on the same architecture and user interface as Amazon SageMaker Studio, but with a subset of Studio capabilities.

With Studio Lab, you can use AWS compute resources to create and run your Jupyter notebooks without signing up for an AWS account. Because Studio Lab is based on open-source JupyterLab, you can take advantage of open-source Jupyter extensions to run your Jupyter notebooks.
Studio Lab compared to Amazon SageMaker Studio

While Studio Lab provides free access to AWS compute resources, Amazon SageMaker Studio provides the following advanced machine learning capabilities that Studio Lab does not support.

- Continuous integration and continuous delivery (SageMaker Pipelines)
- Real-time predictions
- Large-scale distributed training
- Data preparation (Amazon SageMaker Data Wrangler)
- Data labeling (Amazon SageMaker Ground Truth)
- Feature Store
- Bias analysis (Clarify)
- Model deployment
- Model monitoring

Studio also supports fine-grained access control and security by using AWS Identity and Access Management (IAM), Amazon Virtual Private Cloud (Amazon VPC), and AWS Key Management Service (AWS KMS). Studio Lab does not support these Studio features, nor does it support the use of estimators and built-in SageMaker algorithms.

To export your Studio Lab projects for use with Studio, see Export Amazon SageMaker Studio Lab environment to Amazon SageMaker Studio (p. 110).

The following topics give information about Studio Lab and how to use it

Topics
- Amazon SageMaker Studio Lab components overview (p. 91)
- Onboard to Amazon SageMaker Studio Lab (p. 94)
- Manage your account (p. 96)
- Launch your Amazon SageMaker Studio Lab project runtime (p. 97)
- Use Amazon SageMaker Studio Lab starter assets (p. 98)
- Use the Amazon SageMaker Studio Lab project runtime (p. 99)
- Troubleshooting (p. 113)

Amazon SageMaker Studio Lab components overview

Amazon SageMaker Studio Lab consists of the following components. The following topics give more details about these components.

Topics
- Landing page (p. 92)
- User account (p. 92)
- Project overview page (p. 92)
- Preview page (p. 93)
- Project (p. 93)
- Compute instance type (p. 93)
- Project runtime (p. 94)
- Session (p. 94)
Landing page

You can request an account and sign in to an existing account on your landing page. To navigate to the landing page, see the Amazon SageMaker Studio Lab website. For more information about creating a user account, see Onboard to Amazon SageMaker Studio Lab (p. 94).

The following screenshot shows the Studio Lab landing page interface for requesting a user account and signing in.

User account

Your user account gives you access to Studio Lab. For more information about creating a user account, see Onboard to Amazon SageMaker Studio Lab (p. 94).

Project overview page

You can launch a compute instance and view information about your project on this page. To navigate to this page, you must sign in from the Amazon SageMaker Studio Lab website. The URL takes the following format.

https://studiolab.sagemaker.aws/users/<YOUR_USER_NAME>

The following screenshot shows a project overview in the Studio Lab user interface.
Preview page

On this page, you can access a read-only preview of your Jupyter notebook and copy that notebook into your project. To navigate to this page, you must follow the steps in Use GitHub resources (p. 107).

Project

Your project contains all of your files and folders, including your Jupyter notebooks. You have full control over the files in your project. Your project also includes the JupyterLab-based user interface. From this interface, you can interact with your Jupyter notebooks, edit your source code files, integrate with GitHub, and connect to Amazon S3. For more information, see Use the Amazon SageMaker Studio Lab project runtime (p. 99).

The following screenshot shows a Studio Lab project with the file browser open and the Studio Lab Launcher displayed.

Compute instance type

Your Amazon SageMaker Studio Lab project runtime is based on an EC2 instance. You are allotted 15 GB of storage and 16 GB of RAM. Availability of compute instances is not guaranteed and is subject
to demand. If you require additional storage or compute resources, consider switching to Amazon SageMaker Studio.

Amazon SageMaker Studio Lab offers the choice of a CPU (Central Processing Unit) and a GPU (Graphical Processing Unit). The following sections give information about these two options, including selection guidance.

**CPU**

A central processing unit (CPU) is designed to handle a wide range of tasks efficiently, but is limited in how many tasks it can run concurrently. For machine learning, a CPU is recommended for compute intensive algorithms, such as time series, forecasting, and tabular data.

The CPU compute type has 12 hours of compute time.

**GPU**

A graphics processing unit (GPU) is designed to render high-resolution images and video concurrently. A GPU is recommended for deep learning tasks, especially for transformers and computer vision.

The GPU compute type has 4 hours of compute time.

**Compute time**

When compute time for Studio Lab reaches its time limit, the instance stops all running computations. Studio Lab does not support time limit increases.

Studio Lab automatically saves your environment when you update your environment and every time you create a new file. Custom-installed extensions and packages persist even after your runtime has ended.

File edits are periodically saved, but are not saved when your runtime ends. To ensure that you do not lose your progress, save your work manually. If you have content in your Studio Lab project that you don’t want to lose, we recommend that you back up your content elsewhere. For more information about exporting your environment and files, see Export Amazon SageMaker Studio Lab environment to Amazon SageMaker Studio (p. 110).

During long computation, you do not need to keep your project open. For example, you can start training a model, then close your browser. The instance keeps running for up to 12 hours on CPU instances and 4 hours on GPU instances. You can then sign in later to continue your work.

We recommend that you use checkpointing in your deep learning jobs. You can use saved checkpoints to restart a job from the previously saved checkpoint. For more information, see File I/O.

**Project runtime**

The project runtime is the period of time when your compute instance is running.

**Session**

A user session begins every time you launch your project.

**Onboard to Amazon SageMaker Studio Lab**

To onboard to Amazon SageMaker Studio Lab, follow the steps in this guide. In the following sections, you learn how to request a Studio Lab account, create your account, and sign in.
Topics
• Request a Studio Lab account (p. 95)
• Create a Studio Lab account (p. 95)
• Sign in to Studio Lab (p. 95)

Request a Studio Lab account

To use Studio Lab, you must first request approval to create a Studio Lab account. An AWS account cannot be used for onboarding to Studio Lab.

The following steps show how to request a Studio Lab account.

1. Navigate to the Studio Lab landing page.
2. Select Request account.
3. Enter the required information into the form.
4. Select Submit request.
5. If you receive an email to verify your email address, follow the instructions in the email to complete this step.

Your account request must be approved before you can register for a Studio Lab account. Your request will be reviewed within five business days. When your account request is approved, you receive an email with a link to the Studio Lab account registration page. This link expires seven days after your request is approved. If the link expires, you must submit a new account request.

Note: Your account request is denied if your email has been associated with activity that violates our Terms of Service or other agreements.

Referral codes

Studio Lab referral codes enable new account requests to be automatically approved to support machine learning events like workshops, hackathons, and classes. With a referral code, a trusted host can get their participants immediate access to Studio Lab. After an account has been created using a referral code, the account continues to exist after the expiration of the code.

To get a referral code, contact Sales Support. To use a referral code, enter the code as part of the account request form.

Create a Studio Lab account

After your request is approved, complete the following steps to create your Studio Lab account.

1. Select Create account in the account request approval email to open a new page.
2. From the new page, enter your Email, a Password, and a Username.
3. Select Create account.

Sign in to Studio Lab

After you register for your account, you can sign in to Studio Lab.

1. Navigate to the Studio Lab landing page.
2. Select **Sign in** to open a new page.
3. Enter your **Email** or **Username** and **Password**.
4. Select **Sign in** to open a new page to your project.

## Manage your account

The following topic gives information about managing your account, including changing your password, deleting your account, and getting information that we have collected. These topics require that you sign in to your Amazon SageMaker Studio Lab account. For more information, see [Sign in to Studio Lab](p. 95).

### Change your password

Follow these steps to change your Amazon SageMaker Studio Lab password.

1. Navigate to the Studio Lab project overview page. The URL takes the following format.

   ```
   https://studiolab.sagemaker.aws/users/<YOUR_USER_NAME>
   ```

2. From the top-right corner, select your user name to open a dropdown menu.
3. From the dropdown menu, select **Change password** to open a new page.
4. Enter your current password into the **Enter your current password** field.
5. Enter your new password into the **Create a new password** and **Confirm your new password** fields.
6. Select **Submit**.

### Delete your account

Follow these steps to delete your Studio Lab account.

1. Navigate to the Studio Lab project overview page. The URL takes the following format.

   ```
   https://studiolab.sagemaker.aws/users/<YOUR_USER_NAME>
   ```

2. From the top-right corner, select your user name to open a dropdown menu.
3. From the dropdown menu, select **Delete account** to open a new page.
4. Enter your password to confirm the deletion of your Studio Lab account.
5. Select **Delete**.

### Customer information

Studio Lab collects your email address, user name, encrypted password, project files, and metadata. When requesting an account, you can optionally choose to provide your first and last name, country, organization name, occupation, and the reason for your interest in this product. We protect all customer personal data with encryption. For more information about how your personal information is handled, see the [Privacy Notice](#).

When you delete your account, all of your information is deleted immediately. If you have an inquiry about this, submit the [Amazon SageMaker Studio Lab Form](#). For information and support related to AWS compliance, see [Compliance support](#).
Launch your Amazon SageMaker Studio Lab project runtime

The Amazon SageMaker Studio Lab project runtime lets you write and run code directly from your browser. It is based on JupyterLab and has an integrated terminal and console. For more information about JupyterLab, see the JupyterLab Documentation.

The following topic gives information about how to manage your project runtime. These topics require that you sign in to your Amazon SageMaker Studio Lab account. For more information about signing in, see Sign in to Studio Lab (p. 95). For more information about your project, see Amazon SageMaker Studio Lab components overview (p. 91).

Topics

• Start the project runtime (p. 97)
• Stop the project runtime (p. 97)
• View remaining compute time (p. 97)
• Change your compute type (p. 97)

Start the project runtime

To use Studio Lab, you must start your project runtime. This runtime gives you access to the JupyterLab environment.

1. Navigate to the Studio Lab project overview page. The URL takes the following format.

   https://studiolab.sagemaker.aws/users/<YOUR_USER_NAME>

2. Under My Project, select a compute type. For more information about compute types, see Compute instance type (p. 93).
3. Select Start runtime.
4. After the runtime is running, select Open project to open the project runtime environment in a new browser tab.

Stop the project runtime

When you stop your project runtime, your files are not automatically saved. To ensure that you don't lose your work, save all of your changes before stopping your project runtime.

• Under My Project, select Stop runtime.

View remaining compute time

Your project runtime has limited compute time based on the compute type that you select. For more information about compute time in Studio Lab, see Compute instance type (p. 93).

• Under My Project, view Time remaining.

Change your compute type

You can switch your compute type based on your workflow. For more information about compute types, see Compute instance type (p. 93).
Use Amazon SageMaker Studio Lab starter assets

Amazon SageMaker Studio Lab supports the following assets to help machine learning (ML) practitioners get started. This guide shows you how to clone notebooks for your project.

Getting started notebook

Studio Lab comes with a starter notebook that gives general information and guides you through key workflows. When you launch your project runtime for the first time, this notebook automatically opens.

Dive into Deep Learning

Dive into Deep Learning (D2L) is an interactive, open-source book that teaches the ideas, mathematical theory, and code that power machine learning. With over 150 Jupyter notebooks, D2L provides a comprehensive overview of deep learning principles. For more information about D2L, see the D2L website.

The following procedure shows how to clone the D2L Jupyter notebooks to your instance. Your project runtime must be running.

1. Navigate to the Studio Lab project overview page. The URL takes the following format.

   https://studiolab.sagemaker.aws/users/<YOUR_USER_NAME>

2. Under Learn and experiment, find Dive into Deep Learning.

3. From Dive into Deep Learning, select Open D2L notebooks to open a new page with a preview of the notebooks.

4. Select Copy to project.

AWS Machine Learning University

The AWS Machine Learning University (MLU) provides access to the machine learning courses used to train Amazon's own developers. With AWS MLU, any developer can learn how to use machine learning with the learn-at-your-own-pace MLU Accelerator learning series. The MLU Accelerator series is designed to help developers begin their ML journey. It offers three-day foundational courses on these three subjects: Natural Language Processing, Tabular Data, and Computer Vision. For more information, see Machine Learning University.

The following procedure shows how to clone the AWS MLU Jupyter notebooks to your instance. Your project runtime must be running.
1. **Navigate to the Studio Lab project overview page.** The URL takes the following format.

   https://studiolab.sagemaker.aws/users/<YOUR_USER_NAME>

2. **Under Learn and experiment, find AWS Machine Learning University.**

3. **From AWS Machine Learning University, select Open MLU notebooks** to open a new page with a preview of the notebooks.

4. **Select Copy to project.**

**Hugging Face**

Hugging Face models give you the tools to train, fine-tune, and run inference for Natural Language Processing (NLP). For more information, see https://huggingface.co/.

The following procedure shows how to clone the Hugging Face Jupyter notebooks to your instance. Your project runtime must be running.

1. **Navigate to the Studio Lab project overview page.** The URL takes the following format.

   https://studiolab.sagemaker.aws/users/<YOUR_USER_NAME>

2. **Under Resources and community, find Hugging Face.**

3. **From Hugging Face, select Open Hugging Face notebooks** to open a new page with a preview of the notebooks.

4. **Select Copy to project.**

**Use the Amazon SageMaker Studio Lab project runtime**

The following topics give information about using the Amazon SageMaker Studio Lab project runtime. Before you can use the Studio Lab project runtime, you must onboard to Studio Lab by following the steps in Onboard to Amazon SageMaker Studio Lab (p. 94).

**Topics**

- Amazon SageMaker Studio Lab UI overview (p. 99)
- Create or open an Amazon SageMaker Studio Lab notebook (p. 101)
- Use the Amazon SageMaker Studio Lab notebook toolbar (p. 102)
- Manage your environment (p. 104)
- Use external resources in Amazon SageMaker Studio Lab (p. 107)
- Get notebook differences (p. 109)
- Export Amazon SageMaker Studio Lab environment to Amazon SageMaker Studio (p. 110)
- Shut down resources (p. 112)

**Amazon SageMaker Studio Lab UI overview**

Amazon SageMaker Studio Lab extends the JupyterLab interface. Previous users of JupyterLab will notice similarities between the JupyterLab and Studio Lab UI, including the workspace. For an overview of the basic JupyterLab interface, see The JupyterLab Interface.
The following image shows Studio Lab with the file browser open and the Studio Lab Launcher displayed.

![Studio Lab](image)

You will find the *menu bar* at the top of the screen. The *left sidebar* contains icons to open file browsers, resource browsers, and tools. The *status bar* is located at the bottom-left corner of Studio Lab.

The main work area is divided horizontally into two panes. The left pane is the *file and resource browser*. The right pane contains one or more tabs for resources, such as notebooks and terminals.

**Topics**
- Left sidebar (p. 100)
- File and resource browser (p. 101)
- Main work area (p. 101)

**Left sidebar**

The left sidebar includes the following icons. When you hover over an icon, a tooltip displays the icon name. When you choose an icon, the file and resource browser displays the described functionality. For hierarchical entries, a selectable breadcrumb at the top of the browser shows your location in the hierarchy.

<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Folder" /></td>
<td><strong>File browser</strong></td>
</tr>
</tbody>
</table>

Choose the **Upload Files** icon (↑) to add files to Studio Lab.

Double-click a file to open the file in a new tab.

To have adjacent files open, choose a tab that contains a notebook, Python, or text file, and then choose **New View for File**.

Choose the plus (+) sign on the menu at the top of the file browser to open the Studio Lab Launcher.
Use the Studio Lab project runtime

<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Running terminals and kernels</td>
</tr>
<tr>
<td><img src="image" alt="icon" /></td>
<td>You can see a list of all of the running terminals and kernels in your project. For more information, see Shut down resources (p. 112).</td>
</tr>
<tr>
<td></td>
<td>Git</td>
</tr>
<tr>
<td><img src="image" alt="icon" /></td>
<td>You can connect to a Git repository and then access a full range of Git tools and operations. For more information, see Use external resources in Amazon SageMaker Studio Lab (p. 107).</td>
</tr>
<tr>
<td></td>
<td>Table of Contents</td>
</tr>
<tr>
<td><img src="image" alt="icon" /></td>
<td>You can access the Table of Contents for your current Jupyter notebook.</td>
</tr>
<tr>
<td></td>
<td>Extension manager</td>
</tr>
<tr>
<td><img src="image" alt="icon" /></td>
<td>You can enable and manage third-party JupyterLab extensions.</td>
</tr>
</tbody>
</table>

File and resource browser

The file and resource browser shows lists of your notebooks and files. On the menu at the top of the file browser, choose the plus (+) sign to open the Studio Lab Launcher. The Launcher allows you to create a notebook or open a terminal.

Main work area

The main work area has multiple tabs that contain your open notebooks and terminals.

Create or open an Amazon SageMaker Studio Lab notebook

When you create a notebook in Amazon SageMaker Studio Lab or open a notebook in Studio Lab, you must select a kernel for the notebook. The following topics describe how to create and open notebooks in Studio Lab.

For information about shutting down the notebook, see Shut down resources (p. 112).

Topics

- Open a Studio Lab notebook (p. 101)
- Create a notebook from the file menu (p. 102)
- Create a notebook from the Launcher (p. 102)

Open a Studio Lab notebook

Studio Lab can only open notebooks listed in the Studio Lab file browser. To clone a notebook into your file browser from an external repository, see Use external resources in Amazon SageMaker Studio Lab (p. 107).

To open a notebook

1. In the left sidebar, choose the **File Browser** icon ( 文件夹 ) to display the file browser.
2. Browse to a notebook file and double-click it to open the notebook in a new tab.
Create a notebook from the file menu

To create a notebook from the File menu

1. From the Studio Lab menu, choose **File**, choose **New**, and then choose **Notebook**.
2. To use the default kernel, in the **Select Kernel** dialog box, choose **Select**. Otherwise, to select a different kernel, use the dropdown menu.

Create a notebook from the Launcher

To create a notebook from the Launcher

1. Open the Launcher by using the keyboard shortcut **Ctrl + Shift + L**.

   Alternatively, you can open Launcher from the left sidebar: Choose the **File Browser** icon, and then choose the plus (+) icon.
2. To use the default kernel from the Launcher, under **Notebook**, choose **default:Python**. Otherwise, select a different kernel.

After you choose the kernel, your notebook launches and opens in a new Studio Lab tab.

To view the notebook's kernel session, in the left sidebar, choose the **Running Terminals and Kernels** icon ( ). You can stop the notebook's kernel session from this view.

Use the Amazon SageMaker Studio Lab notebook toolbar

Amazon SageMaker Studio Lab notebooks extend the JupyterLab interface. For an overview of the basic JupyterLab interface, see [The JupyterLab Interface](#).

The following image shows the toolbar and an empty cell from a Studio Lab notebook.

When you hover over a toolbar icon, a tooltip displays the icon function. You can find additional notebook commands in the Studio Lab main menu. The toolbar includes the following icons:

<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
</table>
| ![Save and checkpoint](#) | **Save and checkpoint**  
Saves the notebook and updates the checkpoint file. |
| ![Insert cell](#) | **Insert cell**  
Inserts a code cell below the current cell. The current cell is noted by the blue vertical marker in the left margin. |
| ![Cut, copy, and paste cells](#) | **Cut, copy, and paste cells**  
Cuts, copies, and pastes the selected cells. |
<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Run cells" /></td>
<td><strong>Run cells</strong>&lt;br&gt;Runs the selected cells. The cell that follows the last-selected cell becomes the new-selected cell.</td>
</tr>
<tr>
<td><img src="image" alt="Interrupt kernel" /></td>
<td><strong>Interrupt kernel</strong>&lt;br&gt;Interrupts the kernel, which cancels the currently-running operation. The kernel remains active.</td>
</tr>
<tr>
<td><img src="image" alt="Restart kernel" /></td>
<td><strong>Restart kernel</strong>&lt;br&gt;Restarts the kernel. Variables are reset. Unsaved information is not affected.</td>
</tr>
<tr>
<td><img src="image" alt="Restart kernel and re-run notebook" /></td>
<td><strong>Restart kernel and re-run notebook</strong>&lt;br&gt;Restarts the kernel. Variables are reset. Unsaved information is not affected. Then re-runs the entire notebook.</td>
</tr>
<tr>
<td><img src="image" alt="Code" /></td>
<td><strong>Cell type</strong>&lt;br&gt;Displays or changes the current cell type. The cell types are:&lt;br&gt;• Code – Code that the kernel runs.&lt;br&gt;• Markdown – Text rendered as markdown.&lt;br&gt;• Raw – Content, including Markdown markup, that's displayed as text.</td>
</tr>
<tr>
<td><img src="image" alt="Checkpoint diff" /></td>
<td><strong>Checkpoint diff</strong>&lt;br&gt;Opens a new tab that displays the difference between the notebook and the checkpoint file. For more information, see <a href="#">Get notebook differences (p. 109)</a>.</td>
</tr>
<tr>
<td><img src="image" alt="Git diff" /></td>
<td><strong>Git diff</strong>&lt;br&gt;Only enabled if the notebook is opened from a Git repository. Opens a new tab that displays the difference between the notebook and the last Git commit. For more information, see <a href="#">Get notebook differences (p. 109)</a>.</td>
</tr>
<tr>
<td><img src="image" alt="default Kernel" /></td>
<td><strong>Kernel</strong>&lt;br&gt;Displays or changes the kernel that processes the cells in the notebook.&lt;br&gt;No Kernel indicates that the notebook was opened without specifying a kernel. You can edit the notebook, but you can't run any cells.</td>
</tr>
<tr>
<td><img src="image" alt="Kernel busy status" /></td>
<td><strong>Kernel busy status</strong>&lt;br&gt;Displays a kernel's busy status by showing the circle's edge and its interior as the same color. The kernel is busy when it is starting and when it is processing cells. Additional kernel states are displayed in the status bar at the bottom-left corner of Studio Lab.</td>
</tr>
</tbody>
</table>
Manage your environment

Your Amazon SageMaker Studio Lab environment comes with a base image installed that includes key packages and resources. You can customize your environment by adding new packages and libraries to it. You can also create new environments from Studio Lab, import compatible environments, and reset your environment to create space.

**Topics**
- Base image (p. 104)
- Managing conda environments (p. 105)

**Base image**

The default Amazon SageMaker Studio Lab base image includes the following packages.

- Python 3.9
- bzip2
- build-essential
- curl
- git
- libgl1-mesa-glx
- nano
- rsync
- unzip
- wget
- ca-certificates
- pip
- ipykernel-6.4

**Supported ML frameworks and libraries**

Machine learning frameworks simplify machine learning by abstracting complex algorithms and processes. This abstraction helps you get started with machine learning. Libraries are collections of files, programs, and other resources that you can use in your code. Studio Lab supports the following frameworks and libraries, which you must install manually.

- PyTorch 1.9
- TensorFlow 1.15 and 2.6
- MxNet 1.8
- Hugging Face
- AutoGluon 0.3.1
- Scikit-learn 0.24
- PyTorch ecosystem
- OpenCV
- scipy
- numpy

For a list of all of the packages currently installed in your environment, run the following command from your Jupyter notebook.
%pip list

Managing conda environments

The following sections give information about your default conda environment, how to customize it, and how to add new conda environments. For more information about conda environments, see Conda environments. For a list of sample environments that you can install into Studio Lab, see Creating Custom Conda Environments. To use these sample environment YAML files with Studio Lab, see Step 4 – Import your Studio Lab Conda environments in Studio (p. 112).

Your default environment

Studio Lab uses conda environments to encapsulate the software packages that are needed to run notebooks. Your project contains a default conda environment, named default, with the IPython kernel. This environment serves as the default kernel for your Jupyter notebooks.

Customize your environment

You can customize your environment by installing extensions and packages, as needed. You do not need to install your packages every time you work on your project. Any installed extensions and packages persist in your project.

Note

Installed packages count against your 15 GB of instance storage.

To install additional packages to your environment from a Jupyter notebook, insert one of the following commands in a cell at the top of your notebook. These commands install packages in the environment used by that notebook. Any packages that you install are saved in your persistent project directory.

- `%conda install <PACKAGE>`
- `%pip install <PACKAGE>`

We don’t recommend using the `!pip` or `!conda` commands because they can behave in unexpected ways when you have multiple environments. After you install new packages to your environment, restart the kernel to ensure that the packages work in your notebook.

Create and activate new conda environments

If you would like to maintain multiple environments for different use cases, you can create new conda environments in your project. The following sections show how to create and activate new conda environments. For a Jupyter notebook that shows how to create a custom environment, see Setting up a Custom Environment in SageMaker Studio Lab.

Note

Maintaining multiple environments in your project decreases your available memory.

Create

To create a new conda environment, run the following conda command from your terminal. This example creates a new environment with Python 3.9.

```bash
conda create --name <ENVIRONMENT_NAME> python=3.9
```

Activate

To activate any conda environment, run the following command in the terminal.

```bash
conda activate <ENVIRONMENT_NAME>
```
When you run this command, any packages installed using conda or pip are installed in the environment.

To use your new conda environments with notebooks, make sure the ipykernel package is installed in the environment.

```
conda install ipykernel
```

After you have created the environment, you can select it as the kernel for your notebook.

**Using Sample Studio Lab Environments**

Studio Lab provides sample custom environments through the SageMaker Studio Lab Sample Notebooks repository. The following shows how to clone and build these environments.

1. Navigate to your root directory and open the Getting Started notebook.
2. Click the **Clone SageMaker Studio Lab Examples** button to clone the SageMaker Studio Lab Sample Notebooks repository.
3. Navigate to the `studio-lab-examples/custom-environments` directory in File Browser.
4. Open the directory for the environment that you want to build.
5. Right click the `.yml` file in the folder, then select **Build Conda Environment**.
6. After your conda environment has finished building, use the following command to activate it. You can then use the environment.

```
conda activate ENVIRONMENT_NAME
```

**Installing JupyterLab and Jupyter Server extensions**

You can install open-source JupyterLab and Jupyter Server extensions in Studio Lab. These extensions are typically Python packages that are installed using conda or pip.

The following steps show how to install these extensions.

1. Open the terminal and activate the `studiolab` environment.
```
conda activate studiolab
```
2. Install the JupyterLab or Jupyter Server extension.
```
conda install <JUPYTER_EXTENSION>
```
3. Navigate to the Studio Lab project overview page.
4. Select **Stop runtime**.
5. Select **Start runtime**.

**Reset environment**

To remove all of your files and reset your project, run the following command from the terminal.

```
rm -rf */.*
```

The following command deletes a conda environment from your project.

```
conda remove --name <ENVIRONMENT_NAME> --all
```
Use external resources in Amazon SageMaker Studio Lab

With Amazon SageMaker Studio Lab, you can integrate external resources, such as Jupyter notebooks and data, from Git repositories and Amazon S3. You can also add an Open in Amazon SageMaker Studio Lab button to your GitHub repo and notebooks. This button lets you clone your notebooks directly from Studio Lab.

The following topics show how to integrate external resources.

Topics
- Use GitHub resources (p. 107)
- Add an Open in Amazon SageMaker Studio Lab button to your notebook (p. 108)
- Import files from your computer (p. 109)
- Connect to Amazon S3 (p. 109)

Use GitHub resources

Amazon SageMaker Studio Lab offers integration with GitHub. With this integration, you can clone notebooks and repositories directly to your Studio Lab project.

The following topics give information about how to use GitHub resources with Amazon SageMaker Studio Lab.

Amazon SageMaker Studio Lab sample notebooks

To get started with a repository of sample notebooks tailored for Studio Lab, see Amazon SageMaker Studio Lab Sample Notebooks.

This repository provides notebooks for the following use cases and others.

- Computer vision
- Connecting to AWS
- Creating custom environments
- Geospatial data analysis
- Natural language processing
- Using R

Clone a GitHub repo

To clone a GitHub repo to your Amazon SageMaker Studio Lab project, follow these steps.

1. Open the Studio Lab project runtime.
2. From the menu, select Git to open a new dropdown menu.
3. Select Clone Git Repository to open a new window.
4. In the new window, paste the repository's URL.
5. Select Clone.

Clone individual notebooks from GitHub

To open a notebook in Studio Lab, you must have access to the repo that the notebook is in. The following examples describe Studio Lab permission-related behavior in various situations.
If a repo is public, you can automatically clone the notebook into your project from the Studio Lab preview page.

If a repo is private, you are prompted to sign in to GitHub from the Studio Lab preview page. If you have access to a private repo, you can clone the notebook into your project.

If you don't have access to a private repo, you cannot clone the notebook from the Studio Lab preview page.

The following sections show two options for you to copy a GitHub notebook in your Studio Lab project. These options depend on whether the notebook has an **Open in Amazon SageMaker Studio Lab** button.

**Option 1: Copy notebook with an **Open in Amazon SageMaker Studio Lab** button**

The following procedure shows how to copy a notebook that has an **Open in Amazon SageMaker Studio Lab** button. If you want to add this button to your notebook, see **Add an **Open in Amazon SageMaker Studio Lab** button to your notebook** (p. 108).

1. Sign in to Studio Lab following the steps in **Sign in to Studio Lab** (p. 95).
2. In a new browser tab, navigate to the GitHub notebook that you want to clone.
3. In the notebook, select the **Open in Amazon SageMaker Studio Lab** button to open a new page in Studio Lab with a preview of the notebook.
4. If the project runtime is not already running, start it by choosing the **Start runtime** button at the top of the preview page. Wait for the runtime to start before proceeding to the next step.
5. After the project runtime has started, select **Copy to project** to open the project runtime in a new browser tab.
6. In the **Copy from GitHub?** dialog box, select **Copy notebook only**. This copies the notebook file to your project.

**Option 2: Clone any GitHub notebook**

The following procedure shows how to copy any notebook from GitHub.

1. Navigate to the notebook in GitHub.
2. In the browser's address bar, modify the notebook URL, as follows.

```
# Original URL
https://github.com/<PATH_TO_NOTEBOOK>

# Modified URL
https://studiolab.sagemaker.aws/import/github/<PATH_TO_NOTEBOOK>
```

3. Navigate to the modified URL. This opens a preview of the notebook in Studio Lab.
4. If the project runtime is not already running, start it by choosing the **Start runtime** button at the top of the preview page. Wait for the runtime to start before proceeding to the next step.
5. After the project runtime has started, select **Copy to project** to open the project runtime in a new browser tab.
6. In the **Copy from GitHub?** dialog box, select **Copy notebook only** to copy the notebook file to your project.

**Add an **Open in Amazon SageMaker Studio Lab** button to your notebook**

When you add the **Open in Amazon SageMaker Studio Lab** button to your notebooks, others can clone your notebooks or repositories directly to their Studio Lab projects. If you are sharing your notebook within a public GitHub repository, your content will be publicly readable. Do not share private content, such as AWS access keys or AWS Identity and Access Management credentials, in your notebook.
To add the functional **Open in Amazon SageMaker Studio Lab** button to your Jupyter notebook or repository, add the following markdown to the top of your notebook or repository.

```
[![Open In SageMaker Studio Lab](https://studiolab.sagemaker.aws/studiolab.svg)](https://studiolab.sagemaker.aws/import/github/<PATH_TO_YOUR_NOTEBOOK_ON_GITHUB>)
```

### Import files from your computer

The following steps show how to import files from your computer to your Studio Lab project.

1. Open the Studio Lab project runtime.
2. Open the **File Browser** panel.
3. In the actions bar of the **File Browser** panel, select the **Upload Files** button.
4. Select the files that you want to upload from your local machine.
5. Select **Open**.

Alternatively, you can drag and drop files from your computer into the **File Browser** panel.

### Connect to Amazon S3

The AWS CLI enables AWS integration in your Studio Lab project. With this integration, you can pull resources from Amazon S3 to use with your Jupyter notebooks.

To use AWS CLI with Studio Lab, complete the following steps. For a notebook that outlines this integration, see [Using Studio Lab with AWS Resources](#).

1. Install the AWS CLI following the steps in [Installing or updating the latest version of the AWS CLI](#).
2. Configure your AWS credentials by following the steps in [Quick setup](#). The role for your AWS account must have permissions to access the Amazon S3 bucket that you are copying data from.
3. From your Jupyter notebook, clone resources from the Amazon S3 bucket, as needed. The following command shows how to clone all resources from an Amazon S3 path to your project. For more information, see the [AWS CLI Command Reference](#).

```
!aws s3 cp s3://<BUCKET_NAME>/<PATH_TO_RESOURCES>/ <PROJECT_DESTINATION_PATH>/ --recursive
```

### Get notebook differences

You can display the difference between the current notebook and the last checkpoint, or the last Git commit, using the Amazon SageMaker Studio Lab project UI.

**Topics**

- Get the difference between the last checkpoint (p. 109)
- Get the difference between the last commit (p. 110)

### Get the difference between the last checkpoint

When you create a notebook, a hidden checkpoint file that matches the notebook is created. You can view changes between the notebook and the checkpoint file, or revert the notebook to match the checkpoint file.
To save the Studio Lab notebook and update the checkpoint file to match: Choose the **Save notebook and create checkpoint** icon (️). This is located on the Studio Lab menu's left side. The keyboard shortcut for **Save notebook and create checkpoint** is Ctrl + s.

To view changes between the Studio Lab notebook and the checkpoint file: Choose the **Checkpoint diff** icon (️), located in the center of the Studio Lab menu.

To revert the Studio Lab notebook to the checkpoint file: On the main Studio Lab menu, choose **File**, and then **Revert Notebook to Checkpoint**.

### Get the difference between the last commit

If a notebook is opened from a Git repository, you can view the difference between the notebook and the last Git commit.

To view the changes in the notebook from the last Git commit: Choose the **Git diff** icon (️) in the center of the notebook menu.

### Export Amazon SageMaker Studio Lab environment to Amazon SageMaker Studio

Amazon SageMaker Studio offers many features for machine learning and deep learning workflows that are unavailable in Amazon SageMaker Studio Lab. To take advantage of the features offered in Amazon SageMaker Studio, you must first onboard following the steps in **Onboard to Amazon SageMaker Domain** (p. 35).

After you’ve onboarded to Studio, you can migrate your Studio Lab environment and artifacts to Studio.

Studio Lab does not currently support sharing your project with others. However, you may download a copy of your project files to share using the following steps.

#### Topics

- **Step 1 – Export your Studio Lab Conda environment** (p. 110)
- **Step 2 – Export your Studio Lab artifacts to GitHub** (p. 111)
- **Step 3 – Import your Studio Lab artifacts from GitHub to Studio** (p. 111)
- **Step 4 – Import your Studio Lab Conda environments in Studio** (p. 112)

#### Step 1 – Export your Studio Lab Conda environment

When you add libraries to your environment following the steps in **Manage your environment** (p. 104), they become part of your Conda environments. The following procedure shows how to export the definitions of those environments so they can be rebuilt in Studio.

1. From the terminal, list the Conda environments in your Studio Lab.

   ```bash
   conda env list
   ```

   This command outputs a list of the Conda environments and their locations in the file system. When you onboard to Studio Lab, you use the **default-kernel** Conda environment by default.

   ```bash
   # conda environments: #
   default-kernel /home/studio-lab-user/.conda/envs/default-kernel
   ```
We recommend that you do not export the `studiolab` and `base` environments. These environments are not usable in Studio for the following reasons:

- `studiolab`: This sets up the JupyterLab environment for Studio Lab. Studio Lab runs a different major version of JupyterLab than Studio, so it is not usable in Studio.
- `base`: This environment comes with Conda by default. The `base` environment in Studio Lab and the `base` environment in Studio have incompatible versions of many packages.

2. For each Conda environment that you want to migrate to Studio, run the following command. This command exports the Conda environment definition to a YAML file in your Studio Lab home directory.

```
conda env export -n <ENVIRONMENT_NAME> ~/<ENVIRONMENT_NAME>.yml
```

Step 2 – Export your Studio Lab artifacts to GitHub

Next, you must clone your artifacts to a GitHub repository. The repository will be cloned in Studio in Step 3.

The following procedure shows how to synchronize your content with GitHub using the Studio Lab terminal.

1. From the Studio Lab terminal, navigate to your home directory.
2. Initialize the directory as a Git repository using the following command. For more information, see the `git-init` documentation.

```
git init
```

3. Move all of your artifacts, including the Conda environments’ YAML file definitions, to your home directory.
4. Add all relevant files and then commit your changes.

```
git add <FILE_NAME>
git commit -m "<COMMIT_MESSAGE>"
```

5. Push the commit to your remote repository. This repository has the format `https://github.com/<GITHUB_USERNAME>/<REPOSITORY_NAME>` where `<GITHUB_USERNAME>` is your GitHub username and the `<REPOSITORY_NAME>` is your remote repository.

```
git remote add origin git@github.com/<GITHUB_USERNAME>/<REPOSITORY_NAME>
git push -u origin <BRANCH_NAME>
```

Step 3 – Import your Studio Lab artifacts from GitHub to Studio

The following procedure shows how to import your artifacts to Studio from your GitHub repository.

1. Navigate to Studio.
2. From the Launcher, navigate to **Notebooks and compute resources**.
3. For **Select a SageMaker Image**, select **Data Science**. This image comes with Conda preinstalled.
4. Select **Image Terminal**.
5. From the image terminal, run the following command to clone your repository. This command creates a directory named after `<REPOSITORY_NAME>` in your Studio instance. After that, it clones your artifacts in that repository.

```bash
git clone https://github.com/<GITHUB_USERNAME>/<REPOSITORY_NAME>.git
```

**Step 4 – Import your Studio Lab Conda environments in Studio**

After you've cloned your GitHub repository to your Studio instance, you can use the YAML files to recreate your Conda environments in Studio.

For each Conda environment that you want to recreate, run the following commands.

```bash
conda env create --file /<PATH_TO_DIRECTORY>/<ENVIRONMENT_NAME>.yml
conda activate <ENVIRONMENT_NAME>
conda install ipykernel
python -m ipykernel install
```

After these commands are complete, you can select your environment as the kernel for your Studio notebook instances.

**Shut down resources**

In this guide, you will learn how to shut down individual resources, including notebooks, terminals, and kernels. You can also shut down all resources in one of these categories at the same time.

**Topics**

- Shut down an open notebook (p. 112)
- Shut down resources (p. 112)

**Shut down an open notebook**

You can shut down an open notebook from the Amazon SageMaker Studio Lab File menu or from the Running Terminals and Kernels pane.

**Note**

When you shut down a notebook, any unsaved information in the notebook is lost. The notebook is not deleted.

**To shut down an open notebook from the File menu**

1. Save the notebook contents by choosing the icon, located in the notebook menu.
2. Choose File then Close and Shutdown Notebook.
3. Choose OK.

**Shut down resources**

On the left sidebar of Studio Lab, you will find the Running Terminals and Kernels pane and icon. The Running Terminals and Kernels pane has three sections. Each section lists all of the resources...
of that type. You can shut down each resource individually, or shut down all resources in a section simultaneously.

When you shut down all resources in a section, the following occurs:

- **KERNELS** – All kernels, notebooks, and consoles are shut down.
- **TERMINALS** – All terminals are shut down.

**To shut down resources**

1. In the left sidebar, choose the Running Terminals and Kernels icon ( самым).
2. Do either of the following:
   - To shut down a specific resource: Choose the SHUT DOWN icon on the same row as the resource.
   - To shut down all resources in a section: Choose Shut Down All, which is located to the right of the section label. After a confirmation dialog box appears, choose Shut down all to proceed.

**Troubleshooting**

The guide shows common errors that might occur when using Amazon SageMaker Studio Lab. Each error contains a description, as well as a solution to the error.

**Note**

You cannot share your password with multiple users or use Studio Lab to mine cryptocurrency. We don’t recommend using Studio Lab for production tasks because of runtime limits.

**Can't access account**

If you can't access your account, verify that you are using the correct email and password. If you have forgotten your password, use the following steps to reset your password. If you still cannot access your account, you must request and register for a new account using the instructions in Onboard to Amazon SageMaker Studio Lab (p. 94).

**Forgot password**

If you forget your password, you must reset it using the following steps.

1. Navigate to the Studio Lab landing page.
2. Select Sign in.
3. Select Forgot password? to open a new page.
4. Enter the email address that you used to sign up for an account.
5. Select Send reset link to send an email with a password reset link.
6. From the password reset email, select Reset your password.
7. Enter your new password.
8. Select Submit.

**Can't launch project runtime**

If the Studio Lab project runtime does not launch, try launching it again. If this doesn't work, switch the instance type from CPU to GPU (or in reverse). For more information, see Change your compute type (p. 97).
Runtime stopped running unexpectedly

If there is an issue with the environment used to run JupyterLab, then Studio Lab will automatically recreate the environment. Studio Lab does not support manual activation of this process.

Conflicting versions

Because you can add packages and modify your environment as needed, you may run into conflicts between packages in your environment. If there are conflicts between packages in your environment, you must remove the conflicting package.

Environment build fails

When you build an environment from a YAML file, a package-version conflict or file issue might cause a build to fail. To resolve this, remove the environment by running the following command. Do this before attempting to build it again.

```bash
conda remove --name <YOUR_ENVIRONMENT> --all
```

Increasing disk space in your project

If you get a notification that your disk space is full while you're attempting to create or import a file, you can delete files to increase space. For instructions, see Reset environment (p. 106).

Cannot import cv2

If you run into an error when importing cv2 after installing opencv-python, you must uninstall opencv-python and install opencv-python-headless as follows.

```bash
%pip uninstall opencv-python --yes
%pip install opencv-python-headless
```

You can then import cv2 as expected.

Studio Lab becomes unresponsive when opening large files

The Studio Lab IDE may fail to render when large files are opened, resulting in blocked access to Studio Lab resources. To resolve this, reset the Studio Lab workspace using the following procedure.

1. After you open the IDE, copy the URL in your browser's address bar. This URL should be in the https://xxxxxx.studio.us-east-2.sagemaker.aws/studiolab/default/jupyter/lab format. Close the tab.
2. In a new tab, paste the URL and remove anything after https://xxxxxx.studio.us-east-2.sagemaker.aws/studiolab/default/jupyter/lab.
3. Add ?reset to the end of the URL, so it is in the https://xxxxxx.studio.us-east-2.sagemaker.aws/studiolab/default/jupyter/lab?reset format.
4. Navigate to the updated URL. This resets the saved UI state and makes the Studio Lab IDE responsive.
Amazon SageMaker Machine Learning Environments

Amazon SageMaker supports the following machine learning environments.

- **Amazon SageMaker Studio**: Lets you build, train, debug, deploy, and monitor your machine learning models.
- **RStudio on Amazon SageMaker**: RStudio is an IDE for R, with a console, syntax-highlighting editor that supports direct code execution, and tools for plotting, history, debugging and workspace management.
- **Amazon SageMaker Canvas**: Gives you the ability to use machine learning to generate predictions without needing to code.

To use these machine learning environments, you must create an Amazon SageMaker Domain.

**Topics**
- Amazon SageMaker Domain (p. 115)
- Amazon SageMaker Studio (p. 117)
- RStudio on Amazon SageMaker (p. 182)
- Amazon SageMaker Canvas (p. 213)

Amazon SageMaker Domain

Amazon SageMaker Domain supports the SageMaker machine learning environments. SageMaker Domain creates the following entities. For information on the onboarding steps to create a Domain, see Onboard to Amazon SageMaker Domain (p. 35).

- **Domain**: An Amazon SageMaker Domain consists of an associated Amazon Elastic File System (Amazon EFS) volume; a list of authorized users; and a variety of security, application, policy, and Amazon Virtual Private Cloud (Amazon VPC) configurations. An AWS account is limited to one Domain per Region. Users within a Domain can share notebook files and other artifacts with each other.
- **UserProfile**: A user profile represents a single user within a Domain, and is the main way to reference a user for the purposes of sharing, reporting, and other user-oriented features. This entity is created when a user onboards to the Amazon SageMaker Domain.
- **App**: An app represents an application that supports the reading and execution experience of the user’s notebooks, terminals, and consoles. The type of app can be JupyterServer, KernelGateway, RStudioServerPro, or RSession. A user may have multiple Apps active simultaneously.

The following tables describe the status values for the Domain, UserProfile, and App entities. Where applicable, they also give troubleshooting steps.

**Domain status values**

<table>
<thead>
<tr>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pending</td>
<td>Ongoing creation of Domain.</td>
</tr>
<tr>
<td>Value</td>
<td>Description</td>
</tr>
<tr>
<td>-----------</td>
<td>------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>InService</td>
<td>Successful creation of Domain.</td>
</tr>
<tr>
<td>Updating</td>
<td>Ongoing update of Domain.</td>
</tr>
<tr>
<td>Deleting</td>
<td>Ongoing deletion of Domain.</td>
</tr>
<tr>
<td>Failed</td>
<td>Unsuccessful creation of Domain. Call the DescribeDomain API to see the failure reason for Domain creation. Delete the failed Domain and recreate the Domain after fixing the error mentioned in FailureReason.</td>
</tr>
<tr>
<td>Update_Failed</td>
<td>Unsuccessful update of Domain. Call the DescribeDomain API to see the failure reason for Domain update. Call the UpdateDomain API after fixing the error mentioned in FailureReason.</td>
</tr>
<tr>
<td>Delete_Failed</td>
<td>Unsuccessful deletion of Domain. Call the DescribeDomain API to see the failure reason for Domain deletion. Because deletion failed, you might have some resources that are still running, but you cannot use or update the Domain. Call the DeleteDomain API again after fixing the error mentioned in FailureReason.</td>
</tr>
</tbody>
</table>

**UserProfile status values**

<table>
<thead>
<tr>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pending</td>
<td>Ongoing creation of UserProfile.</td>
</tr>
<tr>
<td>InService</td>
<td>Successful creation of UserProfile.</td>
</tr>
<tr>
<td>Updating</td>
<td>Ongoing update of UserProfile.</td>
</tr>
<tr>
<td>Deleting</td>
<td>Ongoing deletion of UserProfile.</td>
</tr>
<tr>
<td>Failed</td>
<td>Unsuccessful creation of UserProfile. Call the DescribeUserProfile API to see the failure reason for UserProfile creation. Delete the failed UserProfile and recreate it after fixing the error mentioned in FailureReason.</td>
</tr>
<tr>
<td>Update_Failed</td>
<td>Unsuccessful update of UserProfile. Call the DescribeUserProfile API to see the failure reason for UserProfile update. Call the UpdateUserProfile API again after fixing the error mentioned in FailureReason.</td>
</tr>
<tr>
<td>Delete_Failed</td>
<td>Unsuccessful deletion of UserProfile. Call the DescribeUserProfile API to see the failure reason for UserProfile deletion. Because deletion failed, you might have some resources that are still running, but you cannot use or update the User Profile.</td>
</tr>
</tbody>
</table>
Amazon SageMaker Developer Guide

SageMaker Studio

<table>
<thead>
<tr>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>UserProfile. Call the DeleteUserProfile API again after fixing the error mentioned in FailureReason.</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>App status values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
</tr>
<tr>
<td>Pending</td>
</tr>
<tr>
<td>InService</td>
</tr>
<tr>
<td>Deleting</td>
</tr>
<tr>
<td>Failed</td>
</tr>
<tr>
<td>Deleted</td>
</tr>
</tbody>
</table>

Amazon SageMaker Studio

Amazon SageMaker Studio is a web-based, integrated development environment (IDE) for machine learning that lets you build, train, debug, deploy, and monitor your machine learning models. SageMaker Studio provides all the tools you need to take your models from data preparation to experimentation to production while boosting your productivity. In a single unified visual interface, customers can perform the following tasks:

- Write and execute code in Jupyter notebooks
- Prepare data for machine learning
- Build and train machine learning models
- Deploy the models and monitor the performance of their predictions
- Track and debug the machine learning experiments

For information on the onboarding steps to sign in to SageMaker Studio, see Onboard to Amazon SageMaker Domain (p. 35).

For the AWS Regions supported by SageMaker Studio, see Supported Regions and Quotas (p. 32).

Topics

- Studio Features (p. 118)
- Amazon SageMaker Studio UI Overview (p. 118)
- JupyterLab Versioning (p. 120)
- Use the Amazon SageMaker Studio Launcher (p. 127)
- Use Amazon SageMaker Studio Notebooks (p. 129)
- Customize Amazon SageMaker Studio (p. 152)
- Perform Common Tasks in Amazon SageMaker Studio (p. 175)
- Amazon SageMaker Studio Pricing (p. 181)
- Troubleshooting Amazon SageMaker Studio (p. 181)
Studio Features

Studio includes the following features:

- SageMaker Autopilot
- SageMaker Clarify
- SageMaker Data Wrangler
- SageMaker Debugger
- SageMaker Experiments
- SageMaker Feature Store
- SageMaker JumpStart
- Amazon SageMaker Model Building Pipelines
- SageMaker Model Registry
- SageMaker Projects
- SageMaker Studio Notebooks
- SageMaker Studio Universal Notebook

Amazon SageMaker Studio UI Overview

Amazon SageMaker Studio extends the JupyterLab interface. Previous users of JupyterLab will notice the similarity of the user interface, including the workspace. Studio adds many additions to the interface. The most prominent additions are detailed in the following sections. For an overview of the basic JupyterLab interface, see The JupyterLab Interface.

The following image shows SageMaker Studio with the file browser open and the Studio Launcher displayed.

At the top of the screen is the menu bar. At the left of the screen is the left sidebar which contains icons to open file browsers, resource browsers, and tools. At the right of the screen is the right sidebar,
represented by the Settings icon (💰), which displays contextual property settings when open. At the bottom of the screen is the status bar.

Above the Settings icon, there's a button to provide feedback about your experiences with SageMaker Studio.

To the left of the Feedback button there's the notification icon. Choose the icon to view notifications from Studio such as new Studio versions and new SageMaker features. To update to a new version of Studio, see Shut Down and Update SageMaker Studio and Studio Apps (p. 179).

The main work area is divided horizontally into two panes. The left pane is the file and resource browser. The right pane contains one or more tabs for resources such as notebooks, terminals, metrics, and graphs.

Topics
- Left sidebar (p. 119)
- File and resource browser (p. 120)
- Main work area (p. 120)
- Settings (p. 120)

Left sidebar

The left sidebar includes the following icons. When you hover over an icon, a tooltip displays the icon name. When you choose an icon, the file and resource browser displays the described functionality. For hierarchical entries, a selectable breadcrumb at the top of the browser shows your location in the hierarchy.

<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
</table>
| ![Folder](file_browser.png) | **File Browser**
Choose the **Upload Files** icon (⇅) to add files to Studio.
Double-click a file to open the file in a new tab.
To have adjacent files open, choose a tab that contains a notebook, Python, or text file, then choose **New View for File**.
Choose the plus (+) sign on the menu at the top of the file browser to open the Studio Launcher. |
| ![Terminal](running_terminals_and_kernels.png) | **Running Terminals and Kernels**
For more information, see Shut Down Resources (p. 144). |
| ![Git](git.png) | **Git**
You can connect to a Git repository and then access a full range of Git tools and operations. For more information, see Clone a Git Repository in SageMaker Studio (p. 176). |
| ![Commands](commands.png) | **Commands (Ctrl + Shift + C)**
The majority of the menu commands are available here. |
### Icon | Description
--- | ---
Notebook Tools | You can access a notebook's metadata through the Advanced Tools section. This icon is displayed only when a notebook is open.
Open Tabs | Provides a list of open tabs, which is useful if you have multiple open tabs.
SageMaker Jumpstart | Provides a list of solutions, model endpoints, or training jobs created with SageMaker Jumpstart.
SageMaker Components and registries | Provides a list of projects, data wrangler flows, pipelines, experiments, trials, models, or endpoints, or access to the feature store.

### File and resource browser

The file and resource browser displays lists of your notebooks, experiments, trials, trial components, endpoints, and low-code solutions. On the menu at the top of the file browser, choose the plus (+) sign to open the Studio Launcher. The Launcher allows you to create a notebook, launch a Python interactive shell, open a terminal, or create a low-code solution.

### Main work area

The main work area consists of multiple tabs that contain your open notebooks and terminals, and detailed information about your experiments and endpoints, as well as low-code solutions. One commonly used tab is the Trial Component List. This list is referred to as the Leaderboard because it's where you can compare experiments and trials. For more information, see View and Compare Amazon SageMaker Experiments, Trials, and Trial Components (p. 2237).

### Settings

The settings pane allows you to adjust table and chart properties. By default, the pane is hidden on the far right of the screen. To open the pane, choose the Settings icon (⚙️) on the top right of the screen.

### JupyterLab Versioning

The Amazon SageMaker Studio interface is based on JupyterLab, which is a web-based interactive development environment for notebooks, code, and data. Studio now supports using both JupyterLab 1 and JupyterLab 3. The default version of JupyterLab in Studio is JupyterLab 3. If you created your domain and user profile before 08/31/2022, then your Studio instance defaults to JupyterLab 1. After 08/31/2022, JupyterLab version 1 on Amazon SageMaker Studio only receives security fixes. You can choose the version that you want to run. However, you can run only a single instance of JupyterLab at one time. You can't run multiple versions of JupyterLab simultaneously.

### Topics
- JupyterLab 3 (p. 121)
- Restricting default JupyterLab version using an IAM policy condition key (p. 121)
Setting a default JupyterLab version (p. 122)
View and update the JupyterLab version of an app from the console (p. 125)
Installing JupyterLab and Jupyter Server extensions (p. 126)

JupyterLab 3

JupyterLab 3 includes the following features that are not available in previous versions. For more information about these features, see JupyterLab 3.0 is released!

- Visual debugger when using the Base Python 2.0 and Data Science 2.0 kernels.
- File browser filter
- Table of Contents (TOC)
- Multi-language support
- Simple mode
- Single interface mode

Important changes to JupyterLab 3

Consider the following when using JupyterLab 3:

- When setting the JupyterLab version using the AWS CLI, select the corresponding image for your Region and JupyterLab version from the image list in From the AWS CLI (p. 122).
- In JupyterLab 3, you must activate the studio conda environment before installing extensions. For more information, see Installing JupyterLab and Jupyter Server extensions (p. 126).
- Debugger is only supported when using the following images:
  - Base Python 2.0
  - Data Science 2.0

Restricting default JupyterLab version using an IAM policy condition key

You can use IAM policy condition keys to restrict the version of JupyterLab that your users can launch.

The following policy shows how to limit the JupyterLab version at the domain level.

```
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "Block users from creating JupyterLab 3 apps at the domain level",
            "Effect": "Deny",
            "Action": [
                "sagemaker:CreateDomain",
                "sagemaker:UpdateDomain"
            ],
            "Resource": "*",
            "Condition": {
                "ForAllValues:StringLike": {
                    "sagemaker:ImageArns": "*image/jupyter-server-3"
                }
            }
        }
    ]
}
```
The following policy shows how to limit the JupyterLab version at the user profile level.

```json
{    "Version": "2012-10-17",    "Statement": [        {            "Sid": "Block users from creating JupyterLab 3 apps at the user profile level",            "Effect": "Deny",            "Action": [                "sagemaker:CreateUserProfile",                "sagemaker:UpdateUserProfile"            ],            "Resource": "*",            "Condition": {                "ForAllValues:StringLike": {                    "sagemaker:ImageArns": "*image/jupyter-server-3"                }            }        }    ]}
```

The following policy shows how to limit the JupyterLab version at the application level.

```json
{    "Version": "2012-10-17",    "Statement": [        {            "Sid": "Block users from creating JupyterLab 3 apps at the application level",            "Effect": "Deny",            "Action": "sagemaker:CreateApp",            "Resource": "*",            "Condition": {                "ForAllValues:StringLike": {                    "sagemaker:ImageArns": "*image/jupyter-server-3"                }            }        }    ]}
```

### Setting a default JupyterLab version

The following sections show how to set a default JupyterLab version for Studio using either the console or the AWS CLI.

#### From the console

You can select the default JupyterLab version to use on either the domain or user profile level during resource creation. To set the default JupyterLab version using the console, see [Onboard to Amazon SageMaker Domain](p. 35).

#### From the AWS CLI

You can select the default JupyterLab version to use on either the domain or user profile level using the AWS CLI.
To set the default JupyterLab version using the AWS CLI, you must include the ARN of the desired default JupyterLab version as part of an AWS CLI command. This ARN differs based on the version and the Region of the SageMaker domain.

The following table lists the ARNs of the available JupyterLab versions for each Region:

<table>
<thead>
<tr>
<th>Region</th>
<th>JL1</th>
<th>JL3</th>
</tr>
</thead>
</table>

The following shows how to create a domain with JupyterLab 3 as the default, using the AWS CLI:

```bash
aws --region <REGION> \
sagemaker create-domain \ 
  --domain-name <NEW_DOMAIN_NAME> \ 
  --auth-mode <AUTHENTICATION_MODE> \ 
  --subnet-ids <SUBNET-IDS> \ 
  --vpc-id <VPC-ID> \ 
  --default-user-settings '{
    "JupyterServerAppSettings": {
      "DefaultResourceSpec": {
        "InstanceType": "system"
      }
    }
  }'
```

The following shows how to update a domain to use JupyterLab 3 as the default, using the AWS CLI:

```bash
aws --region <REGION> \
sagemaker update-domain \ 
  --domain-id <YOUR_DOMAIN_ID> \ 
  --default-user-settings '{
    "JupyterServerAppSettings": {
      "DefaultResourceSpec": {
        "InstanceType": "system"
      }
    }
  }'
```
Create or update user profile

You can set a default JupyterServer version at the user profile level by invoking CreateUserProfile or UpdateUserProfile and passing the UserSettings.JupyterServerAppSettings.DefaultResourceSpec.SageMakerImageArn field.

The following shows how to create a user profile with JupyterLab 3 as the default on an existing domain, using the AWS CLI:

```bash
aws --region <REGION> \
  sagemaker create-user-profile \
  --domain-id <YOUR_DOMAIN_ID> \
  --user-profile-name <NEW_USERPROFILE_NAME> \
  --query UserProfileArn --output text \
  --user-settings '{
    "JupyterServerAppSettings": {
      "DefaultResourceSpec": {
        "InstanceType": "system"
      }
    }
  }'
```

The following shows how to update a user profile to use JupyterLab 3 as the default, using the AWS CLI:

```bash
aws --region <REGION> \
  sagemaker update-user-profile \
  --domain-id <YOUR_DOMAIN_ID> \
  --user-profile-name <EXISTING_USERPROFILE_NAME> \
  --user-settings '{
    "JupyterServerAppSettings": {
      "DefaultResourceSpec": {
        "InstanceType": "system"
      }
    }
  }'
```

View and update the JupyterLab version of an app from the console

The following shows how to view and update the JupyterLab version of an app.

1. Navigate to the SageMaker control panel.
2. Select a user to view their apps.
3. To view the JupyterLab version of an app, select the app's name.
4. To update the JupyterLab version, select Action.
5. From the dropdown menu, select Change JupyterLab version.
6. From the Studio settings page, select the JupyterLab version from the dropdown menu.
7. After the JupyterLab version for the user profile has been successfully updated, restart the JupyterServer app to make the version changes effective.

## Installing JupyterLab and Jupyter Server extensions

The process for installing JupyterLab and Jupyter Server extensions differs depending on the JupyterLab version of your Studio instance. In JupyterLab 1, you can open the terminal and install extensions without activating any conda environment. In JupyterLab 3, you must activate the studio conda environment before installing extensions. The method for this differs if you're installing the extensions from within Studio or using a lifecycle configuration script.

### Installing Extension from within Studio

To install extensions from within Studio, you must activate the studio environment before you install extensions.

```
# Before installing extensions
conda activate studio

# Install your extensions
pip install `<JUPYTER_EXTENSION>`

# After installing extensions
conda deactivate
```

### Installing Extensions using a lifecycle configuration script

If you're installing JupyterLab and Jupyter Server extensions in your lifecycle configuration script, you must modify your script so that it works with JupyterLab 3. The following sections show the code needed for existing and new lifecycle configuration scripts.

#### Existing lifecycle configuration script

If you're reusing an existing lifecycle configuration script that must work with both versions of JupyterLab, use the following code in your script:

```
# Before installing extension
export AWS_SAGEMAKER_JUPYTERSERVER_IMAGE="$(AWS_SAGEMAKER_JUPYTERSERVER_IMAGE:-'jupyter-server')"
if [ "AWS_SAGEMAKER_JUPYTERSERVER_IMAGE" = "jupyter-server-3" ]; then
  eval "$(conda shell.bash hook)"
  conda activate studio
fi;

# Install your extensions
pip install `<JUPYTER_EXTENSION>`

# After installing extension
if [ "AWS_SAGEMAKER_JUPYTERSERVER_IMAGE" = "jupyter-server-3" ]; then
  conda deactivate
fi;
```

#### New lifecycle configuration script

If you're writing a new lifecycle configuration script that only uses JupyterLab 3, you can use the following code in your script:
Use the Amazon SageMaker Studio Launcher

You can use the Amazon SageMaker Studio Launcher to create notebooks and text files, and launch terminals and interactive Python shells.

You can open Studio Launcher in any of the following ways:

- Choose **Amazon SageMaker Studio** at the top-left of Studio.
- Use the keyboard shortcut Ctrl + Shift + L.
- From the Studio menu, choose File and then choose New Launcher.
- If the Studio file browser is open, choose the plus (+) sign on the Studio file browser menu.

The Launcher opens in a new tab in Studio.

The Launcher consists of the following sections:

- **Get started** – Provides material to get started using SageMaker Studio, such as videos and tutorials, and one-click solutions for machine learning problems.
- **ML tasks and components** – Create machine learning tasks and components, such as new feature groups, data flows, and projects.
- **Notebooks and compute resources** – Create a notebook, open an image terminal, or open a Python console.
- **Utilities and files** – Show contextual help from a notebook, create files, or open a system terminal.

Topics

- ML Tasks and Components (p. 127)
- Notebooks and compute resources (p. 128)
- Utilities and files (p. 128)

ML Tasks and Components

The following items are available:

- **New Data Flow**
  
  Launches a new Data Wrangler flow that you can use to import, explore and prepare, and process data for machine learning.

- **New Compilation Job**

  Creates a new compilation job.

- **New Project**
Built-in and custom project templates to organize machine learning components and automate MLOps.

- **New Feature Group**
  Creates a new feature group in the feature store to logically group and manage features.

- **New Autopilot Experiment**
  Creates prediction model from your data in a few clicks.

### Notebooks and compute resources

To create or launch an item, choose the SageMaker image that you want the item to run in from the **SageMaker image** dropdown menu. You can also select the Lifecycle Configuration script that you want to run. For more information, see Use Lifecycle Configurations with Amazon SageMaker Studio (p. 167). Next, choose the item. When you choose an item from this section, you might incur additional usage charges. For more information, see Usage Metering (p. 146).

The following items are available:

- **Notebook**
  Launches the notebook in a kernel session on the chosen SageMaker image. For more information, see Change a Kernel (p. 143).
  Creates the notebook in the folder that you have currently selected in the file browser. To view the file browser, in the left sidebar of Studio, choose the **File Browser** icon ( ).

- **Console**
  Launches the shell in a kernel session on the chosen SageMaker image.
  Opens the shell in the folder that you have currently selected in the file browser.

- **Image terminal**
  Launches the terminal in a terminal session on the chosen SageMaker image.
  Opens the terminal in the root folder for the user (as shown by the Home folder in the file browser).

  **Note**
  CPU instances are launched on a `ml.t3.medium` instance, while GPU instances are launched on a `ml.g4dn.xlarge` instance.

### Utilities and files

Items in this section run in the context of SageMaker Studio and don't incur usage charges.

The following items are available:

- **Show Contextual Help**
  Opens a new tab that displays contextual help for functions in a Studio notebook. To display the help, choose a function in an active notebook. To make it easier to see the help in context, drag the help tab so that it's adjacent to the notebook tab. To open the help tab from within a notebook, press Ctrl + I.

  The following screenshot shows the contextual help for the `Experiment.create` method.
Use Amazon SageMaker Studio Notebooks

Amazon SageMaker Studio notebooks are collaborative notebooks that you can launch quickly because you don’t need to set up compute instances and file storage beforehand. A set of instance types, known as *Fast launch* types are designed to launch in under two minutes. SageMaker Studio notebooks provide persistent storage, which enables you to view and share notebooks even if the instances that the notebooks run on are shut down.

You can share your notebooks with others, so that they can easily reproduce your results and collaborate while building models and exploring your data. You provide access to a read-only copy of the notebook through a secure URL. Dependencies for your notebook are included in the notebook's metadata. When your colleagues copy the notebook, it opens in the same environment as the original notebook.

A SageMaker Studio notebook runs in an environment defined by the following:

- **EC2 instance type** – The hardware configuration the notebook runs on. The configuration includes the number and type of processors (vCPU and GPU), and the amount and type of memory. The instance type determines the pricing rate.
- **SageMaker image** – A container image that is compatible with SageMaker Studio. The image consists of the kernels, language packages, and other files required to run a notebook in Studio. There can be multiple images in an instance. For more information, see Bring your own SageMaker image (p. 152).
- **KernelGateway app** – A SageMaker image runs as a KernelGateway app. The app provides access to the kernels in the image. There is a one-to-one correspondence between a SageMaker image and a SageMaker app.
- **Kernel** – The process that inspects and runs the code contained in the notebook. A kernel is defined by a *kernel spec* in the image. There can be multiple kernels in an image.

You can change any of these resources from within the notebook.

The following diagram outlines how a notebook kernel runs in relation to the KernelGateway App, User, and SageMaker Studio Domain.

Sample SageMaker Studio notebooks are available in the *aws_sagemaker_studio* folder of the Amazon SageMaker example GitHub repository. Each notebook comes with the necessary SageMaker image that opens the notebook with the appropriate kernel.

We recommend that you familiarize yourself with the SageMaker Studio interface and the Studio notebook toolbar before creating or using a Studio notebook. For more information, see Amazon SageMaker Studio UI Overview (p. 118) and Use the SageMaker Studio Notebook Toolbar (p. 134).

**Topics**
- How Are Amazon SageMaker Studio Notebooks Different from Notebook Instances? (p. 131)
- Get Started (p. 131)
- Amazon SageMaker Studio Tour (p. 132)
- Create or Open an Amazon SageMaker Studio Notebook (p. 133)
- Use the SageMaker Studio Notebook Toolbar (p. 134)
- Install External Libraries and Kernels in Amazon SageMaker Studio (p. 136)
- Share and Use an Amazon SageMaker Studio Notebook (p. 138)
- Get Notebook and App Metadata (p. 139)
How Are Amazon SageMaker Studio Notebooks Different from Notebook Instances?

When you're starting a new notebook, we recommend that you create the notebook in Amazon SageMaker Studio instead of launching a notebook instance from the Amazon SageMaker console. There are many benefits to using a SageMaker Studio notebook, including the following:

- Starting a Studio notebook is faster than launching an instance-based notebook. Typically, it is 5-10 times faster than instance-based notebooks.
- Notebook sharing is an integrated feature in SageMaker Studio. Users can generate a shareable link that reproduces the notebook code and also the SageMaker image required to execute it, in just a few clicks.
- SageMaker Studio notebooks come pre-installed with the latest Amazon SageMaker Python SDK.
- SageMaker Studio notebooks are accessed from within Studio. This enables you to build, train, debug, track, and monitor your models without leaving Studio.
- Each member of a Studio team gets their own home directory to store their notebooks and other files. The directory is automatically mounted onto all instances and kernels as they're started, so their notebooks and other files are always available. The home directories are stored in Amazon Elastic File System (Amazon EFS) so that you can access them from other services.
- When using IAM Identity Center, you use your IAM Identity Center credentials through a unique URL to directly access SageMaker Studio. You don't have to interact with the AWS Management Console to run your notebooks.
- Studio notebooks are equipped with a set of predefined SageMaker image settings to get you started faster.

**Note**

Studio notebooks don’t support local mode. However, you can use a notebook instance to train a sample of your dataset locally, and then use the same code in a Studio notebook to train on the full dataset.

When you open a notebook in SageMaker Studio, the view is an extension of the JupyterLab interface. The primary features are the same, so you’ll find the typical features of a Jupyter notebook and JupyterLab. For more information about the Studio interface, see Amazon SageMaker Studio UI Overview (p. 118).

Get Started

To get started, you or your organization's administrator need to complete the Amazon SageMaker Studio onboarding process. For more information, see Onboard to Amazon SageMaker Domain (p. 35).

You can access an SageMaker Studio notebook in any of the following ways:

- You receive an email invitation to access Studio through your organization's IAM Identity Center, which includes a direct link to login to Studio without having to use the Amazon SageMaker console. You can proceed to the the section called “Next Steps” (p. 132).
- You receive a link to a shared Studio notebook, which includes a direct link to log in to Studio without having to use the SageMaker console. You can proceed to the the section called “Next Steps” (p. 132).
• You onboard to Studio and then log in to the SageMaker console. For more information, see Onboard to Amazon SageMaker Domain (p. 35).

Log In from the Amazon SageMaker console

To log in from the SageMaker console

1. Onboard to Amazon SageMaker Studio following the instructions on Onboard to Amazon SageMaker Domain (p. 35). If you've already onboarded, skip to the next step.
2. Open the SageMaker console.
3. Choose Control Panel.
4. The Control Panel opens.
5. In the Control Panel, you'll see a list of user names.

   Next to your user name, choose Open Studio.

Next Steps

Now that you're in Studio, you can try any of the following options:

• Create a SageMaker Studio notebook – Continue to the next section.
• Familiarize yourself with the SageMaker Studio interface – See Amazon SageMaker Studio UI Overview (p. 118).
• Explore Studio end-to-end tutorial notebooks – See Amazon SageMaker Studio Tour (p. 132).

Amazon SageMaker Studio Tour

For a walkthrough that takes you on a tour of the main features of Amazon SageMaker Studio, see the xgboost_customer_churn_studio.ipynb sample notebook from the aws/amazon-sagemaker-examples repository. The code in the notebook trains multiple models and sets up the SageMaker Debugger and SageMaker Model Monitor. The walkthrough shows you how to view the trials, compare the resulting models, show the debugger results, and deploy the best model using the SageMaker Studio UI. You don't need to understand the code to follow this walkthrough.

Prerequisites

To run the notebook for this tour, you need:

• An IAM account to sign in to Studio. For information, see Onboard to Amazon SageMaker Domain (p. 35).
• Basic familiarity with the Studio user interface and Jupyter notebooks. For information, see Amazon SageMaker Studio UI Overview (p. 118).
• A copy of the aws/amazon-sagemaker-examples repository in your Studio environment.

To clone the repository

1. Sign in to SageMaker Studio. For users in IAM Identity Center, sign in using the URL from your invitation email. For IAM users, follow these steps.
   a. Sign in to the SageMaker console.
   b. Choose Control Panel in the left navigation pane.
c. Choose **Launch app** in the row next to your user name.
d. Choose **Studio** from the dropdown menu.

2. On the top menu, choose **File** then **New** then **Terminal**.
3. At the command prompt, run the following command to clone the `aws/amazon-sagemaker-examples` repository.

```
git clone https://github.com/aws/amazon-sagemaker-examples.git
```

### To navigate to the sample notebook

1. From the **File Browser** on the left menu, select **amazon-sagemaker-examples**.
2. Navigate to the example notebook with the following path.
   ```
   ~/amazon-sagemaker-examples/aws_sagemaker_studio/getting_started/
xgboost_customer_churn_studio.ipynb
   ```

**Note**
If you encounter an error when you run the sample notebook, and some time has passed from when you cloned the repository, review the notebook on the remote repository for updates.

### Create or Open an Amazon SageMaker Studio Notebook

When you create a notebook in Amazon SageMaker Studio or open a non-shared notebook in Studio for the first time, you have to select a SageMaker image and kernel for the notebook. SageMaker launches the notebook on a default instance of a type based on the chosen SageMaker image. For CPU based images, the default instance type is `ml.t3.medium` (available as part of the **AWS Free Tier**). For GPU based images, the default instance type is `ml.g4dn.xlarge`.

If you create or open additional notebooks that use the same instance type, whether or not the notebooks use the same kernel, the notebooks run on the same instance of that instance type.

After a notebook is launched, you can change its instance type, and SageMaker image and kernel from within the notebook. For more information, see [Change an Instance Type](p. 142) and [Change a Kernel](p. 143).

You can have only one instance of each instance type. Each instance can have multiple SageMaker images running on it. Each SageMaker image can run multiple kernels or terminal instances.

Billing occurs per instance and starts when the first instance of a given instance type is launched. If you want to create or open a notebook without the risk of incurring charges, open the notebook from the **File** menu and choose **No Kernel** from the **Select Kernel** dialog. You can read and edit a notebook without a running kernel but you can't run cells.

Billing ends when the SageMaker image for the instance is shut down. For more information, see [Usage Metering](p. 146).

For information about shutting down the notebook, see [Shut Down Resources](p. 144).

### Topics

- [Open a Studio notebook](p. 134)
- [Create a Notebook from the File Menu](p. 134)
- [Create a Notebook from the Launcher](p. 134)
Open a Studio notebook

SageMaker Studio can only open notebooks listed in the Studio file browser. For instructions on uploading a notebook to the file browser, see Upload Files to SageMaker Studio (p. 175) or Clone a Git Repository in SageMaker Studio (p. 176).

To open a notebook

1. In the left sidebar, choose the File Browser icon ( ) to display the file browser.
2. Browse to a notebook file and double-click it to open the notebook in a new tab.

Create a Notebook from the File Menu

To create a notebook from the File menu

1. From the Studio menu, choose File, choose New, and then choose Notebook.
2. On the Select Kernel dialog, to use the default kernel, Python 3 (Data Science), choose Select. Otherwise, use the dropdown menu to select a different kernel.

For a list of the available kernels, see Available Amazon SageMaker Kernels (p. 151).

Create a Notebook from the Launcher

To create a notebook from the Launcher

1. To open the Launcher, use the keyboard shortcut Ctrl + Shift + L.
   Alternatively, from the File Browser, choose the plus (+) sign on the left of the menu.
2. On the Launcher, keep the default SageMaker image, Data Science, or use the dropdown menu to select a different image.

For a list of the available images, see Available Amazon SageMaker Images (p. 148).

After you choose the kernel or image, your notebook launches and opens in a new Studio tab. To view the notebook's kernel session, in the left sidebar, choose the Running Terminals, Kernels, and Images icon ( ). You can stop the notebook's kernel session from this view.

Use the SageMaker Studio Notebook Toolbar

Amazon SageMaker Studio notebooks extend the JupyterLab interface. For an overview of the basic JupyterLab interface, see The JupyterLab Interface.

The following image shows the toolbar and an empty cell from a SageMaker Studio notebook.

![SageMaker Studio Notebook Toolbar](image)

When you pause on a toolbar icon, a tooltip displays the icon function. Additional notebook commands are found in the Studio main menu. For a list of available notebook commands and shortcuts, in the left sidebar of Studio, choose the Commands icon ( ), and then scroll to the NOTEBOOK CELL OPERATIONS and NOTEBOOK OPERATIONS sections. The toolbar includes the following icons:
<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="Image" alt="Save and checkpoint icon" /></td>
<td><strong>Save and checkpoint</strong>&lt;br&gt;Saves the notebook and updates the checkpoint file. For more information, see [Get the Difference Between the Last Checkpoint](p. 141).</td>
</tr>
<tr>
<td><img src="Image" alt="Insert cell icon" /></td>
<td><strong>Insert cell</strong>&lt;br&gt;Inserts a code cell below the current cell. The current cell is noted by the blue vertical marker in the left margin.</td>
</tr>
<tr>
<td><img src="Image" alt="Cut, copy, and paste cells icon" /></td>
<td><strong>Cut, copy, and paste cells</strong>&lt;br&gt;Cuts, copies, and pastes the selected cells.</td>
</tr>
<tr>
<td><img src="Image" alt="Run cells icon" /></td>
<td><strong>Run cells</strong>&lt;br&gt;Runs the selected cells and then makes the cell that follows the last selected cell the new selected cell.</td>
</tr>
<tr>
<td><img src="Image" alt="Interrupt kernel icon" /></td>
<td><strong>Interrupt kernel</strong>&lt;br&gt;Interrupts the kernel, which cancels the currently running operation. The kernel remains active.</td>
</tr>
<tr>
<td><img src="Image" alt="Restart kernel icon" /></td>
<td><strong>Restart kernel</strong>&lt;br&gt;Restarts the kernel. Variables are reset. Unsaved information is not affected.</td>
</tr>
<tr>
<td><img src="Image" alt="Cell type icon" /></td>
<td><strong>Cell type</strong>&lt;br&gt;Displays or changes the current cell type. The cell types are:&lt;br&gt;- Code – Code that the kernel runs.&lt;br&gt;- Markdown – Text rendered as markdown.&lt;br&gt;- Raw – Content, including Markdown markup, that's displayed as text.</td>
</tr>
<tr>
<td><img src="Image" alt="Launch terminal icon" /></td>
<td><strong>Launch terminal</strong>&lt;br&gt;Launches a terminal in the SageMaker image hosting the notebook. For an example, see [Get App Metadata](p. 140).</td>
</tr>
<tr>
<td><img src="Image" alt="Checkpoint diff icon" /></td>
<td><strong>Checkpoint diff</strong>&lt;br&gt;Opens a new tab that displays the difference between the notebook and the checkpoint file. For more information, see [Get the Difference Between the Last Checkpoint](p. 141).</td>
</tr>
<tr>
<td><img src="Image" alt="Git diff icon" /></td>
<td><strong>Git diff</strong>&lt;br&gt;Only enabled if the notebook is opened from a Git repository. Opens a new tab that displays the difference between the notebook and the last Git commit. For more information, see [Get the Difference Between the Last Commit](p. 141).</td>
</tr>
<tr>
<td><img src="Image" alt="2 vCPU + 4 GiB icon" /></td>
<td><strong>Instance type</strong></td>
</tr>
</tbody>
</table>
### Amazon SageMaker Developer Guide

#### Use Studio Notebooks

<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
</table>
| ![Icon](image) | Displays or changes the instance type the notebook runs in. The format is as follows:  
*number of vCPUs + amount of memory + number of GPUs*  
Unknown indicates the notebook was opened without specifying a kernel. The notebook runs on the SageMaker Studio instance and doesn't accrue runtime charges. You can't assign the notebook to an instance type. You must specify a kernel and then Studio assigns the notebook to a default type.  
For more information, see [Create or Open an Amazon SageMaker Studio Notebook](p. 133) and [Change an Instance Type](p. 142). |
| ![Icon](image) | Kernel and SageMaker Image  
Displays or changes the kernel that processes the cells in the notebook. The format is as follows:  
*Kernel (SageMaker Image)*  
No Kernel indicates the notebook was opened without specifying a kernel. You can edit the notebook but you can't run any cells.  
For more information, see [Change a Kernel](p. 143). |
| ![Icon](image) | Kernel busy status  
Displays the busy status of the kernel. When the edge of the circle and its interior are the same color, the kernel is busy. The kernel is busy when it is starting and when it is processing cells. Additional kernel states are displayed in the status bar at the bottom-left corner of SageMaker Studio. |
| ![Icon](image) | Share notebook  
Shares the notebook. For more information, see [Share and Use an Amazon SageMaker Studio Notebook](p. 138). |

To select multiple cells, click in the left margin outside of a cell. Hold down the Shift key and use K or the Up key to select previous cells, or use J or the Down key to select following cells.

## Install External Libraries and Kernels in Amazon SageMaker Studio

Amazon SageMaker Studio notebooks come with multiple images already installed. These images contain kernels and Python packages including scikit, Pandas, NumPy, TensorFlow, and MXNet. You can also install your own images that contain your choice of packages and kernels. For more information on installing your own image, see [Bring your own SageMaker image](p. 152).

The different Jupyter kernels in Amazon SageMaker Studio notebooks are separate conda environments. For information about conda environments, see [Managing environments](p. 23).

### Package installation tools

The method that you use to install Python packages from the terminal differs depending on the image. Studio supports the following package installation tools:
• **Notebooks** – The following commands are supported. If one of the following does not work on your image, try the other one.
  • `%conda install`
  • `%pip install`

• **The Jupyter terminal** – You can install packages using pip and conda directly. You can also use `apt-get install` to install system packages from the terminal.

  **Note**
  We do not recommend using `pip install -u` or `pip install --user`, because those commands install packages on the user's Amazon EFS volume and can potentially block JupyterServer app restarts. Instead, use a lifecycle configuration to reinstall the required packages on app restarts as shown in Install packages using lifecycle configurations (p. 138).

We recommend using `%pip` and `%conda` to install packages from within a notebook because they correctly take into account the active environment or interpreter being used. For more information, see Add `%pip` and `%conda` magic functions. You can also use the system command syntax (lines starting with `!`) to install packages. For example, `!pip install` and `!conda install`.

**Conda**

Conda is an open source package management system and environment management system that can install packages and their dependencies. SageMaker supports using conda with either of these two main channels: the default channel or the conda-forge channel. For more information, see Conda channels. The conda-forge channel is a community channel where contributors can upload packages.

  **Note**
  Installing packages from conda-forge can take up to 10 minutes. Timing relates to how conda resolves the dependency graph.

All of the SageMaker provided environments are functional. User installed packages may not function correctly.

Conda has two methods for activating environments: `conda activate` and `source activate`. For more information, see Managing environment.

**Supported conda operations**

• `conda install` of a package in a single environment
• `conda install` of a package in all environments
• Installing a package from the main conda repository
• Installing a package from conda-forge
• Changing the conda install location to use Amazon EBS
• Supporting both `conda activate` and `source activate`

**Pip**

Pip is the tool for installing and managing Python packages. Pip searches for packages on the Python Package Index (PyPI) by default. Unlike conda, pip doesn't have built in environment support. Therefore, pip isn't as thorough as conda when it comes to packages with native or system library dependencies. Pip can be used to install packages in conda environments. You can use alternative package repositories with pip instead of the PyPI.

**Supported pip operations**

• Using pip to install a package without an active conda environment
• Using pip to install a package in a conda environment
• Using pip to install a package in all conda environments
• Changing the pip install location to use Amazon EBS
• Using an alternative repository to install packages with pip

Unsupported

SageMaker aims to support as many package installation operations as possible. However, if the packages were installed by SageMaker and you use the following operations on these packages, it might make your environment unstable:

• Uninstalling
• Downgrading
• Upgrading

Due to potential issues with network conditions or configurations, or the availability of conda or PyPi, packages may not install in a fixed or deterministic amount of time.

Note

Attempting to install a package in an environment with incompatible dependencies can result in a failure. If issues occur, you can contact the library maintainer about updating the package dependencies. When you modify the environment, such as removing or updating existing packages, this may result in instability of that environment.

Install packages using lifecycle configurations

Install custom images and kernels on the Studio instance's Amazon EBS volume so that they persist when you stop and restart the notebook, and that any external libraries you install are not updated by SageMaker. To do that, use a lifecycle configuration that includes both a script that runs when you create the notebook (on-create) and a script that runs each time you restart the notebook (on-start). For more information about using lifecycle configurations with Studio, see Use Lifecycle Configurations with Amazon SageMaker Studio (p. 167). For sample lifecycle configuration scripts, see SageMaker Studio Lifecycle Configuration Samples.

Share and Use an Amazon SageMaker Studio Notebook

You can share your Amazon SageMaker Studio notebooks with your colleagues. The shared notebook is a copy. After you share your notebook, any changes you make to your original notebook aren't reflected in the shared notebook and any changes your colleague's make in their shared copies of the notebook aren't reflected in your original notebook. If you want to share your latest version, you must create a new snapshot and then share it.

Topics

• Share a Notebook (p. 138)
• Use a Shared Notebook (p. 139)

Share a Notebook

The following screenshot shows the menu from a Studio notebook.
To share a notebook

1. In the upper-right corner of the notebook, choose Share.
2. (Optional) In Create shareable snapshot, choose any of the following items:
   • Include Git repo information – Includes a link to the Git repository that contains the notebook. This enables you and your colleague to collaborate and contribute to the same Git repository.
   • Include output – Includes all notebook output that has been saved.

   **Note**
   If you’re an user in IAM Identity Center and you don’t see these options, your IAM Identity Center administrator probably disabled the feature. Contact your administrator.

3. Choose Create.
4. After the snapshot is created, choose Copy link and then choose Close.
5. Share the link with your colleague.

After selecting your sharing options, you are provided with a URL. You can share this link with users that have access to Amazon SageMaker Studio. When the user opens the URL, they're prompted to log in using IAM Identity Center or IAM authentication. This shared notebook becomes a copy, so changes made by the recipient will not be reproduced in your original notebook.

**Use a Shared Notebook**

You use a shared notebook in the same way you would with a notebook that you created yourself. You must first login to your account, then open the shared link. If you don't have an active session, you receive an error.

When you click a link to a shared notebook for the first time, a read-only version of the notebook opens. To edit the shared notebook, choose Create a Copy. This copies the shared notebook to your personal storage.

The copied notebook launches on an instance of the instance type and SageMaker image that the notebook was using when the sender shared it. If you aren't currently running an instance of the instance type, a new instance is started. Customization to the SageMaker image isn't shared. You can also inspect the notebook snapshot by choosing Snapshot Details.

The following are some important considerations about sharing and authentication:

- If you have an active session, you see a read-only view of the notebook until you choose Create a Copy.
- If you don't have an active session, you need to log in.
- If you use IAM to login, after you login, select your user profile then choose Open SageMaker Studio. Then you need to choose the link you were sent.
- If you use IAM Identity Center to login, after you login the shared notebook is opened automatically in Studio.

**Get Notebook and App Metadata**

You can access notebook metadata and App metadata using the Amazon SageMaker UI.

**Topics**

- Get Notebook Metadata (p. 140)
- Get App Metadata (p. 140)
Get Notebook Metadata

Jupyter notebooks contain optional metadata that you can access through the Amazon SageMaker UI.

To view the notebook metadata

1. In the left sidebar, choose the Notebook Tools icon. The icon only displays when there's a notebook available in Studio.
2. Open the Advanced Tools section.

The metadata should look similar to the following.

```
{
  "instance_type": "ml.t3.medium",
  "kernelspec": {
    "display_name": "Python 3 (Data Science)",
    "language": "python",
    "name": "python3__SAGEMAKER_INTERNAL__arn:aws:sagemaker:us-west-2:<acct-id>:image/datascience-1.0"
  },
  "language_info": {
    "codemirror_mode": {
      "name": "ipython",
      "version": 3
    },
    "file_extension": ".py",
    "mimetype": "text/x-python",
    "name": "python",
    "nbconvert_exporter": "python",
    "pygments_lexer": "ipython3",
    "version": "3.7.6"
  }
}
```

Get App Metadata

When you create a notebook in Amazon SageMaker Studio, the App metadata is written to a file named `resource-metadata.json` in the folder `/opt/ml/metadata/`. You can get the App metadata by opening an Image terminal from within the notebook. The metadata gives you the following information, which includes the SageMaker image and instance type the notebook runs in:

- **AppType** – KernelGateway
- **DomainId** – Same as the StudioID
- **UserProfileName** – The profile name of the current user
- **ResourceArn** – The Amazon Resource Name (ARN) of the App, which includes the instance type
- **ResourceName** – The name of the SageMaker image

Additional metadata might be included for internal use by Studio and is subject to change.

To get the App metadata

1. In the center of the notebook menu, choose the Launch Terminal icon. This opens a terminal in the SageMaker image that the notebook runs in.
2. Run the following commands to display the contents of the `resource-metadata.json` file.
The file should look similar to the following.

```json
{
    "AppType": "KernelGateway",
    "DomainId": "d-xxxxxxxxxxxx",
    "UserProfileName": "profile-name",
    "ResourceName": "datascience--1-0-ml"
}
```

**Get Notebook Differences**

You can display the difference between the current notebook and the last checkpoint or the last Git commit using the Amazon SageMaker UI.

The following screenshot shows the menu from a Studio notebook.

**Topics**
- Get the Difference Between the Last Checkpoint (p. 141)
- Get the Difference Between the Last Commit (p. 141)

**Get the Difference Between the Last Checkpoint**

When you create a notebook, a hidden checkpoint file that matches the notebook is created. You can view changes between the notebook and the checkpoint file or revert the notebook to match the checkpoint file.

By default, a notebook is auto-saved every 120 seconds and also when you close the notebook. However, the checkpoint file isn't updated to match the notebook. To save the notebook and update the checkpoint file to match, you must choose the **Save notebook and create checkpoint** icon (rganization) on the left of the notebook menu or use the Ctrl + S keyboard shortcut.

To view the changes between the notebook and the checkpoint file, choose the **Checkpoint diff** icon (organisation) in the center of the notebook menu.

To revert the notebook to the checkpoint file, from the main Studio menu, choose **File** then **Revert Notebook to Checkpoint**.

**Get the Difference Between the Last Commit**

If a notebook is opened from a Git repository, you can view the difference between the notebook and the last Git commit.

To view the changes in the notebook from the last Git commit, choose the **Git diff** icon (organisation) in the center of the notebook menu.
Manage Resources

You can change the instance type, and SageMaker image and kernel from within an Amazon SageMaker Studio notebook. To create a custom kernel to use with your notebooks, see Bring your own SageMaker image (p. 152).

Topics
- Change an Instance Type (p. 142)
- Change a Kernel (p. 143)
- Shut Down Resources (p. 144)

Change an Instance Type

When you open a new Studio notebook for the first time, you are assigned a default Amazon Elastic Compute Cloud (Amazon EC2) instance type to run the notebook. When you open additional notebooks on the same instance type, the notebooks run on the same instance as the first notebook, even if the notebooks use different kernels.

You can change the instance type that your Studio notebook runs on from within the notebook.

The following information only applies to Studio notebooks. For information about how to change the instance type of a Amazon SageMaker notebook instance, see Update a Notebook Instance (p. 299).

Important
If you change the instance type, unsaved information and existing settings for the notebook are lost, and installed packages must be re-installed.

The previous instance type continues to run even if no kernel sessions or apps are active. You must explicitly stop the instance to stop accruing charges. To stop the instance, see Shut Down Resources (p. 144).

The following screenshot shows the menu from a Studio notebook. The processor and memory of the instance type powering the notebook are displayed as 2 vCPU + 4 GiB.

To change the instance type

1. Choose the instance type.
2. In Select instance, choose one of the fast launch instance types that are listed. Or to see all instance types, switch off Fast launch only. The list can be sorted by any column.
3. After choosing a type, choose **Save and continue**.

4. Wait for the new instance to become enabled, and then the new instance type information is displayed.

For a list of the available instance types, see Available SageMaker Studio Instance Types (p. 147).

**Change a Kernel**

With Amazon SageMaker Studio notebooks, you can change the notebook's kernel from within the notebook.

The following screenshot shows the menu from a Studio notebook. The current SageMaker kernel and image are displayed as **Python 3 (Data Science)**, where Python 3 denotes the kernel and Data Science denotes the SageMaker image that contains the kernel. The color of the circle to the right indicates the kernel is idle or busy. The kernel is busy when the center and the edge of the circle are the same color.
To change a notebook's kernel

1. Choose the kernel name.
2. From the drop-down list, choose a kernel.
3. After choosing a kernel, choose Select.
4. Wait for the kernel's status to show as idle, which indicates the kernel has started.

For a list of available SageMaker kernels, see Available Amazon SageMaker Kernels (p. 151).

Shut Down Resources

You can shut down individual resources, including notebooks, terminals, kernels, apps, and instances. You can also shut down all resources in one of these categories at the same time.

Note
Amazon SageMaker Studio does not support shutting down resources from within a notebook.

Topics

- Shut Down an Open Notebook (p. 144)
- Shut Down Resources (p. 144)

Shut Down an Open Notebook

You can shut down an open notebook from the Amazon SageMaker Studio File menu or from the Running Terminal and Kernels pane.

Note
When you shut down a notebook, any unsaved information in the notebook is lost. The notebook is not deleted.

To shut down an open notebook from the File menu

1. Optionally, save the notebook contents by choosing the Disk icon on the left of the notebook menu.
2. Choose File then Close and Shutdown Notebook.
3. Choose OK.

Shut Down Resources

You can reach the Running Terminals and Kernels pane on the left side of Amazon SageMaker Studio with the icon. The Running Terminals and Kernels pane consists of four sections. Each section lists all the resources of that type. You can shut down each resource individually or shut down all the resources in a section at the same time.
When you choose to shut down all resources in a section, the following occurs:

- **RUNNING INSTANCES/RUNNING APPS** – All instances, apps, notebooks, kernel sessions, consoles/shells, and image terminals are shut down. System terminals aren’t shut down.

  **Note**
  When you shutdown the Studio notebook instances, any additional resources, such as SageMaker endpoints, Amazon EMR clusters, and Amazon S3 buckets created from Studio are not deleted. Delete those resources to stop accrual of charges.

- **KERNEL SESSIONS** – All kernels, notebooks and consoles/shells are shut down.

- **TERMINAL SESSIONS** – All image terminals and system terminals are shut down.

**To shut down resources**

1. In the left sidebar, choose the **Running Terminals and Kernels** icon ( ).
2. Do either of the following:

   - To shut down a specific resource, choose the **SHUT DOWN** icon ( ) on the same row as the resource.

     For running instances, a confirmation dialog lists all the resources that will be shut down. For running apps, a confirmation dialog is displayed. Choose **Shut down all** to proceed.

     **Note**
     No confirmation dialog is displayed for kernel sessions or terminal sessions.

   - To shut down all resources in a section, choose the **X** to the right of the section label. A confirmation dialog is displayed. Choose **Shut down all** to proceed.
Usage Metering

There is no additional charge for using Amazon SageMaker Studio. The costs incurred for running Amazon SageMaker Studio notebooks, interactive shells, consoles, and terminals are based on Amazon Elastic Compute Cloud (Amazon EC2) instance usage.

When you run the following resources, you must choose a SageMaker image and kernel:

**From the Studio Launcher**

- Notebook
- Interactive Shell
- Image Terminal

**From the File menu**

- Notebook
- Console

When launched, the resource is run on an Amazon EC2 instance of an instance type based on the chosen SageMaker image and kernel. If an instance of that type was previously launched and is available, the resource is run on that instance.

For CPU based images, the default instance type is `ml.t3.medium`. For GPU based images, the default instance type is `ml.g4dn.xlarge`.

The costs incurred are based on the instance type. You are billed separately for each instance.

Metering starts when an instance is created. Metering ends when all the apps on the instance are shut down, or the instance is shut down. For information about how to shut down an instance, see Shut Down Resources (p. 144).

**Important**

You must shut down the instance to stop incurring charges. If you shut down the notebook running on the instance but don’t shut down the instance, you will still incur charges. When you shut down the Studio notebook instances, any additional resources, such as SageMaker endpoints, Amazon EMR clusters, and Amazon S3 buckets created from Studio are not deleted. Delete those resources to stop accrual of charges.

When you open multiple notebooks on the same instance type, the notebooks run on the same instance even if they’re using different kernels. You are billed only for the time that one instance is running.

You can change the instance type from within the notebook after you open it. For more information, see Change an Instance Type (p. 142).

For information about billing along with pricing examples, see Amazon SageMaker Pricing.

Available Resources

The following sections list the available resources for Amazon SageMaker Studio notebooks.

**Topics**

- Available SageMaker Studio Instance Types (p. 147)
- Available Amazon SageMaker Images (p. 148)
- Available Amazon SageMaker Kernels (p. 151)
Available SageMaker Studio Instance Types

The following Amazon Elastic Compute Cloud (Amazon EC2) instance types are available for use with SageMaker Studio notebooks.

For detailed information on which instance types fit your use case, and their performance capabilities, see Amazon Elastic Compute Cloud Instance types.

For information about available Amazon SageMaker Notebook Instance types, see CreateNotebookInstance.

Note
For most use cases, you should use a ml.t3.medium. This is the default instance type for CPU-based SageMaker images, and is available as part of the AWS Free Tier.

>> Fast launch instances types are optimized to start in under two minutes.

Default instance types

- CPU-based images: ml.t3.medium >> Fast launch
- GPU-based images: ml.g4dn.xlarge >> Fast launch

General purpose (no GPUs)

- ml.t3.medium >> Fast launch
- ml.t3.large
- ml.t3.xlarge
- ml.t3.2xlarge
- ml.m5.large >> Fast launch
- ml.m5.xlarge
- ml.m5.2xlarge
- ml.m5.4xlarge
- ml.m5.8xlarge
- ml.m5.12xlarge
- ml.m5.16xlarge
- ml.m5.24xlarge
- ml.m5d.large
- ml.m5d.xlarge
- ml.m5d.2xlarge
- ml.m5d.4xlarge
- ml.m5d.8xlarge
- ml.m5d.12xlarge
- ml.m5d.16xlarge
- ml.m5d.24xlarge

Compute optimized (no GPUs)

- ml.c5.large >> Fast launch
- ml.c5.xlarge
• ml.c5.2xlarge
• ml.c5.4xlarge
• ml.c5.9xlarge
• ml.c5.12xlarge
• ml.c5.18xlarge
• ml.c5.24xlarge

**Memory optimized (no GPUs)**

• ml.r5.large
• ml.r5.xlarge
• ml.r5.2xlarge
• ml.r5.4xlarge
• ml.r5.8xlarge
• ml.r5.12xlarge
• ml.r5.16xlarge
• ml.r5.24xlarge

**Accelerated computing (1+ GPUs)**

• ml.p3.2xlarge
• ml.p3.8xlarge
• ml.p3.16xlarge
• ml.p3dn.24xlarge
• ml.g4dn.xlarge >> *Fast launch*
• ml.g4dn.2xlarge
• ml.g4dn.4xlarge
• ml.g4dn.8xlarge
• ml.g4dn.12xlarge
• ml.g4dn.16xlarge
• ml.g5.xlarge
• ml.g5.2xlarge
• ml.g5.4xlarge
• ml.g5.8xlarge
• ml.g5.12xlarge
• ml.g5.24xlarge
• ml.g5.48xlarge

**Available Amazon SageMaker Images**

The following SageMaker images are available in Amazon SageMaker Studio. SageMaker images contain the latest Amazon SageMaker Python SDK and the latest version of the kernel. The name in brackets ([ ]) is the resource identifier of the SageMaker image as specified in the Amazon Resource Name (ARN) for the SageMaker image. For more information, see Deep Learning Containers Images.

• *Base Python [python-3.6]*
Use Studio Notebooks

Official Python 3.6 image from DockerHub with boto3 and AWS CLI included.

- **Base Python 2.0** [sagemaker-base-python-38]

Official Python 3.8 image from DockerHub with boto3 and AWS CLI included.

- **Data Science** [datascience-1.0]

  Data Science is a Python 3.7 conda image with the most commonly used Python packages and libraries, such as NumPy and SciKit Learn.

- **Data Science 2.0** [sagemaker-datascience-38]

  Data Science 2.0 is a Python 3.8 conda image with the most commonly used Python packages and libraries, such as NumPy and SciKit Learn.

- **SparkMagic** [sagemaker-sparkmagic]

  Anaconda Individual Edition with PySpark and Spark kernels. For more information, see sparkmagic.

- **MXNet 1.6 Python 3.6 (optimized for CPU)** [mxnet-1.6-cpu-py36]

  The AWS Deep Learning Containers for AWS MX powered by Apache MXNet 1.6 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for MXNet 1.6.0.

- **MXNet 1.6 Python 3.6 (optimized for GPU)** [mxnet-1.6-gpu-py36]

  The AWS Deep Learning Containers for AWS MX powered by Apache MXNet 1.6 with CUDA 10.1 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for MXNet 1.6.0.

- **MXNet 1.8 Python 3.7 (optimized for CPU)** [mxnet-1.8-cpu-py37-ubuntu16.04-v1]

  The AWS Deep Learning Containers for AWS MX powered by Apache MXNet 1.8 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for AWS MX 1.8.0.

- **MXNet 1.8 Python 3.7 (optimized for GPU)** [mxnet-1.8-gpu-py37-ubuntu16.04-v1]

  The AWS Deep Learning Containers for AWS MX powered by Apache MXNet 1.8 with CUDA 11.0 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for MX MX 1.8.0.

- **MXNet 1.9 Python 3.8 (optimized for CPU)** [mxnet-1.9-cpu-py38-ubuntu20.04-sagemaker-v1.0]

  The AWS Deep Learning Containers for AWS MX powered by Apache MXNet 1.9 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for MX 1.9.0 on SageMaker.

- **MXNet 1.9 Python 3.8 (optimized for GPU)** [mxnet-1.9-gpu-py38-cu112-ubuntu20.04-sagemaker-v1.0]

  The AWS Deep Learning Containers for AWS MX powered by Apache MXNet 1.9 with CUDA 11.2 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for MX 1.9.0 on SageMaker.

- **PyTorch 1.10 Python 3.8 (optimized for CPU)** [pytorch-1.10-cpu-py38]

  The AWS Deep Learning Containers for PyTorch 1.10 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for PyTorch 1.10.2 on SageMaker.

- **PyTorch 1.10 Python 3.8 (optimized for GPU)** [pytorch-1.10-gpu-py38]

  The AWS Deep Learning Containers for PyTorch 1.10 with CUDA 11.3 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for PyTorch 1.10.2 on SageMaker.
• **PyTorch 1.4 Python 3.6 (optimized for CPU) [pytorch-1.4-cpu-py36]**

The AWS Deep Learning Containers for PyTorch 1.4 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers v3.2 for PyTorch](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **PyTorch 1.4 Python 3.6 (optimized for GPU) [pytorch-1.4-gpu-py36]**

The AWS Deep Learning Containers for PyTorch 1.4 with CUDA 10.1 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers v3.2 for PyTorch](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **PyTorch 1.6 Python 3.6 (optimized for CPU) [pytorch-1.6-cpu-py36-ubuntu16.04-v1]**

The AWS Deep Learning Containers for PyTorch 1.6 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers for PyTorch 1.6](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **PyTorch 1.6 Python 3.6 (optimized for GPU) [pytorch-1.6-gpu-py36-cu110-ubuntu18.04-v3]**

The AWS Deep Learning Containers for PyTorch 1.6 with CUDA 11.0 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers for PyTorch 1.6.0 with CUDA 11.0](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **PyTorch 1.8 Python 3.6 (optimized for CPU) [1.8.1-cpu-py36]**

The AWS Deep Learning Containers for PyTorch 1.8 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers for PyTorch 1.8.0](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **PyTorch 1.8 Python 3.6 (optimized for GPU) [pytorch-1.8-gpu-py36]**

The AWS Deep Learning Containers for PyTorch 1.8 with CUDA 11.1 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers for PyTorch 1.8.0](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **TensorFlow 1.15 Python 3.6 (optimized for CPU) [tensorflow-1.15-cpu-py36]**

The AWS Deep Learning Containers for TensorFlow 1.15 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers with TensorFlow 1.15.3](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **TensorFlow 1.15 Python 3.6 (optimized for GPU) [tensorflow-1.15-gpu-py36]**

The AWS Deep Learning Containers for TensorFlow 1.15 with CUDA 10.0 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers with TensorFlow 1.15.3](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **TensorFlow 1.15 Python 3.7 (optimized for CPU) [tensorflow-1.15-cpu-py37-ubuntu18.04-v7]**

The AWS Deep Learning Containers for TensorFlow 1.15 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers v7.0 for TensorFlow](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **TensorFlow 1.15 Python 3.7 (optimized for GPU) [tensorflow-1.15-gpu-py37-cu110-ubuntu18.04-v8]**

The AWS Deep Learning Containers for TensorFlow 1.15 with CUDA 11.0 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers v7.0 for TensorFlow](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **TensorFlow 2.1 Python 3.6 (optimized for CPU) [tensorflow-2.1-cpu-py36]**

The AWS Deep Learning Containers for TensorFlow 2.1 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see [AWS Deep Learning Containers v6.2 for TensorFlow](https://aws.amazon.com/about-awls/deep-learning-containers/).  

• **TensorFlow 2.1 Python 3.6 (optimized for GPU) [tensorflow-2.1-gpu-py36]**
The AWS Deep Learning Containers for TensorFlow 2.1 with CUDA 10.1 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers v6.2 for TensorFlow.

- TensorFlow 2.3 Python 3.7 (optimized for CPU) [tensorflow-2.3-cpu-py37-ubuntu18.04-v1]

The AWS Deep Learning Containers for TensorFlow 2.3 include containers for training on CPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers with TensorFlow 2.3.0.

- TensorFlow 2.3 Python 3.7 (optimized for GPU) [tensorflow-2.3-gpu-py37-cu110-ubuntu18.04-v3]

The AWS Deep Learning Containers for TensorFlow 2.3 with CUDA 11.0 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for TensorFlow 2.3.1 with CUDA 11.0.

- TensorFlow 2.6 Python 3.8 (optimized for CPU) [tensorflow-2.6-cpu-py38-ubuntu20.04-v1]

The AWS Deep Learning Containers for TensorFlow 2.6 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for TensorFlow 2.6.

- TensorFlow 2.6 Python 3.8 (optimized for GPU) [tensorflow-2.6-gpu-py38-cu112-ubuntu20.04-v1]

The AWS Deep Learning Containers for TensorFlow 2.6 with CUDA 11.2 include containers for training on GPU, optimized for performance and scale on AWS. For more information, see AWS Deep Learning Containers for TensorFlow 2.6.

Available Amazon SageMaker Kernels

The following Amazon SageMaker kernels are available in SageMaker Studio. The name in parentheses is the SageMaker image hosting the kernel.

Data Science is a conda image with the most commonly used Python packages and libraries, such as NumPy and scikit-learn.

- Python 3 (Base Python) with Python 3.6
- Python 3 (Base Python 2.0) with Python 3.8
- Python 3 (Data Science) with Python 3.7
- Python 3 (Data Science 2.0) with Python 3.8
- PySpark (SparkMagic) with Python 3.7
- Spark (SparkMagic) with Python 3.7
- Python 3 (MXNet 1.6 Python 3.6 CPU Optimized)
- Python 3 (MXNet 1.6 Python 3.6 GPU Optimized)
- Python 3 (MXNet 1.8 Python 3.7 CPU Optimized)
- Python 3 (MXNet 1.8 Python 3.7 GPU Optimized)
- Python 3 (MXNet 1.8 Python 3.8 CPU Optimized)
- Python 3 (MXNet 1.8 Python 3.8 GPU Optimized)
- Python 3 (PyTorch 1.10 Python 3.8 CPU Optimized)
- Python 3 (PyTorch 1.10 Python 3.8 GPU Optimized)
- Python 3 (PyTorch 1.4 Python 3.6 CPU Optimized)
- Python 3 (PyTorch 1.4 Python 3.6 GPU Optimized)
- Python 3 (PyTorch 1.6 Python 3.6 CPU Optimized)
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- Python 3 (PyTorch 1.6 Python 3.6 GPU Optimized)
- Python 3 (PyTorch 1.8 Python 3.6 CPU Optimized)
- Python 3 (PyTorch 1.8 Python 3.6 GPU Optimized)
- Python 3 (SageMaker JumpStart Data Science 1.0) with Python 3.7
- Python 3 (SageMaker JumpStart MXNet 1.0) with Python 3.7
- Python 3 (SageMaker JumpStart PyTorch 1.0) with Python 3.7
- Python 3 (SageMaker JumpStart TensorFlow 1.0) with Python 3.7
- Python 3 (TensorFlow 1.15 Python 3.6 CPU Optimized)
- Python 3 (TensorFlow 1.15 Python 3.6 GPU Optimized)
- Python 3 (TensorFlow 1.15 Python 3.7 CPU Optimized)
- Python 3 (TensorFlow 1.15 Python 3.7 GPU Optimized)
- Python 3 (TensorFlow 2.1 Python 3.6 CPU Optimized)
- Python 3 (TensorFlow 2.1 Python 3.6 GPU Optimized)
- Python 3 (TensorFlow 2.3 Python 3.7 CPU Optimized)
- Python 3 (TensorFlow 2.3 Python 3.7 GPU Optimized)
- Python 3 (TensorFlow 2.6 Python 3.8 CPU Optimized)
- Python 3 (TensorFlow 2.6 Python 3.8 GPU Optimized)

Customize Amazon SageMaker Studio

There are two options for customizing your Amazon SageMaker Studio environment. You bring your own SageMaker image or use a Lifecycle Configuration script. These two options can be used individually or together.

- Bring your own SageMaker image: A SageMaker image is a file that identifies the kernels, language packages, and other dependencies required to run a Jupyter notebook in Amazon SageMaker Studio. Amazon SageMaker provides many built-in images for you to use. If you need different functionality, you can bring your own custom images to Studio.

- Use Lifecycle Configurations with Amazon SageMaker Studio: Lifecycle Configurations are shell scripts triggered by Amazon SageMaker Studio lifecycle events, such as starting a new Studio notebook. You can use Lifecycle Configurations to automate customization for your Studio environment. For example, you can install custom packages, configure notebook extensions, preload datasets, and set up source code repositories.

The following topics show how to use these two options to customize your Amazon SageMaker Studio environment.

Topics
- Bring your own SageMaker image (p. 152)
- Use Lifecycle Configurations with Amazon SageMaker Studio (p. 167)

Bring your own SageMaker image

A SageMaker image is a file that identifies the kernels, language packages, and other dependencies required to run a Jupyter notebook in Amazon SageMaker Studio. These images are used to create an environment that you then run Jupyter notebooks from. Amazon SageMaker provides many built-in images for you to use. For the list of built-in images, see Available Amazon SageMaker Images (p. 148).
If you need different functionality, you can bring your own custom images to Studio. You can create images and image versions, and attach image versions to your domain, using the SageMaker control panel, the AWS SDK for Python (Boto3), and the AWS Command Line Interface (AWS CLI). You can also create images and image versions using the SageMaker console, even if you haven't onboarded to a SageMaker domain. SageMaker provides sample Dockerfiles to use as a starting point for your custom SageMaker images in the SageMaker Studio Custom Image Samples repository.

The following topics explain how to bring your own image using the SageMaker console or AWS CLI, then launch the image in Studio. For a similar blog article, see Bringing your own R environment to Amazon SageMaker Studio. For notebooks that show how to bring your own image for use in training and inference, see Amazon SageMaker Studio Container Build CLI.

**Key terminology**

The following section defines key terms for bringing your own image to use with Studio.

- **Dockerfile**: A Dockerfile is a file that identifies the language packages and other dependencies for your Docker image.
- **Docker image**: The Docker image is a built Dockerfile. This image is checked into Amazon ECR and serves as the basis of the SageMaker image.
- **SageMaker image**: A SageMaker image is a holder for a set of SageMaker image versions based on Docker images. Each image version is immutable.
- **Image version**: An image version of a SageMaker image represents a Docker image and is stored in an Amazon ECR repository. Each image version is immutable. These image versions can be attached to a domain and used with Studio.

**Topics**

- Custom SageMaker image specifications (p. 153)
- Prerequisites (p. 155)
- Add a Docker image compatible with Studio to Amazon ECR (p. 155)
- Create a custom SageMaker image (p. 156)
- Attach a custom SageMaker image (p. 159)
- Launch a custom SageMaker image in Amazon SageMaker Studio (p. 163)
- Clean up resources (p. 166)

**Custom SageMaker image specifications**

The following specifications apply to the container image that is represented by a SageMaker image version.

**Running the image**

ENTRYPOINT and CMD instructions are overridden to enable the image to run as a KernelGateway app.

Port 8888 in the image is reserved for running the KernelGateway web server.

**Stopping the image**

The DeleteApp API issues the equivalent of a `docker stop` command. Other processes in the container won't get the SIGKILL/SIGTERM signals.

**Kernel discovery**

SageMaker recognizes kernels as defined by Jupyter kernel specs.
You can specify a list of kernels to display before running the image. If not specified, python3 is displayed. Use the DescribeAppImageConfig API to view the list of kernels.

Conda environments are recognized as kernel specs by default.

**File system**

The /opt/.sagemakerinternal and /opt/ml directories are reserved. Any data in these directories might not be visible at runtime.

**User data**

Each user in a domain gets a user directory on a shared Amazon Elastic File System volume in the image. The location of the current user's directory on the Amazon EFS volume is configurable. By default, the location of the directory is /home/sagemaker-user.

SageMaker configures POSIX UID/GID mappings between the image and the host. This defaults to mapping the root user's UID/GID (0/0) to the UID/GID on the host.

You can specify these values using the CreateAppImageConfig API.

**GID/UID limits**

Amazon SageMaker Studio only supports the following DefaultUID and DefaultGID combinations:

- DefaultUID: 1000 and DefaultGID: 100, which corresponds to a non-privileged user.
- DefaultUID: 0 and DefaultGID: 0, which corresponds to root access.

**Metadata**

A metadata file is located at /opt/ml/metadata/resource-metadata.json. No additional environment variables are added to the variables defined in the image. For more information, see Get App Metadata (p. 140).

**GPU**

On a GPU instance, the image is run with the --gpus option. Only the CUDA toolkit should be included in the image not the NVIDIA drivers. For more information, see NVIDIA User Guide.

**Metrics and logging**

Logs from the KernelGateway process are sent to Amazon CloudWatch in the customer’s account. The name of the log group is /aws/sagemaker/studio. The name of the log stream is $domainID/$userProfileName/KernelGateway/$appName.

**Image size**

Limited to 25 GB. To view the size of your image, run docker image ls.

**Sample Dockerfile**

The following sample Dockerfile creates an image based Amazon Linux 2, installs third party packages and the python3 kernel, and sets the scope to the non-privileged user.

```
FROM public.ecr.aws/amazonlinux/amazonlinux:2
ARG NB_USER=sagemaker-user
ARG NB_UID=1000
ARG NB_GID=100
```
Prerequisites

You must satisfy the following prerequisites to bring your own container for use with Amazon SageMaker Studio.

- The Docker application. For information about setting up Docker, see Orientation and setup.
- Install the AWS CLI by following the steps in Getting started with the AWS CLI.
- A local copy of any Dockerfile for creating a Studio compatible image. For sample custom images, see the SageMaker Studio custom image samples repository.
- Permissions to access the Amazon Elastic Container Registry (Amazon ECR) service. For more information, see Amazon ECR Managed Policies.
- An AWS Identity and Access Management execution role that has the AmazonSageMakerFullAccess policy attached. If you have onboarded to Amazon SageMaker domain, you can get the role from the Domain Summary section of the SageMaker control panel.
- Install the Studio image build CLI by following the steps in SageMaker Docker Build. This CLI enables you to build a Dockerfile using AWS CodeBuild.

Add a Docker image compatible with Studio to Amazon ECR

You perform the following steps to add a container image to Amazon ECR:

- Create an Amazon ECR repository.
- Authenticate to Amazon ECR.
- Build a Docker image compatible with Studio.
- Push the image to the Amazon ECR repository.

**Note**
The Amazon ECR repository must be in the same AWS Region as Studio.

To build and add a container image to Amazon ECR

1. Create an Amazon ECR repository using the AWS CLI. To create the repository using the Amazon ECR console, see Creating a repository.

```bash
aws ecr create-repository \
  --repository-name smstudio-custom \
  --image-scanning-configuration scanOnPush=true
```

The response should look similar to the following.

```json
{
  "repository": {
```
2. Build the Dockerfile using the Studio image build CLI. The period (.) specifies that the Dockerfile should be in the context of the build command. This command builds the image and uploads the built image to the ECR repo. It then outputs the image URI.

```bash
sm-docker build . -t smstudio-custom -t <acct-id>.dkr.ecr.<region>.amazonaws.com/smstudio-custom:custom
```

The response should look similar to the following.

```
Image URI: <acct-id>.dkr.ecr.<region>.amazonaws.com/<image_name>
```

Create a custom SageMaker image

This topic describes how you can create a custom SageMaker image using the SageMaker console or AWS CLI.

When you create an image from the console, SageMaker also creates an initial image version. The image version represents a container image in Amazon Elastic Container Registry (ECR). The container image must satisfy the requirements to be used in Amazon SageMaker Studio. For more information, see Custom SageMaker image specifications (p. 153). For information on testing your image locally and resolving common issues, see the SageMaker Studio Custom Image Samples repo.

After you have created your custom SageMaker image, you must attach it to your domain to use it with Studio. For more information, see Attach a custom SageMaker image (p. 159).

Create a SageMaker image from the console

The following section demonstrates how to create a custom SageMaker image from the SageMaker console.

To create an image

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the left navigation pane, choose Images.
3. On the Custom images page, choose Create image.
4. For Image source, enter the registry path to the container image in Amazon ECR. The path is in the following format:

```
acct-id.dkr.ecr.<region>.amazonaws.com/repo-name[:tag] or [@digest]
```
5. Choose Next.
6. Under Image properties, enter the following:
   - Image name – The name must be unique to your account in the current AWS Region.
   - (Optional) Display name – The name displayed in the Studio user interface. When not provided, Image name is displayed.
   - (Optional) Description – A description of the image.
• IAM role – The role must have the AmazonSageMakerFullAccess policy attached. Use the dropdown menu to choose one of the following options:
  • Create a new role – Specify any additional Amazon Simple Storage Service (Amazon S3) buckets that you want users of your notebooks to have access to. If you don’t want to allow access to additional buckets, choose None. SageMaker attaches the AmazonSageMakerFullAccess policy to the role. The role allows users of your notebooks access to the S3 buckets listed next to the checkmarks.
  • Enter a custom IAM role ARN – Enter the Amazon Resource Name (ARN) of your IAM role.
  • Use existing role – Choose one of your existing roles from the list.
  • (Optional) Image tags – Choose Add new tag. You can add up to 50 tags. Tags are searchable using the Studio user interface, the SageMaker console, or the SageMaker Search API.

7. Choose Submit.

The new image is displayed in the Custom images list and briefly highlighted. After the image has been successfully created, you can choose the image name to view its properties or choose Create version to create another version.

To create another image version

1. Choose Create version on the same row as the image.
2. For Image source, enter the registry path to the Amazon ECR container image. The container image shouldn’t be the same image as used in a previous version of the SageMaker image.

Create a SageMaker image from the AWS CLI

You perform the following steps to create a SageMaker image from the container image using the AWS CLI.

• Create an Image.
• Create an ImageVersion.
• Create a configuration file.
• Create an AppImageConfig.

To create the SageMaker image entities

1. Create a SageMaker image.

```
aws sagemaker create-image
  --image-name custom-image
  --role-arn arn:aws:iam::<acct-id>:role/service-role/<execution-role>
```

The response should look similar to the following.

```
{
  "ImageArn": "arn:aws:sagemaker:us-east-2:acct-id:image/custom-image"
}
```

2. Create a SageMaker image version from the container image.

```
aws sagemaker create-image-version
  --image-name custom-image
  --base-image <acct-id>.dkr.ecr.<region>.amazonaws.com/smstudio-custom:custom-image
```

```
The response should look similar to the following.

```json
{
    "ImageVersionArn": "arn:aws:sagemaker:us-east-2:acct-id:image-version/custom-image/1"
}
```

3. Check that the image version was successfully created.

```
aws sagemaker describe-image-version \
   --image-name custom-image \ 
   --version 1
```

The response should look similar to the following.

```json
{
    "ImageVersionStatus": "CREATED"
}
```

**Note**
If the response is "ImageVersionStatus": "CREATED_FAILED", the response also includes the failure reason. A permissions issue is a common cause of failure. You also can check your Amazon CloudWatch logs if you experience a failure when starting or running the KernelGateway app for a custom image. The name of the log group is /aws/sagemaker/studio. The name of the log stream is $domainID/$userProfileName/KernelGateway/$appName.

4. Create a configuration file, named `app-image-config-input.json`. The Name value of KernelSpecs must match the name of the kernelSpec available in the Image associated with this AppImageConfig. This value is case sensitive. You can find the available kernelSpecs in an image by running `jupyter-kernelspec list` from a shell inside the container. MountPath is the path within the image to mount your Amazon Elastic File System (Amazon EFS) home directory. It needs to be different from the path you use inside the container because that path will be overridden when your Amazon EFS home directory is mounted.

**Note**
The following DefaultUID and DefaultGID combinations are the only accepted values:
- DefaultUID: 1000 and DefaultGID: 100
- DefaultUID: 0 and DefaultGID: 0

```json
{
    "AppImageConfigName": "custom-image-config",
    "KernelGatewayImageConfig": {
        "KernelSpecs": [{
            "Name": "python3",
            "DisplayName": "Python 3 (ipykernel)"
        }],
        "FileSystemConfig": {
            "MountPath": "/home/sagemaker-user",
            "DefaultUid": 1000,
            "DefaultGid": 100
        }
    }
}
```
5. Create the AppImageConfig using the file created in the previous step.

```
aws sagemaker create-app-image-config \
   --cli-input-json file://app-image-config-input.json
```

The response should look similar to the following.

```
{
}
```

**Attach a custom SageMaker image**

To use a custom SageMaker image, you must attach a version of the image to your domain. When you attach an image version, it appears in the SageMaker Studio Launcher and is available in the **Select image** dropdown list, which users use to launch an activity or change the image used by a notebook.

To make a custom SageMaker image available to all users within a domain, you attach the image to the domain. To make an image available to a single user, you attach the image to the user's profile. When you attach an image, SageMaker uses the latest image version by default. You can also attach a specific image version. After you attach the version, you can choose the version from the SageMaker Launcher or the image selector when you launch a notebook.

There is a limit to the number of image versions that can be attached at any given time. After you reach the limit, you must detach a version in order to attach another version of the image.

The following sections demonstrate how to attach a custom SageMaker image to your domain using either the SageMaker console or the AWS CLI.

**Attach the SageMaker image using the Console**

This topic describes how you can attach an existing custom SageMaker image version to your domain using the SageMaker control panel. You can also create a custom SageMaker image and image version, and then attach that version to your domain. For the procedure to create an image and image version, see [Create a custom SageMaker image](p. 156).

**To attach an existing image**

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the left navigation pane, choose **Control Panel**.
3. On the **Control Panel**, under **Custom SageMaker Studio images attached to domain**, choose **Attach image**.
4. For **Image source**, choose **Existing image**.
5. Choose an existing image from the list.
6. Choose a version of the image from the list.
7. Choose **Next**.
8. Enter values for **Image name**, **Image display name**, and **Description**.
9. Choose the IAM role. For more information, see [Create a custom SageMaker image](p. 156).
10. (Optional) Add tags for the image.
11. Choose **Next**.
12. Under **Studio configuration**, enter or change the following settings. For information on how to get the kernel information from the image, see [DEVELOPMENT](p. 159) in the SageMaker Studio Custom
Image Samples repository. For more information, see the Kernel discovery and User data sections of Custom SageMaker image specifications (p. 153).

- EFS mount path – The path within the image to mount the user's Amazon Elastic File System (EFS) home directory.
- Kernel:
  - For Kernel name, enter the name of an existing kernel in the image.
  - (Optional) For Kernel display name, enter the display name for the kernel.
  - Choose Add kernel.
  - (Optional) Configuration tags – Choose Add new tag and then add a configuration tag.

13. Choose Submit.

- Wait for the image version to be attached to the domain. When attached, the version is displayed in the Custom images list and briefly highlighted.

Attach the SageMaker image using the AWS CLI

The following sections demonstrate how to attach a custom SageMaker image when creating a new domain or updating your existing domain using the AWS CLI.

Attach the SageMaker image to a new domain

The following section demonstrates how to create a new domain with the version attached. These steps require that you specify the Amazon Virtual Private Cloud (VPC) information and execution role required to create the domain. You perform the following steps to create the domain and attach the custom SageMaker image:

- Get your default VPC ID and subnet IDs.
- Create the configuration file for the domain, which specifies the image.
- Create the domain with the configuration file.

To add the custom SageMaker image to your domain

1. Get your default VPC ID.

   ```bash
   aws ec2 describe-vpcs
   --filters Name=isDefault,Values=true
   --query "Vpcs[0].VpcId" --output text
   
   The response should look similar to the following.
   
   vpc-xxxxxxxx
   
   2. Get your default subnet IDs using the VPC ID from the previous step.

   ```bash
   aws ec2 describe-subnets
   --filters Name=vpc-id,Values=<vpc-id>
   --query "Subnets[*].SubnetId" --output json
   
   The response should look similar to the following.

   ["subnet-b55171dd",
    "subnet-8a5f99c6",
    
   
   160
3. Create a configuration file named `create-domain-input.json`. Insert the VPC ID, subnet IDs, `ImageName`, and `AppImageConfigName` from the previous steps. Because `ImageVersionNumber` isn't specified, the latest version of the image is used, which is the only version in this case.

```json
{
    "DomainName": "domain-with-custom-image",
    "VpcId": "<vpc-id>",
    "SubnetIds": [
        "<subnet-ids>"
    ],
    "DefaultUserSettings": {
        "ExecutionRole": "<execution-role>",
        "KernelGatewayAppSettings": {
            "CustomImages": [
                {
                    "ImageName": "custom-image",
                    "AppImageConfigName": "custom-image-config"
                }
            ]
        }
    },
    "AuthMode": "IAM"
}
```

4. Create the domain with the attached custom SageMaker image.

```bash
aws sagemaker create-domain \
  --cli-input-json file://create-domain-input.json
```

The response should look similar to the following.

```json
{
    "Url": "https://d-xxxxxxxxxxxx.studio.us-east-2.sagemaker.aws/..."
}
```

**Attach the SageMaker image to your current domain**

If you have onboarded to a SageMaker domain, you can attach the custom image to your current domain. For more information about onboarding to a SageMaker domain, see [Onboard to Amazon SageMaker Domain](p. 35). You don't need to specify the VPC information and execution role when attaching a custom image to your current domain. After you attach the version, you must delete all the apps in your domain and reopen Studio. For information about deleting the apps, see [Delete an Amazon SageMaker Domain](p. 43).

**Note**

You can have only one domain. If you have onboarded to SageMaker domain, you must delete your current domain before you can use this method. For more information, see [Delete an Amazon SageMaker Domain](p. 43).

You perform the following steps to add the SageMaker image to your current domain.

- Get your `DomainID` from SageMaker control panel.
- Use the `DomainID` to get the `DefaultUserSettings` for the domain.
- Add the `ImageName` and `AppImageConfig` as a `CustomImage` to the `DefaultUserSettings`.
- Update your domain to include the custom image.
To add the custom SageMaker image to your domain

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. From the top left of the navigation pane, choose Control Panel.
3. From the Control Panel, under Domain, find the DomainId. The ID is in the following format: d-xxxxxxxxxxxxx.

4. Use the domain ID to get the description of the domain.

   ```bash
   aws sagemaker describe-domain \
   --domain-id <d-xxxxxxxxxxxxx>
   ``

   The response should look similar to the following.

   ```json
   {
   "DomainId": "d-xxxxxxxxxxxx",  
   "DefaultUserSettings": {  
   "KernelGatewayAppSettings": {  
   "CustomImages": [    
   ],  
   ...  
   }  
   }
   }
   ```

5. Save the default user settings section of the response to a file named default-user-settings.json.

6. Insert the ImageName and AppImageConfigName from the previous steps as a custom image. Because ImageVersionNumber isn't specified, the latest version of the image is used, which is the only version in this case.

   ```json
   {    
   "DefaultUserSettings": {    
   "KernelGatewayAppSettings": {    
   "CustomImages": [    
   {    
   "ImageName": "string",    
   "AppImageConfigName": "string"    
   }    
   ],    
   ```
7. Use the domain ID and default user settings file to update your domain.

```
aws sagemaker update-domain \
  --domain-id <d-xxxxxxxxxxxx> \
  --cli-input-json file://default-user-settings.json
```

The response should look similar to the following.

```
{
  "DomainArn": "arn:aws:sagemaker:us-east-2:acct-id:domain/d-xxxxxxxxxxxx"
}
```

View the attached image in the SageMaker control panel

After you create the custom SageMaker image and attach it to your domain, the image appears in the custom images list in the control panel.

Launch a custom SageMaker image in Amazon SageMaker Studio

After you create your custom SageMaker image and attach it to your domain, the image appears in the image selector dialog box of the Studio Launcher, and the kernel appears in the kernel selector dialog box.

To launch and select your custom image

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Use the keyboard shortcut Ctrl + Shift + L to open Studio Launcher.
3. Open the **Select a SageMaker image** dropdown menu.

4. Choose your custom image.
5. Launch a notebook or interactive shell in the custom image.

6. In an open notebook, you can switch to the custom kernel by choosing a different kernel in the Select Kernel dialog box.
Note
If you encounter an error when launching the image, check your Amazon CloudWatch logs. The name of the log group is /aws/sagemaker/studio. The name of the log stream is $domainID/$userProfileName/KernelGateway/$appName.

Clean up resources

The following sections show how to clean up the resources you created in the previous sections from the SageMaker console or AWS CLI. You perform the following steps to clean up the resources:

- Detach the image and image versions from your domain.
- Delete the image, image version, and app image config.
- Delete the container image and repository from Amazon ECR. For more information, see Deleting a repository.

Clean up resources from the SageMaker console

The following section shows how to clean up resources from the SageMaker console.

When you detach an image from a domain, all versions of the image are detached. When an image is detached, all users of the domain lose access to the image versions. A running notebook that has a kernel session on an image version when the version is detached, continues to run. When the notebook is stopped or the kernel is shut down, the image version becomes unavailable.
To detach an image

1. In the Control Panel, under Custom SageMaker Studio images attached to domain, choose the image and then choose Detach.
2. (Optional) To delete the image and all versions from SageMaker, select Also delete the selected images .... This does not delete the associated container images from Amazon ECR.
3. Choose Detach.

Clean up resources from the AWS CLI

The following section shows how to clean up resources from the SageMaker console.

To clean up resources

1. Detach the image and image versions from your domain by passing an empty custom image list to the domain. Open the default-user-settings.json file you created in ?? (p. 161).
2. Delete the custom images and then save the file.

   ```json
   "DefaultUserSettings": {
     "KernelGatewayAppSettings": {
       "CustomImages": [],
       ..
       },
     ..
   }
   ``

3. Use the domain ID and default user settings file to update your domain.

   ```bash
   aws sagemaker update-domain \
   --domain-id <d-xxxxxxxxxxxx> \
   --cli-input-json file://default-user-settings.json
   ```

   The response should look similar to the following.

   ```json
   {
     "DomainArn": "arn:aws:sagemaker:us-east-2:acct-id:domain/d-xxxxxxxxxxxx"
   }
   ```

4. Delete the app image config.

   ```bash
   aws sagemaker delete-app-image-config \
   --app-image-config-name custom-image-config
   ```

5. Delete the SageMaker image, which also deletes all image versions. The container images in ECR that are represented by the image versions are not deleted.

   ```bash
   aws sagemaker delete-image \
   --image-name custom-image
   ```

Use Lifecycle Configurations with Amazon SageMaker Studio

Lifecycle Configurations are shell scripts triggered by Amazon SageMaker Studio lifecycle events, such as starting a new Studio notebook. You can use Lifecycle Configurations to automate customization for
Customize Studio

your Studio environment. This customization includes installing custom packages, configuring notebook extensions, preloading datasets, and setting up source code repositories.

Using Lifecycle Configurations gives you flexibility and control to configure Studio to meet your specific needs. For example, you can create a minimal set of base container images with the most commonly used packages and libraries, then use Lifecycle Configurations to install additional packages for specific use cases across your data science and machine learning teams.

For example Lifecycle Configuration scripts, see the Studio Lifecycle Configuration examples repo. For a blog on implementing Lifecycle Configurations, see Customize Amazon SageMaker Studio using Lifecycle Configurations.

Note
Each script has a limit of 16384 characters.

Topics
• Creating and Associating a Lifecycle Configuration (p. 168)
• Setting Default Lifecycle Configurations (p. 172)
• Debugging Lifecycle Configurations (p. 173)
• Updating and deleting Lifecycle Configurations (p. 175)

Creating and Associating a Lifecycle Configuration

Amazon SageMaker Studio provides interactive applications that enable Studio's visual interface, code authoring, and run experience. This series shows how to create a lifecycle configuration and associate it with Amazon SageMaker Studio.

Application types can be either JupyterServer or KernelGateway.

• JupyterServer applications: This application type enables access to the visual interface for Studio. Every user in Studio gets their own Jupyter Server application.
• KernelGateway applications: This application type enables access to the code run environment and kernels for your Studio notebooks and terminals. For more information, see Jupyter Kernel Gateway.

For more information about Studio's architecture and Studio applications, see Use Amazon SageMaker Studio Notebooks.

Topics
• Create a Lifecycle Configuration from the AWS CLI (p. 168)
• Create a Lifecycle Configuration from the SageMaker Console (p. 170)

Create a Lifecycle Configuration from the AWS CLI

The following topic shows how to create a lifecycle configuration using the AWS CLI to automate customization for your Studio environment.

Prerequisites

Before you begin, complete the following prerequisites:

• Update the AWS CLI by following the steps in Installing the current AWS CLI Version.
• From your local machine, run aws configure and provide your AWS credentials. For information about AWS credentials, see Understanding and getting your AWS credentials.
• Onboard to Amazon SageMaker Studio. For more information, see Onboard to Amazon SageMaker Studio.
Step 1: Create a Lifecycle Configuration

The following procedure shows how to create a lifecycle configuration script that prints Hello World.

1. From your local machine, create a file named my-script.sh with the following content.

```bash
#!/bin/bash
set -eux
echo 'Hello World!'
```

2. Convert your my-script.sh file into base64 format. This requirement prevents errors that occur from spacing and line break encoding.

```bash
LCC_CONTENT=`openssl base64 -A -in my-script.sh`
```

3. Create a Studio lifecycle configuration. The following command creates a lifecycle configuration that runs when you launch an associated KernelGateway application.

```bash
aws sagemaker create-studio-lifecycle-config \
--region <your-region> \
--studio-lifecycle-config-name my-studio-lcc \
--studio-lifecycle-config-content $LCC_CONTENT \
--studio-lifecycle-config-app-type KernelGateway
```

Note the ARN of the newly created lifecycle configuration that is returned. This ARN is required to attach the lifecycle configuration to your application.

Step 2: Attach the Lifecycle Configuration to your Studio domain or user profile

To attach the lifecycle configuration, you must update the UserSettings for your Studio domain or an individual user profile. Lifecycle configuration scripts that are associated at the domain level are inherited by all users. However, scripts that are associated at the user profile level are scoped to a specific user.

The following example shows how to create a new user profile with the lifecycle configuration attached. To update an existing user profile, use the update-user-profile command.

Add the lifecycle configuration ARN from the previous step to the settings for the appropriate AppType. For example, place it in the JupyterServerAppSettings of the user. You can add multiple lifecycle configuration at the same time by using a list of lifecycle configuration.

```bash
# Create a new UserProfile
aws sagemaker create-user-profile --domain-id <DOMAIN-ID> \
--user-profile-name <USER-PROFILE-NAME> \
--region <REGION> \
--user-settings '{
"JupyterServerAppSettings": {
  "LifecycleConfigArns":
  ["<LIFECYCLE-CONFIGURATION-ARN-LIST>"
  ]
}
'
```

Step 3: Launch application with Lifecycle Configuration

After you attach a lifecycle configuration to a user profile, the user can select it when launching an application using the AWS CLI. This section describes how to launch an application with an attached lifecycle configuration.
Launch the application and specify the lifecycle configuration ARN in the ResourceSpec argument of the CreateApp API.

- The following example shows how to create a JupyterServer application. When creating the app-type JupyterServer, the app-name must be default.

```
aws sagemaker create-app --domain-id <DOMAIN-ID> \
  --region <YOUR-REGION> \ 
  --user-profile-name <USERPROFILE-NAME> \ 
  --app-type JupyterServer \ 
  --resource-spec LifecycleConfigArn=<LIFECYCLE-CONFIGURATION-ARN> \ 
  --app-name default
```

- The following example shows how to create a KernelGateway application.

```
aws sagemaker create-app --domain-id <DOMAIN-ID> \
  --region <YOUR-REGION> \ 
  --user-profile-name <USERPROFILE-NAME> \ 
  --app-type KernelGateway \ 
  --resource-spec LifecycleConfigArn=<LIFECYCLE-CONFIGURATION-ARN>,SageMakerImageArn=<SAGEMAKER-IMAGE-ARN>,InstanceType=<INSTANCE-TYPE> \ 
  --app-name <APP-NAME>
```

Create a Lifecycle Configuration from the SageMaker Console

The following topic shows how to create a lifecycle configuration from the Amazon SageMaker console to automate customization for your Studio environment.

Prerequisites

Before you can begin this tutorial, complete the following prerequisite:

- Onboard to Amazon SageMaker Studio. For more information, see Onboard to Amazon SageMaker Studio.

Step 1: Create a new Lifecycle Configuration

You can create a lifecycle configuration by entering a script from the Amazon SageMaker console.

The following procedure shows how to create a lifecycle configuration script that prints **Hello World**.

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. From the navigation panel, under SageMaker dashboard, choose Lifecycle configurations.
3. Choose the Studio tab.
4. Choose Create configuration.
5. Under Select configuration type, select the type of application that the lifecycle configuration should be attached to.
6. Choose Next.
7. In the section called Configuration settings, enter a name for your lifecycle configuration.
8. In the Scripts section, enter the following content.

```bash
#!/bin/bash
set -eux
echo 'Hello World!'
```
9. (Optional) Create a tag for your lifecycle configuration.

10. Choose Create Configuration.

**Step 2: Attach the Lifecycle Configuration to Studio domain or user profile**

Lifecycle configuration scripts associated at the domain level are inherited by all users. However, scripts that are associated at the user profile level are scoped to a specific user.

The following sections show how to attach a lifecycle configuration to your domain and user profile.

**Attach to Studio domain**

The following shows how to attach a lifecycle configuration to your existing domain in Studio.

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. From the left navigation panel, choose Control panel.
3. From the Control panel, choose the Lifecycle configurations tab.
4. Choose Attach.
5. Under Source, choose Existing configuration.
6. Under Studio lifecycle configurations, select the lifecycle configuration that you created in the previous step.
7. Select Attach to domain.

**Attach to your user profile**

The following shows how to attach a lifecycle configuration to your existing user profile.

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. From the left navigation panel, choose Control panel.
3. Under Users, select the user profile.
4. From the User Details page, choose Edit.
5. On the left navigation, choose Studio settings.
6. Under Lifecycle configurations attached to user, choose Attach.
7. Under Source, choose Existing configuration.
8. Under Studio lifecycle configurations, select the lifecycle configuration that you created in the previous step.
9. Choose Attach to user profile.

**Step 3: Launch an application with the Lifecycle Configuration**

After you attach a lifecycle configuration to a user profile, the user can select it when launching an application using the Studio Launcher. The following sections describe how to launch an application with an attached lifecycle configuration.

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Launch the Studio Domain. For more information, see Use the Amazon SageMaker Studio Launcher (p. 127).
3. In the launcher, navigate to the Notebooks and compute resources section.
4. Select a SageMaker image.
5. Select a start-up script. If there is no default lifecycle configuration, this value defaults to No script. Otherwise, this value is equal to your default lifecycle configuration. After you select a lifecycle configuration, you can view the entire script.

6. Choose Notebook to launch a new notebook kernel with your selected image and lifecycle configuration.

**Step 4: View logs for a Lifecycle Configuration**

You can view the logs for your lifecycle configuration after it has been attached to a Studio domain or user profile.

1. First, provide access to CloudWatch for your AWS Identity and Access Management (IAM) role. Add read permissions for the following log group /aws/sagemaker/studio and for the following log stream `<Domain>/<UserProfile>/<AppType>/<AppName>/LifecycleConfigOnStart`. For information about adding permissions, see Enabling logging from certain AWS services.

2. From within Studio, navigate to the Running instances tab to monitor your lifecycle configuration.

3. Select an application from the list of running applications. Applications with attached lifecycle configurations have an attached indicator icon.

4. Select the indicator icon for your application. This opens a new panel that lists the lifecycle configuration.

5. From the new panel, select View logs. This opens a new tab that displays the logs.

**Setting Default Lifecycle Configurations**

To set a Lifecycle Configuration as the default for your Domain or UserProfile programatically, you can create a new resource or update an existing resource. To associate a Lifecycle Configuration as a default, you'll first need to create a Lifecycle Configuration following the steps in Creating and Associating a Lifecycle Configuration (p. 168). Default Lifecycle Configurations set up at the domain level are inherited by all users, while those set up at the user level are scoped to a specific user.

**Note**

User level defaults override defaults set up at the domain level.

To set up a default Lifecycle Configuration, it must be added to the DefaultResourceSpec of the appropriate app type. The behavior of your Lifecycle Configuration depends on whether it is added to the DefaultResourceSpec of a JupyterServer or KernelGateway app.

- **JupyterServer apps:** When added to the DefaultResourceSpec of a JupyterServer app, the default Lifecycle Configuration script runs automatically when the user logs into Studio for the first time or restarts Studio. This can be used to automate one-time set-up actions for the Studio developer environment, such as installing notebook extensions or setting up a GitHub repo. For an example of this, see Customize Amazon SageMaker Studio using Lifecycle Configurations.

- **KernelGateway apps:** When added to the DefaultResourceSpec of a KernelGateway app, Studio defaults to selecting the Lifecycle Configuration script from the Studio launcher. Users can launch a notebook or terminal with the default script selected or they can select a different one from the list of Lifecycle Configurations.

**Note**

A default KernelGateway Lifecycle Configuration specified in DefaultResourceSpec applies to all KernelGateway images in the Studio Domain unless the user selects a different script from the list presented in the Studio launcher. The default script also runs if No Script is selected by the user. For more information on selecting a script, see Step 3: Launch an application with the Lifecycle Configuration (p. 171).
Associate a default Lifecycle Configuration when creating a new Domain or UserProfile

To associate a Lifecycle Configuration when creating a new Studio Domain or UserProfile, you need the ARN of the Lifecycle Configuration that you created. This ARN is passed to one of the following API calls:

- `create-user-profile`
- `create-domain`

For example, the following API call creates a new UserProfile with an associated Lifecycle Configuration.

```bash
aws sagemaker create-user-profile --domain-id <DOMAIN-ID> \
--user-profile-name <USER-PROFILE-NAME> \
--region <REGION> \
--user-settings '{
  "KernelGatewayAppSettings": {
    "DefaultResourceSpec": {
      "InstanceType": "ml.t3.medium",
      "LifecycleConfigArn": "<LIFECYCLE-CONFIGURATION-ARN>"
    }
  }
}'
```

Associate a default Lifecycle Configuration when updating a Domain or UserProfile

To associate a Lifecycle Configuration when updating an existing Studio Domain or UserProfile, you need the ARN of the Lifecycle Configuration that you created. This ARN is passed to one of the following API calls:

- `update-user-profile`
- `update-domain`

The Lifecycle Configuration ARN should be placed in 2 places, the DefaultResourceSpec and the LifecycleConfigArns list in KernelGatewayAppSettings. For example, the following API call updates a UserProfile with an associated Lifecycle Configuration.

```bash
aws sagemaker update-user-profile --domain-id <DOMAIN-ID> \
--user-profile-name <USER-PROFILE-NAME> \
--region <REGION> \
--user-settings '{
  "KernelGatewayAppSettings": {
    "DefaultResourceSpec": {
      "InstanceType": "ml.t3.medium",
      "LifecycleConfigArn": "<LIFECYCLE-CONFIGURATION-ARN>"
    }
  }
}'
```

Debugging Lifecycle Configurations

The following topics show how to get information about and debug your Lifecycle Configurations.

Topics

- Verify Lifecycle Configuration Process from Amazon CloudWatch Logs (p. 174)
- JupyterServer App failure (p. 174)
- KernelGateway App failure (p. 174)
- Lifecycle Config timeout (p. 175)
Verify Lifecycle Configuration Process from Amazon CloudWatch Logs

Lifecycle Configurations only log STDOUT and STDERR. STDOUT is the default output for bash scripts, while STDERR can be written to by appending `&2` to the end of a bash command. For example, `echo 'hello' >&2`. Logs for your Lifecycle Configurations are published to your AWS Account via CloudWatch. These logs can be found in the `/aws/sagemaker/studio` Log Stream from the AWS CloudWatch console.

2. Select Logs from the left side. From the dropdown menu, select Log Groups.
4. On the `aws/sagemaker/studio` Log Group screen, navigate to the Log Streams tab.
5. To find the logs for a specific app, search Log Streams using the following format:

   `<DomainId>/< UserProfileName>/<AppType>/<AppName>

   For example, to find the Lifecycle Configuration logs for Domain d-m851cu8vbqzmz, UserProfile i-sonic-js, AppType JupyterServer and AppName test-lcc-echo, use the following search string:

   d-m851cu8vbqzmz/i-sonic-js/JupyterServer/test-lcc-echo

6. Select the log stream appended with `LifecycleConfigOnStart` to view the script execution logs.

**JupyterServer App failure**

If your JupyterServer App crashes because of an issue with the attached Lifecycle Configuration, Studio displays the following error message on the Studio startup screen.

```
Failed to create SageMaker Studio due to start-up script failure
```

Click the View script logs link to view the CloudWatch logs for your JupyterServer app.

In the case where the faulty Lifecycle Configuration is specified in the `DefaultResourceSpec` of your Studio Domain or UserProfile, Studio continues to use the Lifecycle Configuration even after restarting Studio.

To resolve this error, follow the steps in Setting Default Lifecycle Configurations (p. 172) to remove the Lifecycle Configuration script from the `DefaultResourceSpec` or select another script using the AWS CLI. Then launch a new JupyterServer app.

**KernelGateway App failure**

If your KernelGateway App crashes because of an issue with the attached Lifecycle Configuration, Studio displays the error message in your Studio Notebook.

Click the View script logs link to view the CloudWatch logs for your KernelGateway app.

In this case, your Lifecycle Configuration is specified in the Studio Launcher when launching a new Studio Notebook.

To resolve this error, use the Studio launcher to select a different Lifecycle Configuration or select No script.

**Note**

A default KernelGateway Lifecycle Configuration specified in `DefaultResourceSpec` applies to all KernelGateway images in the Studio Domain unless the user selects a different script from
the list presented in the Studio launcher. The default script also runs if No Script is selected by the user. For more information on selecting a script, see Step 3: Launch an application with the Lifecycle Configuration (p. 171).

Lifecycle Config timeout

There is a Lifecycle Configuration timeout limitation of 5 minutes. If a Lifecycle Configuration script takes longer than 5 minutes to run, Studio throws an error.

To resolve this error, ensure that your Lifecycle Configuration script completes in less than 5 minutes.

To help decrease the run time of scripts, try the following:

- Cut down on necessary steps. For example, limit which conda environments to install large packages in.
- Run tasks in parallel processes.
- Use the nohup command in your script.

Updating and deleting Lifecycle Configurations

A Lifecycle Configuration script cannot be changed after it has been created. To update your script, you must create a new Lifecycle Configuration script and use the update-domain and update-user-profile APIs to attach the Lifecycle Configuration script to the respective Domain or UserProfile. For more information, see Creating and Associating a Lifecycle Configuration (p. 168).

To delete an existing Lifecycle Configuration, use the DeleteStudioLifecycleConfig API. To successfully delete a Lifecycle Configuration, no running Apps can be using it.

Perform Common Tasks in Amazon SageMaker Studio

The following sections describe how to perform common tasks in Amazon SageMaker Studio. For an overview of the Studio interface, see Amazon SageMaker Studio UI Overview (p. 118).

Topics

- Upload Files to SageMaker Studio (p. 175)
- Clone a Git Repository in SageMaker Studio (p. 176)
- Stop a Training Job in SageMaker Studio (p. 176)
- Use TensorBoard in Amazon SageMaker Studio (p. 176)
- Manage Your EFS Storage Volume in SageMaker Studio (p. 178)
- Provide Feedback on SageMaker Studio (p. 178)
- Shut Down and Update SageMaker Studio and Studio Apps (p. 179)

Upload Files to SageMaker Studio

When you onboard to Amazon SageMaker Studio, a home directory is created for you in the Amazon Elastic File System (Amazon EFS) volume that was created for your team. Studio can open only files that have been uploaded to your directory. The Studio file browser maps to your home directory.

Note

Studio does not support uploading folders. Only individual files can be uploaded.
To upload files to your home directory

1. In the left sidebar, choose the File Browser icon ( 文件).
2. In the file browser, choose the Upload Files icon ( 文件上传).
3. Select the files you want to upload and then choose Open.
4. Double-click a file to open the file in a new tab in Studio.

Clone a Git Repository in SageMaker Studio

Amazon SageMaker Studio can connect only to a local repository. In this example, you clone the aws/amazon-sagemaker-examples repository (repo).

To clone the repo

1. In the left sidebar, choose the File Browser icon ( 文件).
2. Choose the root folder or the folder you want to clone the repo into.
3. In the left sidebar, choose the Git icon ( Git).
4. Choose Clone a Repository.
5. Enter the URI for the SageMaker examples repo https://github.com/aws/amazon-sagemaker-examples.git.
6. Choose CLONE.
7. If the repo requires credentials, you are prompted to enter your username and personal access token.
8. Wait for the download to finish. After the repo has been cloned, the File Browser opens to display the cloned repo.
9. Double-click the repo to open it.
10. Choose the Git icon to view the Git user interface which now tracks the examples repo.
11. To track a different repo, open the repo in the file browser and then choose the Git icon.

Stop a Training Job in SageMaker Studio

You can stop a training job with the Amazon SageMaker Studio UI. When you stop a training job, its status changes to Stopping at which time billing ceases. An algorithm can delay termination in order to save model artifacts after which the job status changes to Stopped. For more information, see the stop_training_job method in the AWS SDK for Python (Boto3).

To stop a training job

1. Follow the View and Compare Experiments, Trials, and Trial Components (p. 2237) procedure on this page until you open the Describe Trial Component tab.
2. At the upper-right side of the tab, choose Stop training job. The Status at the top left of the tab changes to Stopped.
3. To view the training time and billing time, choose AWS Settings.

Use TensorBoard in Amazon SageMaker Studio

The following doc outlines how to install and run TensorBoard in Amazon SageMaker Studio.
Prerequisites

This tutorial requires an Amazon SageMaker Studio Domain.

Set Up TensorBoardCallback

1. Launch Studio.
2. In the Amazon SageMaker Studio Launcher under Notebooks and compute resources, select the TensorFlow 2.3 Python 3.7(optimized for CPU) Studio Image.
3. Launch a notebook to run the commands in the following steps. You run these commands from within a notebook cell.
4. Import the required packages.

```python
import os
import datetime
import tensorflow as tf
```
5. Create your Keras model.

```python
mnist = tf.keras.datasets.mnist
(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

def create_model():
    return tf.keras.models.Sequential([tf.keras.layers.Flatten(input_shape=(28, 28)),
                                        tf.keras.layers.Dense(512, activation='relu'),
                                        tf.keras.layers.Dropout(0.2),
                                        tf.keras.layers.Dense(10, activation='softmax')])
```
6. Create a directory for your TensorBoard logs

```python
LOG_DIR = os.path.join(os.getcwd(), "logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
```
7. Run training with TensorBoard.

```python
model = create_model()
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=LOG_DIR,
                                                        histogram_freq=1)
model.fit(x=x_train,
y=y_train,
epochs=5,
validation_data=(x_test, y_test),
callbacks=[tf.keras.callbacks.TensorBoard(log_dir=LOG_DIR)])
```
8. Generate the EFS path for the TensorBoard logs. You use this path to set up your logs from the terminal.

```python
EFS_PATH_LOG_DIR = "".join(LOG_DIR.strip("/").split('/')[1:-1])
print(EFS_PATH_LOG_DIR)
```
Install TensorBoard

1. Click on the Amazon SageMaker Studio button on the top left corner of Studio to open the Amazon SageMaker Studio Launcher. This launcher must be opened from your root directory.
2. In the Launcher under Utilities and files, click System terminal.
3. From the terminal, run the following commands. Copy EFS_PATH_LOG_DIR from the Jupyter notebook. You must run this from the /home/sagemaker-user root directory.

   ```
   pip install tensorboard
tensorboard --logdir <EFS_PATH_LOG_DIR>
   ```

Launch TensorBoard

1. To launch TensorBoard, copy your Studio URL and replace lab? with proxy/6006/ as follows. You must include the trailing / character.

   ```
   https://<YOUR_URL>.studio.region.sagemaker.aws/jupyter/default/proxy/6006/
   ```

2. Navigate to the URL to examine your results.

Manage Your EFS Storage Volume in SageMaker Studio

The first time a user on your team onboards to Amazon SageMaker Studio, Amazon SageMaker creates an Amazon Elastic File System (Amazon EFS) volume for the team. A home directory is created in the volume for each user who onboards to Studio as part of your team. Notebook files and data files are stored in these directories. Users don't have access to other team member's home directories.

**Important**

Don't delete the Amazon EFS volume. If you delete it, the domain will no longer function and all of your users will lose their work.

To find your Amazon EFS volume

1. Open the SageMaker console.
2. Choose Control Panel at the top left of the page.
3. From the Control Panel, under Domain, find the Domain ID. The ID will be in the following format: d-xxxxxxxxxxxx.
4. Pass the Domain ID, as DomainId, to the describe_domain method.
5. In the response from describe_domain, note the value for the HomeEfsFileSystemId key. This is the Amazon EFS file system ID.
6. Open the Amazon EFS console. Make sure the AWS Region is the same Region that's used by Studio.
7. Under File systems, choose the file system ID from the previous step.
8. To verify that you've chosen the correct file system, select the Tags heading. The value corresponding to the ManagedByAmazonSageMakerResourceId key should match the Studio ID.

For information on how to access the Amazon EFS volume, see Using file systems in Amazon EFS.

To delete the Amazon EFS volume, see Deleting an Amazon EFS file system.

Provide Feedback on SageMaker Studio

Amazon SageMaker takes your feedback seriously. We encourage you to provide feedback.
To provide feedback

1. At the upper-right of SageMaker Studio, choose Feedback.
2. Choose a smiley emoji to let us know how satisfied you are with SageMaker Studio and add any feedback you’d care to share with us.
3. Decide whether to share your identity with us, then choose Submit.

Shut Down and Update SageMaker Studio and Studio Apps

The following topics show how to shut down and update SageMaker Studio and Studio Apps.

Amazon SageMaker does not update Amazon SageMaker Studio apps when it is in service.

Studio provides a notification icon in the upper-right corner of the Studio UI. This notification icon displays the number of unread notices. To read the notices, select the icon.

Studio provides two types of notifications:

- Upgrade – Displayed when Studio or one of the Studio apps have released a new version. To update, see Shut Down and Update SageMaker Studio and Studio Apps (p. 179).
- Information – Displayed for new features and other information.

To reset the notification icon, you must select the link in each notice. Read notifications may still display in the icon. This does not indicate that updates are still needed after you have updated Studio and Studio Apps.

To learn how to update Amazon SageMaker Data Wrangler, see Shut down and Update Studio Apps (p. 180).

To ensure that you have the most recent software updates, update Amazon SageMaker Studio and your Studio apps using the methods outlined in the following topics.

Topics

- Shut down and Update SageMaker Studio (p. 179)
- Shut down and Update Studio Apps (p. 180)

Shut down and Update SageMaker Studio

To update Amazon SageMaker Studio to the latest release, you must shut down the JupyterServer app. You can shut down the JupyterServer app from the SageMaker console or from within Studio. After the JupyterServer app is shut down, you must reopen Studio through the SageMaker console which creates a new version of the JupyterServer app.

Any unsaved notebook information is lost in the process. The user data in the Amazon EFS volume isn’t impacted.

Some of the services within Studio, like Data Wrangler, run on their own app. To update these services you must delete the app for that service. To learn more, see Shut down and Update Studio Apps (p. 180).

Note

A JupyterServer app is associated with a single Studio user. When you update the app for one user it doesn’t affect other users.
The following topic shows how to update the JupyterServer App from the SageMaker console or from inside Studio.

**To update the JupyterServer app from the SageMaker console**

2. Choose Control panel.
3. Under Users, select your user name.
5. Choose Yes, delete app.
6. Type delete in the confirmation box.
7. Choose Delete.
8. After the app has been deleted, launch a new Studio app to get the latest version.

**To update the JupyterServer app from inside Studio**

1. Launch Studio.
2. On the top menu, choose File then Shut Down.
3. Choose one of the following options:
   - **Shutdown Server** – Shuts down the JupyterServer app. Terminal sessions, kernel sessions, SageMaker images, and instances aren't shut down. These resources continue to accrue charges.
   - **Shutdown All** – Shuts down all apps, terminal sessions, kernel sessions, SageMaker images, and instances. These resources no longer accrue charges.
4. Close the window.
5. After the app has been deleted, launch a new Studio app to use the latest version.

**Shut down and Update Studio Apps**

To update an Amazon SageMaker Studio app to the latest release, you must first shut down the corresponding KernelGateway app from the SageMaker console. After the KernelGateway app is shut down, you must reopen it through SageMaker Studio by running a new kernel. The kernel automatically updates. Any unsaved notebook information is lost in the process. The user data in the Amazon EFS volume isn't impacted.

**Note**

A KernelGateway app is associated with a single Studio user. When you update the app for one user it doesn't effect other users.

**To update the KernelGateway app**

2. Choose Control panel.
3. Under Users, select your user name.
4. Under Apps, in the row displaying the App name, choose Delete app.

   To update Data Wrangler, delete the app that starts with sagemaker-data-wrang.
5. Choose Yes, delete app.
6. Type delete in the confirmation box.
7. Choose Delete.
8. After the app has been deleted, launch a new kernel from within Studio to use the latest version.

Amazon SageMaker Studio Pricing

When the first member of your team onboards to Amazon SageMaker Studio, Amazon SageMaker creates an Amazon Elastic File System (Amazon EFS) volume for the team. In the SageMaker Control Panel, when the Studio Status displays as Ready, the Amazon EFS volume has been created.

When this member, or any member of the team, opens Studio, a home directory is created in the volume for the member. A storage charge is incurred for this directory. Subsequently, additional storage charges are incurred for the notebooks and data files stored in the member's home directory. For pricing information on Amazon EFS, see Amazon EFS Pricing.

Additional costs are incurred when other operations are run inside Studio, for example, running a notebook, running training jobs, and hosting a model.

For information on the costs associated with using Studio notebooks, see Usage Metering (p. 146).

For information about billing along with pricing examples, see Amazon SageMaker Pricing.

Troubleshooting Amazon SageMaker Studio

The following are common errors that you might run into when using Amazon SageMaker Studio. Each error is followed by a solution to the error.

- **SageMaker Studio core functionalities are not available.**

  If you get this error message when opening Studio, it might be due to Python package version conflicts. This occurs if you used the following commands in a notebook or terminal to install Python packages that have version conflicts with SageMaker package dependencies.

  ```
  !pip install
  pip install --user
  ```

  To resolve this issue, complete the following steps:
  1. Uninstall recently installed Python packages. If you’re not sure which package to uninstall, reach out using the feedback button on the lower left of the AWS Management Console.
  2. Restart Studio:
      a. Shut down Studio from the File menu.
      b. Wait for 1 minute.
      c. Re-open Studio by refreshing the page or opening it from the AWS Management Console.

  The problem should be resolved if you have uninstalled the package which caused the conflict. To install packages without causing this issue again, use `pip install` without the `--user` flag.

  If the issue persists, create a new user profile and set up your environment with that user profile.

  If these solutions don’t fix the issue, reach out using the feedback button on the lower left of the AWS Management Console.

- **Unable to open Studio from the AWS Management Console.**

  If you are continually unable to open Studio, and are unable to make a new running instance with all default settings, reach out using the feedback button on the lower left of the AWS Management Console.
RStudio on Amazon SageMaker

RStudio is an integrated development environment for R, with a console, syntax-highlighting editor that supports direct code execution, and tools for plotting, history, debugging and workspace management. Amazon SageMaker supports RStudio as a fully-managed integrated development environment (IDE) integrated with Amazon SageMaker Domain.

RStudio allows customers to create data science insights using an R environment. With RStudio integration, you can launch an RStudio environment in the Domain to run your RStudio workflows on SageMaker resources. For more information about RStudio, see the RStudio website.

Topics
- RStudio components (p. 182)
- Differences from RStudio Workbench (p. 183)
- Manage RStudio on Amazon SageMaker (p. 183)
- Use RStudio on Amazon SageMaker (p. 211)

SageMaker integrates RStudio through the creation of a RStudioServerPro app.

The following are supported by RStudio on SageMaker.

- R developers use the RStudio IDE interface with popular developer tools from the R ecosystem. Users can launch new RStudio sessions, write R code, install dependencies from RStudio Package Manager, and publish Shiny apps using RStudio Connect.
- R developers can quickly scale underlying compute resources to run large scale data processing and statistical analysis.
- Platform administrators can set up user identities, authorization, networking, storage, and security for their data science teams through AWS IAM Identity Center (successor to AWS Single Sign-On) and AWS Identity and Access Management integration. This includes connection to private Amazon Virtual Private Cloud (Amazon VPC) resources and internet-free mode with AWS PrivateLink.
- Integration with AWS License Manager.

For information on the onboarding steps to create a Domain with RStudio enabled, see Onboard to Amazon SageMaker Domain (p. 35).

For information about the AWS Regions that RStudio on SageMaker is supported in, see Supported Regions and Quotas (p. 32).

RStudio components

- **RStudioServerPro**: The RStudioServerPro app is a multiuser app that is a shared resource among all user profiles in the Domain. Once an RStudio app is created in a Domain, the admin can give permissions to users in the Domain.
- **RStudio user**: RStudio users are users within the Domain that are authorized to use the RStudio license.
- **RStudio admin**: An RStudio on Amazon SageMaker admin can access the RStudio administrative dashboard. RStudio on Amazon SageMaker admins differ from "stock" RStudio Workbench admins because they do not have root access to the instance running the RStudioServerPro app and can't modify the RStudio configuration file.
- **RStudio Server**: The RStudio Server instance is responsible for serving the RStudio UI to all authorized Users. This instance is launched on an Amazon SageMaker instance.
- **RSession**: An RSession is a browser-based interface to the RStudio IDE running on an Amazon SageMaker instance. Users can create and interact with their RStudio projects through the RSession.
• **RSessionGateway**: The RSessionGateway app is used to support an RSession.

• **RStudio administrative dashboard**: This dashboard gives information on the RStudio users in the Amazon SageMaker Domain and their sessions. This dashboard can only be accessed by users that have RStudio admin authorization.

### Differences from RStudio Workbench

RStudio on Amazon SageMaker has some significant differences from RStudio Workbench.

• When using RStudio on SageMaker, users don’t have access to the RStudio configuration files. Amazon SageMaker manages the configuration file and sets defaults. You can modify the RStudio Connect and RStudio Package Manager URLs when creating your RStudio-enabled Amazon SageMaker Domain.

• Project sharing, realtime collaboration, and Job Launcher are not currently supported when using RStudio on Amazon SageMaker.

• When using RStudio on SageMaker, the RStudio IDE runs on Amazon SageMaker instances for on-demand containerized compute resources.

• RStudio on SageMaker only supports the RStudio IDE and does not support other IDEs supported by an RStudio Workbench installation.

### Manage RStudio on Amazon SageMaker

The following topics give information on managing RStudio on Amazon SageMaker. This includes information on your RStudio environment configuration, user sessions, and necessary resources. For information on how to use RStudio on SageMaker, see [Use RStudio on Amazon SageMaker](p. 211).

For information about creating a Amazon SageMaker Domain with RStudio enabled, see [Onboard to Amazon SageMaker Domain](p. 35).

For information about the AWS Regions that RStudio on SageMaker is supported in, see [Supported Regions and Quotas](p. 32).

**Topics**

- RStudio license (p. 183)
- Upgrade the RStudio Version (p. 184)
- Network and Storage (p. 185)
- RStudioServerPro instance type (p. 186)
- RStudio Connect URL (p. 186)
- RStudio Package Manager (p. 187)
- Create an Amazon SageMaker Domain with RStudio using the AWS CLI (p. 187)
- Bring your own image to RStudio on SageMaker (p. 192)
- Manage users (p. 205)
- RStudio administrative dashboard (p. 207)
- Shut down and restart RStudio (p. 208)
- Manage billing and cost (p. 209)
- Diagnose issues and get support (p. 210)

**RStudio license**

RStudio on Amazon SageMaker is a paid product and requires that each user is appropriately licensed. Licenses for RStudio on Amazon SageMaker may be obtained from RStudio PBC directly, or by
purchasing a subscription to RStudio Workbench on AWS Marketplace. For existing customers of RStudio Workbench Enterprise, licenses are issued at no additional cost.

To use an RStudio license with Amazon SageMaker, you must first have a valid RStudio license registered with AWS License Manager. Subscriptions to RStudio Workbench on AWS Marketplace automatically trigger license creation with AWS License Manager. For licenses purchased directly through RStudio PBC, a licenses grant for your AWS Account must be created. Contact RStudio for direct license purchases or to enable existing licenses in AWS License Manager. For more information about registering a license with AWS License Manager, see Seller issued licenses in AWS License Manager.

The following topics show how to acquire and validate a license granted by RStudio PBC.

**Get an RStudio license**

1. If you don't have an RStudio license, you may purchase one at RStudio Pricing or by contacting sales@rstudio.com. When buying or updating an RStudio license, you must provide the AWS Account that will host your Amazon SageMaker Domain.
   
   If you have an existing RStudio license, contact your RStudio Sales representative or sales@rstudio.com to add RStudio on Amazon SageMaker to your existing RStudio Workbench Enterprise license, or to convert your RStudio Workbench Standard license. The RStudio Sales representative will send you the appropriate electronic order form.

2. RStudio grants a RStudio Workbench license to your AWS Account through AWS License Manager in the US East (N. Virginia) Region. Although the RStudio license is granted in the US East (N. Virginia) Region, your license can be consumed in any AWS Region that RStudio on Amazon SageMaker is supported in. You can expect the license grant process to complete within three business days after you share your AWS account ID with RStudio.

3. When this license is granted, you receive an email from your RStudio Sales representative with instructions to accept your license grant.

**Validate your RStudio license to be used with Amazon SageMaker**

1. Log into the AWS License Manager console in the same region as your Amazon SageMaker Domain. If you are using AWS License Manager for the first time, you need to grant permission to use AWS License Manager.

2. Select Create Customer managed license.

3. Select I grant AWS License Manager the required permissions and select Grant Permissions.

4. Navigate to Granted Licenses on the left panel.

5. Select the license grant with RSW-SageMaker as the Product name and select View.

6. From the license detail page, select Accept & activate license.

**RStudio administrative dashboard**

You can use the RStudio administrative dashboard to see the number of users on the license following the steps in RStudio administrative dashboard (p. 207).

**Upgrade the RStudio Version**

In this guide, you'll get information about the latest version update for RStudio on SageMaker. You must update your version to provide continued functionality. To upgrade to the latest RStudio version on Amazon SageMaker, complete the steps in Shut down and restart RStudio (p. 208).

**Latest version updates**

The updated RStudio version is 2022.02.2-485.pro2. This version supports:
• Enhanced R help system, introduced with R 4.2.0.
• Added editor support for the R pipe-bind placeholder (\_).
• Encryption between RStudioServerPro and RSessions. This update requires upgrading existing RStudio-enabled SageMaker domains. For more information, see Upgrade Scenarios (p. 185).

All newly created SageMaker domains with RStudio and RSessions support this new version. To use this new version with existing SageMaker domains with RStudio, you must relaunch your RStudioServerPro application. For more information about the changes in this release, see the RStudio Release Notes.

Upgrade Scenarios

All new RStudio applications are created using the 2022.02.2-485.pro2 release. The RStudioServerPro application is deployed when the domain is created, and it persists unless it's deleted. If you have an existing RStudio-enabled domain, you must upgrade the RStudioServerPro application to support end-to-end encryption with new RSessions. If you create a new domain, you don't need to upgrade.

Your upgrade status is one of the following:

• If you create a new domain with RStudio Enabled: RStudio applications for newly created domains are created using the 2022.02.2-485.pro2 release and support end-to-end encryption. No further action is required.
• You have a pre-existing SageMaker domain with RStudio and update the RStudioServerPro App: This enables end-to-end encryption and requires no further changes for new RSessions. You must delete and re-create your existing RSessions applications.
• You have a pre-existing SageMaker domain with RStudio and do not update the RStudioServerPro App: If you don’t update your application, there is a version mismatch with all new RSessions. There may be functionality issues because of the version mismatch. Traffic encryption between RStudioServerPro and RSessions is also not available. We recommend that you update your RStudioServerPro application to the new version.

Changes to BYOI Images

If you are using a BYOI image with RStudio, you must upgrade your custom images to use the 2022.02.2-485.pro2 release and redeploy your existing RSessions. If you attempt to load a non-compatible image in an RSessions of a domain using the 2022.02.2-485.pro2 version, the RSessions fails because it cannot parse parameters that it receives. Your RSessions will not function properly and will not support end-to-end encryption. You must update all of the deployed custom images in your existing RStudioServerPro app.

Network and Storage

The following topic describes network access and data storage considerations for your RStudio instance. For general information about network access and data storage when using Amazon SageMaker, see Data Protection in Amazon SageMaker (p. 3495).

Encryption

RStudio on Amazon SageMaker supports encryption at rest.

Use RStudio in VPC-only mode

RStudio in Amazon SageMaker supports AWS PrivateLink integration. With this integration, you can use RStudio on SageMaker in VPC-only mode without direct access to the internet. When you use
RStudio in VPC-only mode, your security groups are automatically managed by the service. This includes connectivity between your RServer and your RSessions.

The following are required to use RStudio in VPC-only mode. For more information on selecting a VPC, see Choose a VPC (p. 42).

- A private subnet with either access the internet to make a call to Amazon SageMaker & License Manager, or Amazon Virtual Private Cloud (Amazon VPC) endpoints for both Amazon SageMaker & License Manager.
- A Security Group ID for use with the Domain in Domain Settings. This must allow all outbound access.
- A Security Group ID for use with the Amazon VPC endpoint. This security group must allow inbound traffic from the Domain Security Group ID.
- Amazon VPC Endpoint for sagemaker.api and AWS License Manager. This must be in the same Amazon VPC as the private subnet.

RStudioServerPro instance type

When deciding which Amazon EC2 instance type to use for your RStudioServerPro app, the main factor to consider is bandwidth. Bandwidth is important because the RStudioServerPro instance is responsible for serving the RStudio UI to all users. This includes UI heavy workflows, such as generating figures, animations, and displaying many data rows. Therefore, there may be some UI performance degradation depending on the workload across all users. The following are the available instance types to use for your RStudioServerPro. For pricing information about these instances, see Amazon SageMaker Pricing.

- `ml.t3.medium`: This instance type is recommended for Domains with low UI use and is free to use.
- `ml.c5.4xlarge`: This instance type is recommended for Domains with moderate UI use.
- `ml.c5.9xlarge`: This instance type is recommended for Domains with heavy UI use.

Changing RStudio instance type

To change the instance type of your RStudioServerPro, pass the new instance type as part of a call to the `update-domain` CLI command. You then need to delete the existing RStudioServerPro app using the `delete-app` CLI command and create a new RStudioServerPro app using the `create-app` CLI command.

RStudio Connect URL

RStudio Connect is a publishing platform for Shiny applications, R Markdown reports, dashboards, plots, and more. RStudio Connect makes it easy to surface machine learning and data science insights by making hosting content simple and scalable. If you have an RStudio Connect server, then you can set the server as the default place where apps are published. For more information about RStudio Connect, see RStudio Connect.

When you onboard to RStudio on Amazon SageMaker Domain, an RStudio Connect server is not created. You can create an RStudio Connect server on an Amazon EC2 instance to use Connect with Amazon SageMaker Domain. For information about how to set up your RStudio Connect server, see Host RStudio Connect and Package Manager for ML development in RStudio on Amazon SageMaker.

Add an RStudio Connect URL

If you have an RStudio Connect URL, you can update the default URL so that your RStudio Users can publish to it.

1. Navigate to the Control Panel.
2. Under Domain, choose **Edit Settings**. This opens a new page.
3. From the new page, select **RStudio Settings** on the left side.
4. Under **RStudio Connect URL**, enter the RStudio Connect URL to add.
5. Select **Submit**.

**CLI**

You can set a default RStudio Connect URL when you create your Amazon SageMaker Domain. The only way to update your RStudio Connect URL from the AWS CLI is to delete your Domain and create a new one with the updated RStudio Connect URL.

**RStudio Package Manager**

RStudio Package Manager is a repository management server used to organize and centralize packages across your organization. For more information on RStudio Package Manager, see [RStudio Package Manager](#). If you don’t supply your own Package Manager URL, Amazon SageMaker Domain uses the default Package Manager repository when you onboard RStudio following the steps in [Onboard to Amazon SageMaker Domain](#) (p. 35). For more information, see [Host RStudio Connect and Package Manager for ML development in RStudio on Amazon SageMaker](#).

**Update Package Manager URL**

You can update the Package Manager URL used for your RStudio-enabled Domain as follows.

1. Navigate to the **Control Panel**.
2. Under Domain, select **Edit Settings**. This opens a new page.
3. From the new page, select **RStudio Settings** on the left side.
4. Under **RStudio Package Manager**, enter your RStudio Package Manager URL.
5. Select **Submit**.

**CLI**

The only way to update your Package Manager URL from the AWS CLI is to delete your Domain and create a new one with the updated Package Manager URL.

**Create an Amazon SageMaker Domain with RStudio using the AWS CLI**

The following topic shows how to onboard to Amazon SageMaker Domain with RStudio enabled using the AWS CLI. To onboard using the AWS Management Console, see [Onboard to Amazon SageMaker Domain](#) (p. 35).

**Prerequisites**

- Install and configure **AWS CLI version 2**
- Configure the **AWS CLI** with IAM credentials

**Create DomainExecution role**

To launch the RStudio App, you must provide a DomainExecution role. This role is used to determine whether RStudio needs to be launched as part of Amazon SageMaker Domain creation. This role is also used by Amazon SageMaker to access the RStudio License and push RStudio logs.
Note
The DomainExecution role should have at least AWS License Manager permissions to access RStudio License, and CloudWatch permissions to push logs in your account.

The following procedure shows how to create the DomainExecution role with the AWS CLI.

1. Create a file named assume-role-policy.json with the following content.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Action": "sts:AssumeRole",
         "Effect": "Allow",
         "Principal": {
            "Service": ["sagemaker.amazonaws.com"]
         }
      }
   ]
}
```

2. Create the DomainExecution role. `<REGION>` should be the AWS Region to launch your Domain in.

```bash
aws iam create-role --region <REGION> --role-name DomainExecution --assume-role-policy-document file://assume-role-policy.json
```

3. Create a file named domain-setting-policy.json with the following content. This policy allows the RStudioServerPro app to access necessary resources and allows Amazon SageMaker to automatically launch an RStudioServerPro app when the existing RStudioServerPro app is in a Deleted or Failed status.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Sid": "VisualEditor0",
         "Effect": "Allow",
         "Action": ["license-manager:ExtendLicenseConsumption",
                    "license-manager:ListReceivedLicenses",
                    "license-manager:GetLicense",
                    "license-manager:CheckoutLicense",
                    "license-manager:CheckInLicense",
                    "logs:CreateLogDelivery",
                    "logs:CreateLogGroup",
                    "logs:CreateLogStream",
                    "logs:DeleteLogDelivery",
                    "logs:Describe*",
                    "logs:GetLogDelivery",
                    "logs:GetLogEvents",
                    "logs:ListLogDeliveries",
                    "logs:PutLogEvents",
                    "logs:PutResourcePolicy",
                    "logs:UpdateLogDelivery",
                    "sagemaker:CreateApp"
         ],
         "Resource": "**"
      }
   ]
}
```
4. Create the Domain setting policy that is attached to the DomainExecution role. Be aware of the PolicyArn from the response, you will need to enter that ARN in the following steps.

```bash
aws iam create-policy --region <REGION> --policy-name domain-setting-policy --policy-document file://domain-setting-policy.json
```

5. Attach domain-setting-policy to the DomainExecution role. Use the PolicyArn returned in the previous step.

```bash
aws iam attach-role-policy --role-name DomainExecution --policy-arn <POLICY_ARN>
```

### Create Amazon SageMaker Domain with RStudio App

The RStudioServerPro app is launched automatically when you create a Amazon SageMaker Domain using the `create-domain` CLI command with the `RStudioServerProDomainSettings` parameter specified. When launching the RStudioServerPro App, Amazon SageMaker checks for a valid RStudio license in the account and fails Domain creation if the license is not found.

The creation of a Amazon SageMaker Domain differs based on the authentication method and the network type. These options must be used together, with one authentication method and one network connection type selected. For more information about the requirements to create a new Domain, see CreateDomain.

The following authentication methods are supported.

- IAM Auth
- SSO Auth

The following network connection types are supported:

- PublicInternet
- VPCOnly

#### Authentication methods

##### IAM Auth Mode

The following shows how to create a Amazon SageMaker Domain with RStudio enabled and an IAM Auth Network Type. For more information about AWS Identity and Access Management, see What is IAM?

- DomainExecutionRoleArn should be the ARN for the role created in the previous step.
- ExecutionRole is the ARN of the role given to users in the Amazon SageMaker Domain.
- vpc-id should be the ID of your Amazon Virtual Private Cloud. subnet-ids should be a space-separated list of subnet IDs. For information about vpc-id and subnet-ids, see VPCs and subnets.
- RStudioPackageManagerUrl and RStudioConnectUrl are optional and should be set to the URLs of your RStudio Package Manager and RStudio Connect server, respectively.
- app-network-access-type should be either PublicInternetOnly or VPCOnly.

```bash
aws sagemaker create-domain --region <REGION> --domain-name <DOMAIN_NAME> \
--auth-mode IAM \
--default-user-settings ExecutionRole=<DEFAULT_USER_EXECUTIONROLE> \
```
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Authentication using IAM Identity Center

The following shows how to create a Amazon SageMaker Domain with RStudio enabled and an SSO Auth Network Type. AWS IAM Identity Center (successor to AWS Single Sign-On) must be enabled for the region that the domain is launched on. For more information about IAM Identity Center, see What is AWS IAM Identity Center (successor to AWS Single Sign-On)?.

- DomainExecutionRoleArn should be the ARN for the role created in the previous step.
- ExecutionRole is the ARN of the role given to users in the Amazon SageMaker Domain.
- vpc-id should be the ID of your Amazon Virtual Private Cloud. subnet-ids should be a space-separated list of subnet IDs. For information about vpc-id and subnet-ids, see VPCs and subnets.
- RStudioPackageManagerUrl and RStudioConnectUrl are optional and should be set to the URLs of your RStudio Package Manager and RStudio Connect server, respectively.
- app-network-access-type should be either PublicInternetOnly or VPCOnly.

```
aws sagemaker create-domain --region <REGION> --domain-name <DOMAIN_NAME> \
--auth-mode SSO \ 
--default-user-settings ExecutionRole=<DEFAULT_USER_EXECUTIONROLE> \ 
--domain-settings 
RStudioServerProDomainSettings={RStudioPackageManagerUrl=<PACKAGE_MANAGER_URL>,RStudioConnectUrl=<CONNECT_URL> \ 
---vpc-id <VPC_ID> \ 
--subnet-ids <SUBNET_IDS> \ 
--app-network-access-type <NETWORK_ACCESS_TYPE>
```

Connection types

PublicInternet/Direct Internet network type

The following shows how to create a Amazon SageMaker Domain with RStudio enabled and a PublicInternet Network Type.

- DomainExecutionRoleArn should be the ARN for the role created in the previous step.
- ExecutionRole is the ARN of the role given to users in the Amazon SageMaker Domain.
- vpc-id should be the ID of your Amazon Virtual Private Cloud. subnet-ids should be a space-separated list of subnet IDs. For information about vpc-id and subnet-ids, see VPCs and subnets.
- RStudioPackageManagerUrl and RStudioConnectUrl are optional and should be set to the URLs of your RStudio Package Manager and RStudio Connect server, respectively.
- auth-mode should be either SSO or IAM.

```
aws sagemaker create-domain --region <REGION> --domain-name <DOMAIN_NAME> \
--auth-mode <AUTH_MODE> \ 
--default-user-settings ExecutionRole=<DEFAULT_USER_EXECUTIONROLE> \ 
--domain-settings 
RStudioServerProDomainSettings={RStudioPackageManagerUrl=<PACKAGE_MANAGER_URL>,RStudioConnectUrl=<CONNECT_URL> \ 
---vpc-id <VPC_ID> \ 
```
VPCOnly mode

The following shows how to launch a Amazon SageMaker Domain with RStudio enabled and a VPCOnly Network Type. For more information about using the VPCOnly network access type, see Connect SageMaker Studio Notebooks in a VPC to External Resources (p. 3631).

- DomainExecutionRoleArn should be the ARN for the role created in the previous step.
- ExecutionRole is the ARN of the role given to users in the Amazon SageMaker Domain.
- vpc-id should be the ID of your Amazon Virtual Private Cloud. subnet-ids should be a space-separated list of subnet IDs. Your private subnet must be able to either access the internet to make a call to Amazon SageMaker, and AWS License Manager or have Amazon VPC endpoints for both Amazon SageMaker and AWS License Manager. For information about Amazon VPC endpoints, see Interface Amazon VPC endpoints For information about vpc-id and subnet-ids, see VPCs and subnets.
- SecurityGroups must allow outbound access to the Amazon SageMaker and AWS License Manager endpoints.
- auth-mode should be either SSO or IAM.

Note
When using Amazon Virtual Private Cloud endpoints, the security group attached to your Amazon Virtual Private Cloud endpoints must allow inbound traffic from the security group you pass as part of the domain-setting parameter of the create-domain CLI call.

With RStudio, Amazon SageMaker manages security groups for you. This means that Amazon SageMaker manages security group rules to ensure RSessions can access RStudioServerPro Apps. Amazon SageMaker creates one security group rule per user profile.

```
aws sagemaker create-domain --region <REGION> --domain-name <DOMAIN_NAME> \
  --auth-mode <AUTH_MODE> \
  --default-user-settings SecurityGroups=<USER_SECURITY_GROUP>,ExecutionRole=<DEFAULT_USER_EXECUTIONROLE> \
  --domain-settings SecurityGroupIds=<DOMAIN_SECURITY_GROUP>,RStudioServerProDomainSettings={DomainExecutionRoleArn=<DOMAINEXECUTION_ROLE_ARN> \
    --vpc-id <VPC_ID> \
    --subnet-ids "<SUBNET_IDS>" \
    --app-network-access-type VPCOnly --app-security-group-management Service
```

Note: The RStudioServerPro app is launched by a special user profile named domain-shared. As a result, this app is not returned as part of list-app API calls by any other user profiles.

You may have to increase the Amazon VPC quota in your account to increase the number of users. For more information, see Amazon VPC quotas.

Verify Domain creation

Use the following command to verify that your Domain has been created with a Status of InService. Your domain-id is appended to the Domains ARN. For example, arn:aws:sagemaker:<REGION>:<ACCOUNT_ID>:domain/<DOMAIN_ID>.

```
aws sagemaker describe-domain --domain-id <DOMAIN_ID> --region <REGION>
```
Bring your own image to RStudio on SageMaker

A SageMaker image is a file that identifies language packages and other dependencies that are required to run RStudio on Amazon SageMaker. SageMaker uses these images to create an environment where you run RStudio. Amazon SageMaker provides a built-in RStudio image for you to use. If you need different functionality, you can bring your own custom images.

The process to bring your own image to use with RStudio on SageMaker takes three steps:

1. Build a custom image from a Dockerfile and push it to a repository in Amazon Elastic Container Registry (Amazon ECR).
2. Create a SageMaker image that points to a container image in Amazon ECR and attach it to your SageMaker domain.
3. Launch a new session in RStudio with your custom image.

You can create images and image versions, and attach image versions to your domain, using the SageMaker control panel, the AWS SDK for Python (Boto3), and the AWS Command Line Interface (AWS CLI). You can also create images and image versions using the SageMaker console, even if you haven’t onboarded to a domain.

The following topics show how to bring your own image to RStudio on SageMaker by creating, attaching, and launching a custom image.

Key terminology

The following section defines key terms for bringing your own image to use with RStudio on SageMaker.

- **Dockerfile**: A Dockerfile is a file that identifies the language packages and other dependencies for your Docker image.
- **Docker image**: The Docker image is a built Dockerfile. This image is checked into Amazon ECR and serves as the basis of the SageMaker image.
- **SageMaker image**: A SageMaker image is a holder for a set of SageMaker image versions based on Docker images.
- **Image version**: An image version of a SageMaker image represents a Docker image that is compatible with RStudio and stored in an Amazon ECR repository. Each image version is immutable. These image versions can be attached to a domain and used with RStudio on SageMaker.

Prerequisites

You must complete the following prerequisites before bringing your own image to use with RStudio on Amazon SageMaker.

- If you have an existing domain with RStudio that was created before April 7, 2022, you must delete your RStudioServerPro application and recreate it. For information about how to delete an application, see Shut down and Update SageMaker Studio (p. 179).
- Install the Docker application. For information about setting up Docker, see Orientation and setup.
- Create a local copy of an RStudio-compatible Dockerfile that works with SageMaker. For information about creating a sample RStudio dockerfile, see Use a custom image to bring your own development environment to RStudio on Amazon SageMaker.
- Use an AWS Identity and Access Management execution role that has the AmazonSageMakerFullAccess policy attached. If you have onboarded to Amazon SageMaker domain, you can get the role from the Domain Summary section of the SageMaker control panel.

Add the following permissions to access the Amazon Elastic Container Registry (Amazon ECR) service to your execution role.
Custom RStudio image specifications

In this guide, you'll learn custom RStudio image specifications to use when you bring your own image. There are two sets of requirements that you must satisfy with your custom RStudio image to use it with Amazon SageMaker. These requirements are imposed by RStudio PBC and the Amazon SageMaker Studio platform. If either of these sets of requirements aren't satisfied, then your custom image won't function properly.

**RStudio PBC requirements**

RStudio PBC requirements are laid out in the Using Docker images with RStudio Workbench / RStudio Server Pro, Launcher, and Kubernetes article. Follow the instructions in this article to create the base of your custom RStudio image.

For instructions about how to install multiple R versions in your custom image, see Installing multiple versions of R on Linux.

**Amazon SageMaker Studio requirements**

Amazon SageMaker Studio imposes the following set of installation requirements for your RStudio image.

- You must use an RStudio base image of at least 2022.02.2-485.pro2. For more information, see Upgrade the RStudio Version (p. 184).
- You must install the following packages:

```bash
yum install -y sudo \
openjdk-11-jdk \
libpng-dev \
```
& & yum clean all \
& & /opt/R/${R_VERSION}/bin/R -e "install.packages('reticulate', repos='https://
packagemanager.rstudio.com/cran/_/centos7/latest')" \
& & /opt/python/${PYTHON_VERSION}/bin/pip install --upgrade \
  'boto3>1.0<2.0' \
  'awscli>1.0<2.0' \
  'sagemaker[local]<3'

- You must provide default values for the RSTUDIO_CONNECT_URL and
  RSTUDIO_PACKAGE_MANAGER_URL environment values.

| ENV RSTUDIO_CONNECT_URL "YOUR_CONNECT_URL" |
| ENV RSTUDIO_PACKAGE_MANAGER_URL "YOUR_PACKAGE_MANAGER_URL" |

The following general specifications apply to the image that is represented by an RStudio image version.

**Running the image**

ENTRYPOINT and CMD instructions are overridden so that the image is run as an RSession application.

**Stopping the image**

The DeleteApp API issues the equivalent of a docker stop command. Other processes in the container won't get the SIGKILL/SIGTERM signals.

**File system**

The /opt/.sagemakerinternal and /opt/ml directories are reserved. Any data in these directories might not be visible at runtime.

**User data**

Each user in a SageMaker domain gets a user directory on a shared Amazon Elastic File System volume in the image. The location of the current user's directory on the Amazon Elastic File System volume is /home/sagemaker-user.

**Metadata**

A metadata file is located at /opt/ml/metadata/resource-metadata.json. No additional environment variables are added to the variables defined in the image. For more information, see Get App Metadata (p. 140).

**GPU**

On a GPU instance, the image is run with the --gpus option. Only the CUDA toolkit should be included in the image, not the NVIDIA drivers. For more information, see NVIDIA User Guide.

**Metrics and logging**

Logs from the RSession process are sent to Amazon CloudWatch in the customer's account. The name of the log group is /aws/sagemaker/studio. The name of the log stream is $domainID/$userProfileName/RSession/$appName.

**Image size**

Image size is limited to 25 GB. To view the size of your image, run docker image ls.

**Create a custom RStudio image**

This topic describes how you can create a custom RStudio image using the SageMaker console and the AWS CLI. If you use the AWS CLI, you must run the steps from your local machine. The following steps do not work from within Amazon SageMaker Studio.
When you create an image, SageMaker also creates an initial image version. The image version represents a container image in Amazon Elastic Container Registry (ECR). The container image must satisfy the requirements to be used in RStudio. For more information, see Custom RStudio image specifications (p. 193).

For information about testing your image locally and resolving common issues, see the SageMaker Studio Custom Image Samples repo.

Topics
- Add a SageMaker-compatible RStudio Docker container image to Amazon ECR (p. 195)
- Create a SageMaker image from the console (p. 196)
- Create an image from the AWS CLI (p. 197)

Add a SageMaker-compatible RStudio Docker container image to Amazon ECR

Use the following steps to add a Docker container image to Amazon ECR:

- Create an Amazon ECR repository.
- Authenticate to Amazon ECR.
- Build a SageMaker-compatible RStudio Docker image.
- Push the image to the Amazon ECR repository.

**Note**
The Amazon ECR repository must be in the same AWS Region as your domain.

To build and add a Docker image to Amazon ECR

1. Create an Amazon ECR repository using the AWS CLI. To create the repository using the Amazon ECR console, see Creating a repository.

   ```bash
   aws ecr create-repository --repository-name rstudio-custom --image-scanning-configuration scanOnPush=true
   ```

   Response:

   ```json
   {
     "repository": {
       "repositoryArn": "arn:aws:ecr:us-east-2:acct-id:repository/rstudio-custom",
       "registryId": "acct-id",
       "repositoryName": "rstudio-custom",
       "repositoryUri": "acct-id.dkr.ecr.us-east-2.amazonaws.com/rstudio-custom",
       ...
     }
   }
   ```

2. Authenticate to Amazon ECR using the repository URI returned as a response from the create-repository command. Make sure that the Docker application is running. For more information, see Registry Authentication.

   ```bash
   aws ecr get-login-password | \
   docker login --username AWS --password-stdin <repository-uri>
   ```

   Response:
3. **Build the Docker image.** Run the following command from the directory that includes your Dockerfile.

   ```bash
docker build .
   ``

4. **Tag your built image with a unique tag.**

   ```bash
docker tag <image-id> "<repository-uri>:<tag>"
   ``

5. **Push the container image to the Amazon ECR repository.** For more information, see ImagePush and Pushing an image.

   ```bash
docker push <repository-uri>:<tag>
   ``

   **Response:**

   ```
The push refers to repository [<account-id>.dkr.ecr.us-east-2.amazonaws.com/rstudio-custom]
r: digest: <digest> size: 3066
   ```

---

**Create a SageMaker image from the console**

**To create an image**

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the left navigation pane, choose **Images**.
3. On the **Custom images** page, choose **Create image**.
4. For **Image source**, enter the registry path to the container image in Amazon ECR. The path is in the following format:

   ```
   acct-id.dkr.ecr.region.amazonaws.com/repo-name[:tag] or [@digest]
   ```

5. Choose **Next**.
6. Under **Image properties**, enter the following:

   - **Image name** – The name must be unique to your account in the current AWS Region.
   - (Optional) **Image display name** – The name displayed in the domain user interface. When not provided, Image name is displayed.
   - (Optional) **Description** – A description of the image.
   - **IAM role** – The role must have the AmazonSageMakerFullAccess policy attached. Use the dropdown menu to choose one of the following options:
     - Create a new role – Specify any additional Amazon Simple Storage Service (Amazon S3) buckets that you want your notebooks users to access. If you don't want to allow access to additional buckets, choose **None**.
     - Enter a custom IAM role ARN – Enter the Amazon Resource Name (ARN) of your IAM role.
     - Use existing role – Choose one of your existing roles from the list.
   - (Optional) **Image tags** – Choose **Add new tag**. You can add up to 50 tags. Tags are searchable using the SageMaker console or the SageMaker Search API.
8. Choose **Submit**.

The new image is displayed in the **Custom images** list and briefly highlighted. After the image has been successfully created, you can choose the image name to view its properties or choose **Create version** to create another version.

**To create another image version**

1. Choose **Create version** on the same row as the image.
2. For **Image source**, enter the registry path to the Amazon ECR image. The image shouldn't be the same image as used in a previous version of the SageMaker image.

To use the custom image in RStudio, you must attach it to your domain. For more information, see **Attach a custom SageMaker image** (p. 198).

**Create an image from the AWS CLI**

This section shows how to create a custom Amazon SageMaker image using the AWS CLI.

Use the following steps to create a SageMaker image:

- Create an Image.
- Create an ImageVersion.
- Create a configuration file.
- Create an AppImageConfig.

**To create the SageMaker image entities**

1. Create a SageMaker image. The role ARN must have at least the AmazonSageMakerFullAccessPolicy policy attached.

   ```bash
   aws sagemaker create-image \
   --image-name rstudio-custom-image \
   --role-arn arn:aws:iam::<acct-id>:role/service-role/<execution-role>
   ```

   **Response:**

   ```json
   {
     "ImageArn": "arn:aws:sagemaker:us-east-2:<acct-id>:image/rstudio-custom-image"
   }
   ```

2. Create a SageMaker image version from the image. Pass the unique tag value that you chose when you pushed the image to Amazon ECR.

   ```bash
   aws sagemaker create-image-version \
   --image-name rstudio-custom-image \
   --base-image <repository-uri>:@<tag>
   ```

   **Response:**

   ```json
   {
   }
   ```
3. Check that the image version was successfully created.

```sh
aws sagemaker describe-image-version \
  --image-name rstudio-custom-image \
  --version 1
```

Response:

```json
{
  "ImageVersionStatus": "CREATED"
}
```

**Note**

If the response is "ImageVersionStatus": "CREATED_FAILED", the response also includes the failure reason. A permissions issue is a common cause of failure. You also can check your Amazon CloudWatch Logs. The name of the log group is /aws/sagemaker/studio. The name of the log stream is $domainID/$userProfileName/KernelGateway/$appName.

4. Create a configuration file, named `app-image-config-input.json`. The app image config is used to configuration for running a SageMaker image as a Kernel Gateway application.

```json
{
  "AppImageConfigName": "rstudio-custom-config"
}
```

5. Create the AppImageConfig using the file that you created in the previous step.

```sh
aws sagemaker create-app-image-config \
  --cli-input-json file://app-image-config-input.json
```

Response:

```json
{
}
```

**Attach a custom SageMaker image**

This guide shows how to attach a custom RStudio image to your domain using the SageMaker console or the AWS Command Line Interface (AWS CLI).

To use a custom SageMaker image, you must attach a custom RStudio image to your domain. When you attach an image version, it appears in the RStudio Launcher and is available in the Select image dropdown list. You use the dropdown to change the image used by RStudio.

There is a limit to the number of image versions that you can attach. After you reach the limit, you must first detach a version so that you can attach a different version of the image.

**Topics**

- Attach an image version to your domain using the console (p. 199)
• Attach an existing image version to your domain using the AWS CLI (p. 199)

Attach an image version to your domain using the console

You can attach a custom SageMaker image version to your domain using the console's control panel. You can also create a custom SageMaker image, and an image version, and then attach that version to your domain.

To attach an existing image

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the left navigation pane, choose Control panel.
4. For Image source, choose Existing image or New image.

   If you select Existing image, choose an image from the Amazon SageMaker image store.

   If you select New image, provide the Amazon ECR registry path for your Docker image. The path must be in the same AWS Region as the domain. The Amazon ECR repo must be in the same account as your domain, or cross-account permissions for SageMaker must be enabled.

5. Choose an existing image from the list.
6. Choose a version of the image from the list.
7. Choose Next.
8. Enter values for Image name, Image display name, and Description.
9. Choose the IAM role. For more information, see Create a custom RStudio image (p. 194).
10. (Optional) Add tags for the image.
11. (Optional) Choose Add new tag, then add a configuration tag.
12. For Image type, select RStudio Image.
13. Choose Submit.

Wait for the image version to be attached to the domain. After the version is attached, it appears in the Custom images list and is briefly highlighted.

Attach an existing image version to your domain using the AWS CLI

Two methods are presented to attach the image version to your domain using the AWS CLI. In the first method, you create a new domain with the version attached. This method is simpler but you must specify the Amazon Virtual Private Cloud (Amazon VPC) information and execution role that's required to create the domain.

If you have already onboarded to the SageMaker domain, you can use the second method to attach the image version to your current domain. In this case, you don't need to specify the Amazon VPC information and execution role. After you attach the version, delete all of the applications in your domain and relaunch RStudio.

Attach the SageMaker image to a new domain

To use this method, you must specify an execution role that has the AmazonSageMakerFullAccess policy attached.

Note
You can have only one domain. If you have onboarded to a SageMaker domain, you must delete your current domain before you can use this method. For more information, see Delete an Amazon SageMaker Domain (p. 43).
Use the following steps to create the domain and attach the custom SageMaker image:

- Get your default VPC ID and subnet IDs.
- Create the configuration file for the domain, which specifies the image.
- Create the domain with the configuration file.

**To add the custom SageMaker image to your domain**

1. Get your default VPC ID.
   
   ```
   aws ec2 describe-vpcs \
   --filters Name=isDefault,Values=true \
   --query "Vpcs[0].VpcId" --output text
   ```
   
   Response:
   
   `vpc-xxxxxxxx`

2. Get your default subnet IDs using the VPC ID from the previous step.

   ```
   aws ec2 describe-subnets \
   --filters Name=vpc-id,Values=<vpc-id> \
   --query "Subnets[*].SubnetId" --output json
   ```
   
   Response:
   
   `[
   "subnet-b55171dd",
   "subnet-8a5f99c6",
   "subnet-e88d1392"
   ]`

3. Create a configuration file named `create-domain-input.json`. Insert the VPC ID, subnet IDs, `ImageName`, and `AppImageConfigName` from the previous steps. Because `ImageVersionNumber` isn’t specified, the latest version of the image is used, which is the only version in this case. Your execution role must satisfy the requirements in Prerequisites (p. 192).

   ```
   {
   "DomainName": "domain-with-custom-r-image",
   "VpcId": "<vpc-id>",
   "SubnetIds": [ "<subnet-ids>" ],
   "DomainSettings": {
   "RStudioServerProDomainSettings": {
   "DomainExecutionRoleArn": "<execution-role>"
   }
   },
   "DefaultUserSettings": {
   "ExecutionRole": "<execution-role>",
   "RSessionAppSettings": {
   "CustomImages": [
   { "AppImageConfigName": "rstudio-custom-config",
   "ImageName": "rstudio-custom-image"
   }]
   }
   }
   ```
4. Create the domain with the attached custom SageMaker image.

```
aws sagemaker create-domain \
   --cli-input-json file://create-domain-input.json
```

Response:

```
{
   "Url": "https://d-xxxxxxxxxxxx.studio.us-east-2.sagemaker.aws/..."
}
```

### Attach the SageMaker image to an existing domain

This method assumes that you've already onboarded to Amazon SageMaker domain. For more information, see [Onboard to Amazon SageMaker Domain](p. 35).

**Note**

You must delete all of the applications in your domain before you update the domain with the new image version. For information about deleting these applications, see [Delete an Amazon SageMaker Domain](p. 45).

Use the following steps to add the SageMaker image to your current domain.

- Get your DomainID from the SageMaker console.
- Use the DomainID to get the DefaultUserSettings for the domain.
- Add the ImageName and AppImageConfig as a CustomImage to the DefaultUserSettings.
- Update your domain to include the custom image.

### To add the custom SageMaker image to your domain

2. From the left navigation pane, choose Control panel.
3. From the Control panel, under Domain, find the Domain ID. The ID is in the following format: d-xxxxxxxxxxxx.
4. Use the domain ID to get the description of the domain.

```bash
aws sagemaker describe-domain \
--domain-id <d-xxxxxxxxxxxxx>
```

Response:

```json
{
  "DomainId": "d-xxxxxxxxxxxxx",
  "DefaultUserSettings": {
    "KernelGatewayAppSettings": {
      "CustomImages": [],
      ...
    },
    ...
  }
}
```

5. Save the `DefaultUserSettings` section of the response to a file named `update-domain-input.json`. 
6. Insert the ImageName and AppImageConfigName from the previous steps as a custom image. Because ImageVersionNumber isn't specified, the latest version of the image is used, which is the only version in this case.

```json
{
    "DefaultUserSettings": {
        "RSessionAppSettings": {
            "CustomImages": [
                {
                    "ImageName": "rstudio-custom-image",
                    "AppImageConfigName": "rstudio-custom-config"
                }
            ]
        }
    }
}
```

7. Use the domain ID and default user settings file to update your domain.

```
aws sagemaker update-domain \
    --domain-id <d-xxxxxxxxxxxx> \
    --cli-input-json file://update-domain-input.json
```

Response:

```json
{
    "DomainArn": "/arn:aws:sagemaker:us-east-2:acct-id:domain/d-xxxxxxxxxxxx"
}
```

8. Delete the RStudioServerPro application. You must restart the RStudioServerPro domain-shared application for the RStudio Launcher UI to pick up the latest changes.

```
aws sagemaker delete-app \
    --domain-id <d-xxxxxxxxxxxx> --user-profile-name domain-shared \
    --app-type RStudioServerPro --app-name default
```

9. Create a new RStudioServerPro application. You must create this application using the AWS CLI.

```
aws sagemaker create-app \
    --domain-id <d-xxxxxxxxxxxx> --user-profile-name domain-shared \
    --app-type RStudioServerPro --app-name default
```

Launch a custom SageMaker image in RStudio

You can use your custom image when launching an RStudio application from the console. After you create your custom SageMaker image and attach it to your domain, the image appears in the image selector dialog box of the RStudio Launcher. To launch a new RStudio app, follow the steps in Open RStudio Launcher and launch RSessions (p. 211) and select your custom image as shown in the following image.
Clean up image resources

This guide shows how to clean up RStudio image resources that you created in the previous sections. To delete an image, complete the following steps using either the SageMaker console or the AWS CLI, as shown in this guide.

- Detach the image and image versions from your domain.
- Delete the image, image version, and app image config.

After you've completed these steps, you can delete the container image and repository from Amazon ECR. For more information about how to delete the container image and repository, see Deleting a repository.

Clean up resources from the SageMaker console

When you detach an image from a domain, all versions of the image are detached. When an image is detached, all users of the domain lose access to the image versions.

To detach an image

1. In the SageMaker control panel, under Custom images attached to domain, choose the image and then choose Detach.
2. (Optional) To delete the image and all versions from SageMaker, select Also delete the selected images .... This does not delete the associated images from Amazon ECR.
3. Choose Detach.

Clean up resources from the AWS CLI

To clean up resources

1. Detach the image and image versions from your domain by passing an empty custom image list to the domain. Open the update-domain-input.json file that you created in ?? (p. 161).
2. Delete the RSessionAppSettings custom images and then save the file. Do not modify the KernelGatewayAppSettings custom images.

```json
{
    "DomainId": "d-xxxxxxxxxxxx",
    "DefaultUserSettings": {
        "KernelGatewayAppSettings": {
            "CustomImages": []
        }
    }
}
```
3. Use the domain ID and default user settings file to update your domain.

```bash
aws sagemaker update-domain \
--domain-id <d-xxxxxxxxxxxx> \
--cli-input-json file://update-domain-input.json
```

Response:

```json
{
  "DomainArn": "arn:aws:sagemaker:us-east-2:acct-id:domain/d-xxxxxxxxxxxx"
}
```

4. Delete the app image config.

```bash
aws sagemaker delete-app-image-config \
--app-image-config-name rstudio-image-config
```

5. Delete the SageMaker image, which also deletes all image versions. The container images in Amazon ECR that are represented by the image versions are not deleted.

```bash
aws sagemaker delete-image \
--image-name rstudio-image
```

### Manage users

After your RStudio-enabled Amazon SageMaker Domain is running, you can add user profiles (UserProfiles) to the Domain. The following topics show how to create user profiles that are authorized to use RStudio, as well as update an existing user profile. For information on how to delete an RStudio App, UserProfile, or Domain, follow the steps in [Delete an Amazon SageMaker Domain](#).

**Note**

The limit for the total number of UserProfiles in a Amazon SageMaker Domain is 60.

There are two types of users:

- Unauthorized: This user cannot access the RStudio app.
- Authorized: This user can access the RStudio app and use one of the RStudio license seats. By default, a new user is Authorized if the Domain is enabled for RStudio.

If a user is authorized, they can be given one of the following levels of access to RStudio:

- RStudio User: This is a standard RStudio user and can access RStudio.
- RStudio Admin: The admin of your Amazon SageMaker Domain has the ability to create users, add existing users, and update the permissions of existing users. Admins can also access the RStudio
Administrative dashboard. However, this admin is not able to update parameters that are managed by Amazon SageMaker.

Methods to create a user

The following topics show how to create a user in your RStudio-enabled Amazon SageMaker Domain.

Create user IAM

The following procedure shows how to add users to a Amazon SageMaker Domain created using IAM. For more information about using IAM with Amazon SageMaker, see How Amazon SageMaker Works with IAM.

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Navigate to the Control Panel.
3. Select Add user. This opens a new User Settings page.
4. Under User profile, enter a name for your user and select an IAM role. You can create a new IAM role or use an existing role. The IAM role must have the AmazonSageMakerFullAccess policy attached.
5. Select Next.
6. Under SageMaker Projects and Jumpstart, select whether to enable Amazon SageMaker project templates and Amazon SageMaker JumpStart for Studio users.
7. Select Next.
8. Under RStudio Workbench, verify that an RStudio Workbench license is detected.
9. Under License Authorization, select whether you want to create the user with one of the following authorizations.
   - Unauthorized
   - RStudio Admin
   - RStudio User
10. Select Submit.

Create user using IAM Identity Center

The following procedure shows how to add users to a Amazon SageMaker Domain created using AWS IAM Identity Center (successor to AWS Single Sign-On). For information about AWS IAM Identity Center (successor to AWS Single Sign-On), see What is AWS IAM Identity Center (successor to AWS Single Sign-On).

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Navigate to the Control Panel.
3. Select Assign users and groups. This opens a new Assign users and groups page.
4. Select a user or group from the list. For information about adding users and groups, see Manage identities in AWS IAM Identity Center.
5. Select Assign users and groups.

Create user CLI

The following command shows how to add users to a Amazon SageMaker Domain with IAM authentication. A User can belong to either the R_STUDIO_USER or R_STUDIO_ADMIN User group.

```bash
aws sagemaker create-user-profile --region <REGION> \
  --domain-id <DOMAIN-ID> \
  --user-profile-name <USER_PROFILE_NAME-ID>
```
The following command shows how to add users to a Amazon SageMaker Domain with authentication using IAM Identity Center. A user can belong to either the R_STUDIO_USER or R_STUDIO_ADMIN User group.

```
aws sagemaker create-user-profile --region <REGION>  
   --domain-id <DOMAIN-ID>  
   --user-profile-name <USER_PROFILE_NAME-ID>  
   --user-settings RStudioServerProAppSettings={UserGroup=<USER-GROUP>}  
   --single-sign-on-user-identifier UserName  
   --single-sign-on-user-value <USER-NAME>
```

**Update existing user**

You cannot update the authorization of an existing user. You must delete the existing user and create a new one with the updated authorization.

**Log in to RStudio as another user**

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Navigate to the Control Panel.
3. Select a user name from the list of users. This opens a new page with details about the user profile and the apps that are running.
5. From the dropdown, select RStudio to launch an RStudio instance.

**Terminate sessions for another user**

1. From the list of running apps, identify the app you want to delete.
2. Click the respective Delete app button for the app you are deleting.

**Delete another user**

You cannot delete a user if the user is running any apps. Delete all apps before attempting to delete a user.

1. From the User Profile page, select Edit. This opens a new General settings page.
2. Under Delete user, select Delete user.

**RStudio administrative dashboard**

This topic shows how to access and use the RStudio administrative dashboard. With the RStudio administrative dashboard, admins can manage users and RSessions, as well as view information about RStudio Server instance utilization and Amazon CloudWatch Logs.

**Launch the RStudio administrative dashboard**

The R_STUDIO_ADMIN authorization allows the user to access the RStudio administrative dashboard. An R_STUDIO_ADMIN user can access the RStudio administrative dashboard by replacing workspaces with admin in their RStudio URL manually. The following shows how to modify the URL to access the RStudio administrative dashboard.

For example, the following RStudio URL:
Can be converted to:

https://<DOMAIN-ID>.studio.us-east-2.sagemaker.aws/rstudio/default/s/<SESSION-ID>/admin

Dashboard tab

This tab gives an overview of your RStudio Server instance utilization, as well as information on the number of active RSessions.

Sessions tab

This tab gives information on the active RSessions, such as the user that launched the RSessions, the time that the RSessions have been running, and their resource utilization.

Users tab

This tab gives information on the RStudio authorized users in the Domain, such as the time that the last RSession was launched and their resource utilization. The following procedure shows how to get information about the user's historical resource utilization.

1. From the list of users, select the user that you want to view information for. This opens a new page that is specific to the user.
2. To view the user's historical resource utilization, select the Stats tab. This tab gives information about the historical CPU and memory usage, as well as the number of active RSessions.
3. To view Amazon CloudWatch Logs specific to the user, select the Logs tab.

Stats tab

This tab gives information on the historical utilization of your RStudio Server instance.

Logs tab

This tab displays Amazon CloudWatch Logs for the RStudio Server instance. For more information about logging events with Amazon CloudWatch Logs, see What is Amazon CloudWatch Logs?.

Shut down and restart RStudio

To shut down and restart your RStudio Workbench and the associated RStudioServerPro app, you must first shut down all of your existing RSessions. You can shut down the RSessionGateway apps from within RStudio. You can then shut down the RStudioServerPro app using the AWS CLI. After the RStudioServerPro app is shut down, you must reopen RStudio through the SageMaker console.

Any unsaved notebook information is lost in the process. The user data in the Amazon EFS volume isn't impacted.

**Note**

If you are using a custom image with RStudio, ensure that your docker image is using an RStudio version that is compatible with the version of RStudio Workbench being used by SageMaker after you restart your RStudioServerPro app.

The following topics show how to shut down the RSessionGateway and RStudioServerPro apps and restart them.
Suspend your RSessions

Complete the following procedure to suspend all of your RSessions.

1. From the RStudio Launcher, identify the RSesson that you want to suspend.
2. Select **Suspend** for the session.
3. Repeat this for all RSessions.

Delete your RSessions

Complete the following procedure to shut down all of your RSessions.

1. From the RStudio Launcher, identify the RSesson that you want to delete.
2. Select **Quit** for the session. This opens a new **Quit Session** window.
3. From the **Quit Session** window, select **Force Quit**, to end all child processes in the session.
4. Select **Quit Session** to confirm deletion of the session.
5. Repeat this for all RSessions.

Delete your RStudioServerPro app

Run the following commands from the AWS CLI to delete and restart your RStudioServerPro app.

1. Delete the RStudioServerPro application by using your current domain id.

   ```bash
   aws sagemaker delete-app \
   --domain-id <domainId> \n   --user-profile-name domain-shared \n   --app-type RStudioServerPro \n   --app-name default
   ```

2. Re-create the RStudioServerPro application.

   ```bash
   aws sagemaker create-app \
   --domain-id <domainId> \n   --user-profile-name domain-shared \n   --app-type RStudioServerPro \n   --app-name default
   ```

Manage billing and cost

To track the costs associated with your RStudio environment, you can use the AWS Billing and Cost Management service. AWS Billing and Cost Management provides useful tools to help you gather information related to your cost and usage, analyze your cost drivers and usage trends, and take action to budget your spending. For more information, see **What is AWS Billing and Cost Management?**.

The following describes components required to run RStudio on Amazon SageMaker and how each component factors into billing for your RStudio instance.

- **RStudio License** – There is no extra charge for using your RStudio license with Amazon SageMaker. For more information about your RStudio license, see RStudio license (p. 183).
- **RSesson** - These are RStudio working sessions launched by end users. You are charged while the RSesson is running.
- **RStudio Server** - A multi-tenant server manages all the RSessions. You can choose the instance type to run RStudio Server on, and pay the related costs. The default instance, "system", is free, but you
can choose to pay for higher tiers. For more information about the available instance types for your RStudio Server, see RStudioServerPro instance type (p. 186).

Tracking billing at user level

To track billing at the user level using Cost Allocation Tags, see Using Cost Allocation Tags.

Diagnose issues and get support

The following sections describe how to diagnose issues with RStudio on Amazon SageMaker. To get support for RStudio on Amazon SageMaker, contact Amazon SageMaker support. For help with purchasing an RStudio license or modifying the number of license seats, contact sales@rstudio.com.

Upgrade your version

If you receive a warning that there is a version mismatch between your RSession and RStudioServerPro apps, then you must upgrade the version of your RStudioServerPro app. For more information, see Upgrade the RStudio Version (p. 184).

View Metrics and Logs

You can monitor your workflow performance while using RStudio on Amazon SageMaker. View data logs and information about metrics with the RStudio administrative dashboard or Amazon CloudWatch.

View your RStudio logs from the RStudio administrative dashboard

You can view metrics and logs directly from the RStudio administrative dashboard.

1. Log in to your Amazon SageMaker Domain.
2. Navigate to the RStudio administrative dashboard following the steps in RStudio administrative dashboard (p. 207).
3. Select the Logs tab.

View your RStudio logs from Amazon CloudWatch Logs

Amazon CloudWatch monitors your AWS resources and the applications that you run on AWS in real time. You can use Amazon CloudWatch to collect and track metrics, which are variables that you can measure for your resources and applications. To ensure that your RStudio apps have permissions for Amazon CloudWatch, you must include the permissions described in Onboard to Amazon SageMaker Domain (p. 35). You don’t need to do any setup to gather Amazon CloudWatch Logs.

The following steps show how to view Amazon CloudWatch Logs for your RSession.

These logs can be found in the /aws/sagemaker/studio log stream from the AWS CloudWatch console.

2. Select Logs from the left side. From the dropdown menu, select Log groups.
3. On the Log groups screen, search for aws/sagemaker/studio. Select the Log group.
4. On the aws/sagemaker/studio Log group screen, navigate to the Log streams tab.
5. To find the logs for your Domain, search Log streams using the following format:

   `<DomainId>/domain-shared/rstudioserverpro/default`
Use RStudio on Amazon SageMaker

With RStudio support in Amazon SageMaker, you can put your production workflows in place and take advantage of SageMaker features. The following topics show how to launch an RStudio session and complete key workflows. For information about managing RStudio on SageMaker, see Manage RStudio on Amazon SageMaker (p. 183).

For information about the onboarding steps to create an Amazon SageMaker Domain with RStudio enabled, see Onboard to Amazon SageMaker Domain (p. 35).

For information about the AWS Regions that RStudio on SageMaker is supported in, see Supported Regions and Quotas (p. 32).

Topics
- Collaborate in RStudio (p. 211)
- Base R image (p. 211)
- Open RStudio Launcher and launch RSessions (p. 211)
- Publish to RStudio Connect (p. 213)
- Access Amazon SageMaker features with RStudio on Amazon SageMaker (p. 213)

Collaborate in RStudio

To share your RStudio project, you can connect RStudio to your Git repo. For information on setting this up, see Version Control with Git and SVN.

Note: Project sharing and realtime collaboration are not currently supported when using RStudio on Amazon SageMaker.

Base R image

When launching your RStudio instance, the Base R image serves as the basis of your instance. This image extends the r-session-complete Docker image.

This Base R image includes the following:
- R v4.0 or higher
- awscli, sagemaker, and boto3 Python packages
- Reticulate package for R SDK integration

Open RStudio Launcher and launch RSessions

The following topics show how to use the RStudio Launcher to launch RSessions.

Open RStudio Launcher

Open RStudio Launcher from the Amazon SageMaker Console

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Navigate to the Control Panel.
3. After your user has been created, select Launch app.
4. Select either Studio or RStudio to launch a new app of that type.
Open RStudio Launcher from the AWS CLI

The procedure to open the RStudio Launcher using the AWS CLI differs depending on the method used to manage your users.

**IAM Identity Center**

1. Use the AWS access portal to open your Amazon SageMaker Domain.
2. Modify the URL path to "/rstudio/default" as follows.

```
# Studio URL
https://<domain-id>.studio.<region>.sagemaker.aws/jupyter/default/lab
# modified URL
https://<domain-id>.studio.<region>.sagemaker.aws/rstudio/default
```

**IAM**

To open the RStudio Launcher from the AWS CLI in IAM mode, complete the following procedure.

1. Create a presigned URL using the following command.

```
aws sagemaker create-presigned-domain-url --region <REGION> \ 
  --domain-id <DOMAIN-ID> \ 
  --user-profile-name <USER-PROFILE-NAME>
```
2. Append &redirect=RStudioServerPro to the generated URL.
3. Navigate to the updated URL.

**Launch RSessions**

After you’ve launched the RStudio Launcher, you can create a new RSession.

1. Select New Session.
2. Enter a Session Name.
3. Select an instance type that your RSession runs on. This defaults to ml.t3.medium.
4. Select an Image that your RSession uses as the kernel.
5. Select Start Session.
6. After your session has been created, you can start it by selecting the name.

**Note**

If you receive a warning that there is a version mismatch between your RSession and RStudioServerPro apps, then you must upgrade the version of your RStudioServerPro app. For more information, see Upgrade the RStudio Version (p. 184).

**Suspend your RSessions**

1. From the RStudio Launcher, identify the RSession that you want to suspend.
2. Select Suspend for the session.

**Delete your RSessions**

1. From the RStudio Launcher, identify the RSession that you want to delete.
2. Select Quit for the session. This opens a new Quit Session window.
3. From the Quit Session window, select Force Quit, to end all child processes in the session.
4. Select Quit Session to confirm deletion of the session.

Publish to RStudio Connect

RStudio Connect enables data scientists to publish insights, dashboard and web applications from RStudio on Amazon SageMaker. For more information, see Host RStudio Connect and Package Manager for ML development in RStudio on Amazon SageMaker.

For more information on RStudio Connect, see the RStudio Connect User Guide.

Access Amazon SageMaker features with RStudio on Amazon SageMaker

One of the benefits of using RStudio on Amazon SageMaker is the integration of Amazon SageMaker features. This includes integration with Amazon SageMaker Studio and Reticulate.

Use Amazon SageMaker Studio JupyterLab and RStudio on Amazon SageMaker

Your Amazon SageMaker Studio JupyterLab and RStudio instances share the same Amazon EFS file system. This means that files that you import and create using JupyterLab can be accessed using RStudio and vice versa. This allows you to work on the same files using both JupyterLab and RStudio without having to move your files between the two. For more information on this workflow, see the Announcing Fully Managed RStudio on Amazon SageMaker for Data Scientists blog.

Use Amazon SageMaker SDK with reticulate

The reticulate package is used as an R interface to Amazon SageMaker Python SDK to make API calls to Amazon SageMaker. The reticulate package translates between R and Python objects, and Amazon SageMaker provides a serverless data science environment to train and deploy Machine Learning (ML) models at scale. For general information about the reticulate package, see R Interface to Python.

For a blog that outlines how to use the reticulate package with Amazon SageMaker, see Using R with Amazon SageMaker.

The following examples show how to use reticulate for specific use cases.

- For a notebook that describes how to use reticulate to do batch transform to make predictions, see Batch Transform Using R with Amazon SageMaker.
- For a notebook that describes how to use reticulate to conduct hyperparameter tuning and generate predictions, see Hyperparameter Optimization Using R with Amazon SageMaker.

Amazon SageMaker Canvas

Amazon SageMaker Canvas gives you the ability to use machine learning to generate predictions without needing to code. The following are some use cases where you can use SageMaker Canvas:

- Reducing employee churn
- Detecting fraud
- Forecasting sales
- Optimizing inventory

In SageMaker Canvas, you do the following:

1. Import your data from one or more data sources.
2. Build a predictive model.
3. Evaluate the model's performance.
4. Import more data.
5. Train another model.

You use the SageMaker Canvas UI to import your data and perform analyses. You can also use it to import your models into Amazon SageMaker, giving you the ability to collaborate with data scientists.

To learn more about pricing, see the SageMaker Canvas pricing page.

SageMaker Canvas is currently available in the following Regions: US East (Ohio), US East (N. Virginia), US West (Oregon), Asia Pacific (Mumbai), Asia Pacific (Seoul), Asia Pacific (Singapore), Asia Pacific (Sydney), Asia Pacific (Tokyo), Europe (Frankfurt), and Europe (Ireland).

Topics
- Are you a first-time SageMaker Canvas user? (p. 214)
- Getting started with using Amazon SageMaker Canvas (p. 214)
- Setting Up and Managing Amazon SageMaker Canvas (for IT Administrators) (p. 227)
- Importing data in Amazon SageMaker Canvas (p. 247)
- Build a model (p. 257)
- Evaluating Your Model's Performance in Amazon SageMaker Canvas (p. 278)
- Making predictions on your data (p. 283)
- Logging out of Amazon SageMaker Canvas (p. 284)
- Time Series Forecasts in Amazon SageMaker Canvas (p. 284)
- Updating a Model in Amazon SageMaker Canvas (p. 288)
- Share your models with data scientists (p. 289)
- Manage billing and cost in SageMaker Canvas (p. 289)

Are you a first-time SageMaker Canvas user?

If you are a first-time user of SageMaker Canvas, we recommend that you begin by reading the following sections:

- For IT administrators – Setting Up and Managing Amazon SageMaker Canvas (for IT Administrators) (p. 227)
- For analysts and individual users – Getting started with using Amazon SageMaker Canvas (p. 214)

Getting started with using Amazon SageMaker Canvas

This guide tells you how to get started with using SageMaker Canvas. If you're an IT administrator, see Setting Up and Managing Amazon SageMaker Canvas (for IT Administrators) (p. 227) to set up SageMaker Canvas for your users.

If you're a business user or analyst, read the following sections.

Topics
- Prerequisites for setting up Amazon SageMaker Canvas (p. 215)
- Step 1: Log in to Amazon SageMaker Canvas as a business user (p. 217)
Prerequisites for setting up Amazon SageMaker Canvas

To set up Amazon SageMaker Canvas, you either contact your administrator or do the following:

- Set up an Amazon SageMaker Domain
- Optional: Give yourself the ability to upload local files
- Optional: Give yourself permissions to do time series forecasts
- Optional: Give yourself permissions to import Amazon Redshift data

**Important**

For you to set up Amazon SageMaker Canvas, your version of Amazon SageMaker Studio must be 3.19.0 or later. For information about updating Amazon SageMaker Studio, see Shut down and Update SageMaker Studio (p. 179).

To onboard to Domain using IAM Identity Center

1. Open the SageMaker console.
2. Choose Control Panel at the top left of the page.
4. Select Configure.

Use the following procedure to configure the general settings.

1. Under Permission, for IAM role, choose an option from the role selector.
   - If you choose Enter a custom IAM role ARN, the role must have at a minimum, an attached trust policy that grants SageMaker permission to assume the role. For more information, see SageMaker Roles (p. 3536).
   - If you choose Create a new role, the Create an IAM role dialog opens:
     - Choose Create role. SageMaker creates a new IAM AmazonSageMaker-ExecutionPolicy role with the AmazonSageMakerFullAccess policy attached.
2. Under Network and storage, specify the following:
   - Your VPC information – For more information, see Choose a VPC (p. 42) and Configure Amazon SageMaker Canvas in a VPC without internet access (p. 244).
   - (Optional) Encryption key – SageMaker uses an AWS KMS key to encrypt your Amazon Elastic File System (Amazon EFS) and Amazon Elastic Block Store (Amazon EBS) file systems. By default, it uses an AWS managed key. To use a customer managed key, enter its key ID or Amazon Resource Name (ARN). For more information, see Protect Data at Rest Using Encryption (p. 3496).

   **Note**
   - Encryption in transit is only available for Amazon SageMaker Studio.
3. Select Next.

Use the following procedure to configure Amazon SageMaker Studio.
1. Under **Notebook Sharing Configuration**, turn on notebook sharing.
2. Select **Next**.

Use the following procedure to configure the SageMaker Canvas settings.

1. For the **Canvas base permissions configuration**, leave the **Enable Canvas base permissions** option turned on (it is turned on by default). This establishes the minimum required permissions to use the SageMaker Canvas app.
2. (Optional) For the **Time series forecasting configuration**, leave the **Enable time series forecasting** option turned on to give your users permissions to do time series forecasting in SageMaker Canvas (it is turned on by default).
3. (Optional) If you left **Enable time series forecasting** turned on, select **Create and use a new execution role**, or select **Use an existing execution role** if you already have an IAM role with the required Amazon Forecast permissions attached (for more information, see the IAM role setup method (p. 239)).
4. (Optional) Add **Tags** to track your cost and usage trends in AWS Billing and Cost Management. SageMaker adds the tags you specify in the Domain to all of the SageMaker Canvas apps you create in the Domain. For more information about billing and tags, see Manage billing and cost in SageMaker Canvas (p. 289).
5. Finish making any other changes to your Domain setup, and then choose **Submit**.

If you encounter an error during post-building analysis that tells you to increase your quota for `ml.m5.2xlarge` instances, use the following information to resolve the issue. To allow SageMaker Canvas to complete post-building analysis of models, you must increase the SageMaker Hosting endpoint limit for the `ml.m5.2xlarge` instance type to a non-zero value in your AWS account. After building a model, SageMaker Canvas hosts the model on a SageMaker Hosting endpoint and uses the endpoint to generate the post-building analysis. If you don't increase the default account limit of 0 for `ml.m5.2xlarge` instances, SageMaker Canvas cannot complete this step and generates an error during post-building analysis.

Use the following procedure to request a limit increase for your account.

1. Open the **AWS Support Center console**.
2. On the **AWS Support Center** page, choose **Create Case** and then choose **Service limit increase**.
3. In the **Case classification** panel under **Limit type**, search for SageMaker.
4. In the **Request** panel, choose the **Region** that you are working in. For **Resource Type**, choose **SageMaker Hosting**.
5. For **Limit**, choose **ml.m5.2xlarge** instances.
6. For **New Limit Value**, verify that the value is at least 1.
7. In **Case description**, provide a brief explanation of why you need the **Service limit increase**. For example, "SageMaker Canvas uses this instance type for model analysis."
8. In **Contact options**, provide some details about how you would like to be contacted by the AWS service support team on the status of your **Service limit increase** request.
9. Choose **Submit**.

You can now access SageMaker Canvas by doing the following.

1. Navigate to the **SageMaker console**.
2. Under **Control Panel**, choose **Canvas**.
3. Choose **Launch app**.
4. Choose **Canvas**.
SageMaker Canvas creates an Amazon S3 bucket with a name that uses the following pattern: sagemaker-Region-your-account-id.

If you'd like to have the ability to upload files from your local machine to SageMaker Canvas, you attach a CORS policy to it.

To attach a CORS policy, use the following procedure.

2. Choose the bucket with the name that uses the following pattern: sagemaker-AWS-Region-AWS-account-id.
3. Choose Permissions.
4. Navigate to Cross-origins resource sharing (CORS).
5. Choose Edit.
6. Add the following CORS policy:

```json
[
  {
    "AllowedHeaders": ["*"],
    "AllowedMethods": ["POST"],
    "AllowedOrigins": ["*"],
    "ExposeHeaders": []
  }
]
```
7. Choose Save changes.

After updating the CORS policy, you still might not be successful in uploading your files. The browser might be caching the CORS settings from a previous upload attempt. If you're running into issues, clear your browser cache and try again.

You might want to give yourself the ability to perform forecasts on time series data. You can add time series forecasting permissions when setting up your Domain, or you can edit the permissions for a user profile after creating your Domain. The required permissions are the AmazonSageMakerCanvasForecastAccess managed policy and a trust relationship with Amazon Forecast to the AWS IAM role you chose when setting up the user profile. For instructions on how to add these permissions to your IAM role, see Give Your Users Permissions to Perform Time Series Forecasting (p. 237).

If you want to import data from Amazon Redshift, you must give yourself additional permissions. You must add the AmazonRedshiftFullAccess managed policy to the AWS IAM role you chose when setting up the user profile. For instructions on how to add the policy to the role, see Give Users Permissions to Import Amazon Redshift Data (p. 243).

**Step 1: Log in to Amazon SageMaker Canvas as a business user**

Contact your administrator to guide you through the process of setting up Amazon SageMaker Canvas. When you log into SageMaker Canvas for the first time, there is a welcome message with quick getting started tutorials that you can follow for a walkthrough of the SageMaker Canvas application.
You can follow the **Get started with Canvas** tutorial for a high-level overview of the SageMaker Canvas application. There are also shorter tutorials that guide you through the individual steps of using SageMaker Canvas. These tutorials show you how to import a dataset, build a model, analyze the results of a built model, and generate predictions with your model. You can revisit the tutorials at any time by choosing the **Help** button and then choosing **Quick tutorials** on the left navigation bar inside the SageMaker Canvas application.
Step 2: Import and manage data

Format your data so that you can analyze it in Amazon SageMaker Canvas by importing it into a dataset. You import data from multiple sources into a single dataset.

You can import data from the following sources:
- Local files
- Amazon S3
- Amazon Redshift
- Snowflake

Use the following procedure to import a dataset.

To import your data, do the following.

1. In the left navigation pane, choose **Datasets**.
2. Choose **Import Data**.
3. Optional: Add a connection to an external data source, such as an external Amazon S3 bucket, Amazon Redshift, or Snowflake. For more information about importing data, see [Use Snowflake with Amazon SageMaker Canvas](p. 250).
4. Select one or more files from your Amazon S3 bucket or your local folder. Your data must meet the following requirements:
   - Your file can't exceed 5 GB.
   - Currently, your file must be in .csv format. Its values must be comma delimited and must not have newline characters except when denoting a new row.
   - Your data can't have more than 1000 columns.
5. Optional: To preview the datasets that you've uploaded and to review the headers, navigate to the section following the datasets that you're uploading.
6. Choose **Import**.

The following images show how SageMaker Canvas previews files that you've uploaded locally by choosing **Preview**.
The following image shows the import page for datasets that are stored on Amazon S3.
The preceding information walks you through how to import the data. For more information, see Importing data in Amazon SageMaker Canvas (p. 247).

Step 3: Build a model

Build a model that you can use to make predictions on new data. To build a model, you choose the **Target column** in your dataset for which you want to make predictions. Amazon SageMaker Canvas looks at the data in the column and makes recommendations for the types of models that you can train. Choose the model type that works best for your use case.

You can choose **Preview model** before you build the model to get a sense of how well the model can make predictions. The prediction accuracy for **Preview model** is generally lower than the actual prediction accuracy of the model you’ve built. However, it is usually similar to the value of the model.

The following information shows you how to build a model and provides you with contextual information. For more information about model building, see Build a model (p. 257).

Use the following procedure to build a model.

1. In the navigation pane, choose Models.
2. Choose New Model and specify a name for the model.
3. Choose the data that you want to use to build a model. If you haven’t imported the data yet, you can choose Import data.
4. Select the target that you would like to predict out of the columns in the dropdown list. SageMaker Canvas automatically chooses the problem type for you.
5. Optional: Choose the checkboxes next to the names of the columns to drop them from the dataset.
6. Optional: Choose Analyze data to get a general sense of the model's performance before you build it.
7. Choose the downward arrow next to Quick build.
8. Choose Quick build or Standard build.

The following image shows the Quick build and Standard build options.
The following image shows the data in a table view. Choosing a column opens descriptive statistics and visualizations for the column.

The following image shows the columns in a dataset. The checkboxes that have been grayed out indicate that they won't be used to build the model. You can see that the unselected boxes appear in the Model Recipe. The model recipe lists the changes that you've made to the dataset that you've provided.
The following image shows how choosing **Preview model** quickly creates an analysis of how well a fully built model may perform and which columns had the most impact on the models predictions.

After you start model building, Amazon SageMaker Canvas automatically cleans and pre-processes your data. It builds up to 250 models and chooses the one that is the most accurate. The time it takes for Amazon SageMaker Canvas to build a model depends on whether you're doing a **Quick build** or a **Standard build** and the size of the dataset. A **Quick build** usually takes 2-20 minutes to build, whereas a **Standard build** usually takes 2-4 hours to build. You can safely navigate away from the model building page and come back to it when SageMaker Canvas finishes building your model.

The following image shows the process of model building.
Step 4: Evaluate your model

Before using your model to make predictions on new data, you can evaluate how well it performed. You can use information such as the impact that each column had on the predictions. The following image shows an example evaluation page with an explanation of the score and the column impact.

You can use the Scoring tab to get visualizations and metrics on your model's ability to make predictions.
Step 5: Make predictions

You can make one of the following types of predictions.

- **Batch** – Predictions for an entire dataset.
- **Single** – Predictions for a single value that you specify.

For each set of predictions, SageMaker Canvas returns the following:

- The predicted values
- The probability of the predicted value being correct
- The dataset that you've specified for generating predictions

Use the following procedure to make a single prediction with your model.

1. Choose **Single prediction**.
2. Change the input values to see how the predicted value changes from the average prediction.
3. Choose **Update** to get the new prediction.
To make batch predictions, choose a dataset and use the following procedure to generate batch predictions.

1. Choose **Batch prediction**.
2. Choose **Select Dataset**.
3. Choose the dataset.
4. Choose **Generate predictions**.

The following images visualize the preceding procedure.
For batch predictions, you can download the model's predictions as a .csv file. When the Status of the predictions output is Ready, you can download the file by choosing the More options icon and then choosing Download. If you dropped any columns when building your model, SageMaker Canvas adds the dropped columns back to the batch predictions.

**Note**
SageMaker Canvas does not add the dropped columns to your batch predictions for time series models.

You might not be able to make predictions on some datasets because they might have incompatible schemas. A schema is the organizational structure. For a dataset, it is the names of the columns and the data type of the data in the columns.

An incompatible schema might happen for one of the following reasons:

- The dataset that you're using to make predictions has fewer columns than the dataset that you're using to build the model.
- The data types in the columns you used to build the dataset might be different from the data types in dataset that you're using to make predictions.
- The dataset that you're using to make predictions and the dataset that you've used to build the model have column names that don't match. The column names are case sensitive. "Column1" is not the same as "column1".

**Setting Up and Managing Amazon SageMaker Canvas (for IT Administrators)**

You can use the information in this section to help your users do the following:

- Optional: Give your users permissions to upload their files locally.
- Set up Okta SSO for your users.
- Update SageMaker Canvas.
- Clean up or delete the installation of SageMaker Canvas.
- Optional: Set up Amazon Forecast so users can do time series forecasting.
- Optional: Set up an Amazon Virtual Private Cloud.
- Optional: Encrypt data using AWS Key Management Service.
- Optional: Give your users permissions to import Redshift data.
You can also set up SageMaker Canvas for your users with AWS CloudFormation. For more information, see AWS::SageMaker::App in the AWS CloudFormation User Guide.

Topics
- Give Your Users Permissions to Upload Local Files (p. 228)
- Set Up SageMaker Canvas for Your Users (p. 230)
- Encrypt Your SageMaker Canvas Data with AWS KMS (p. 234)
- Give Your Users Permissions to Perform Time Series Forecasting (p. 237)
- Update SageMaker Canvas for Your Users (p. 241)
- Request a Quota Increase (p. 242)
- Give Users Permissions to Import Amazon Redshift Data (p. 243)
- Manage apps (p. 243)
- Configure Amazon SageMaker Canvas in a VPC without internet access (p. 244)

Give Your Users Permissions to Upload Local Files

If your users are uploading files from their local machines to SageMaker Canvas, you must attach a CORS configuration to the Amazon S3 bucket that they’re using. When one of your users first accesses SageMaker Canvas, SageMaker creates an Amazon S3 bucket with a name that uses the following pattern: sagemaker-{region}-{account-ID}. SageMaker Canvas adds your users' data to the bucket whenever they upload a file.

To give users permissions to upload local files to the bucket, you can attach a CORS configuration to it using either of the following procedures. You can use the first method when setting up your Domain or editing the existing Domain settings, where you opt in to allow SageMaker to attach the CORS configuration to the default bucket for you. The second method is the manual method, where you can attach the CORS configuration to the bucket yourself.

Domain setup method

To give your users permissions to upload local files, you can choose Enable Canvas permissions when setting up your Domain. This attaches a CORS configuration to the SageMaker Amazon S3 bucket created for your account and gives all users in the Domain permission to upload local files into SageMaker Canvas. By default, the permissions option is turned on when you set up a Domain, but you can turn off this option if you don’t want to give your users permission to upload files.

Note
If you have an existing CORS configuration on the SageMaker Amazon S3 bucket, turning on Enable Canvas permissions overwrites the existing configuration with the new configuration.

The following procedure shows how you can turn on this option when doing a Quick setup for your Domain in the console.

1. In the User profile section, enter a Name for the user.
2. Select an Execution role for the user.
3. Turn on Enable SageMaker Canvas permissions (by default this option is turned on).
4. Finish setting up the Domain.

If you are doing a Standard setup for your Domain, then use the following procedure for the Canvas settings section to turn on local file upload.

1. For Enable and configure Canvas permissions, select Local file upload (it's already checked by default).
2. Choose **Next**.
3. Finish setting up the Domain.

Your users can now upload local files into their SageMaker Canvas application.

You can also turn on or turn off local upload permissions for an existing Domain by using the following procedure.

1. Go to the **Amazon SageMaker console**.
2. In the **Control Panel**, choose **Edit domain settings**.
3. Go to **Canvas settings**.
4. Select or deselect **Local file upload**.
5. Finish any other modifications you want to make to the Domain, and then **Submit** your changes.

### Amazon S3 bucket method

If you want to manually attach the CORS configuration to the SageMaker Amazon S3 bucket, use the following procedure.

2. Choose the bucket with the name that uses the following pattern: `sagemaker-{region}-{account-ID}`.
3. Choose **Permissions**.
4. Navigate to **Cross-origins resource sharing (CORS)**.
5. Choose **Edit**.
6. Add the following CORS policy:

   ```json
   [
     {
       "AllowedHeaders": [
         "*
       ],
       "AllowedMethods": [
         "POST"
       ],
       "AllowedOrigins": [
         "*
       ],
       "ExposeHeaders": []
     }
   ]
   ```

7. Choose **Save changes**.

In the preceding procedure, the CORS policy must have "POST" listed under **AllowedMethods**.

After you've gone through the procedure, you should have:

- An IAM role assigned to each of your users.
- Amazon SageMaker Studio runtime permissions for each of your users. SageMaker Canvas uses Studio to run the commands from your users.
- If the users are uploading files from their local machines, a CORS policy attached to their Amazon S3 bucket.
If your users still can’t upload the local files after you update the CORS policy, the browser might be caching the CORS settings from a previous upload attempt. If they’re running into issues, instruct them to clear their browser cache and try again.

**Set Up SageMaker Canvas for Your Users**

To set up Amazon SageMaker Canvas, do the following:

- Create an Amazon SageMaker Domain.
- Create user profiles for the Domain.
- Set up Okta Single Sign On (Okta SSO) for your users.
- Activate link sharing for models.

Use Okta Single-Sign On (Okta SSO) to give your users access to Amazon SageMaker Canvas. SageMaker Canvas supports SAML 2.0 SSO methods. The following sections guide you through procedures to set up Okta SSO.

To set up a Domain, see [Onboard to Amazon SageMaker Studio Using IAM](#). You can use the following information to help you complete the procedure in the section:

- You can ignore the step about creating projects.
- You don't need to provide access to additional Amazon S3 buckets. Your users can use the default bucket that we provide when we create a role.
- To give your users access to share their notebooks with data scientists, turn on Notebook Sharing Configuration.
- Use Amazon SageMaker Studio version 3.19.0 or later. For information about updating Amazon SageMaker Studio, see [Shut down and Update SageMaker Studio](#) (p. 179).

Use the following procedure to set up Okta. For all of the following procedures, you specify the same IAM role for *IAM-role*.

**Add the SageMaker Canvas Application To Okta**

Set up the sign-on method for Okta.

1. Sign in to the Okta Admin dashboard.
2. Choose Add application. Search for AWS Account Federation.
3. Choose Add.
4. Optional: Change the name to Amazon SageMaker Canvas.
5. Choose Next.
6. Choose SAML 2.0 as the Sign-On method.
7. Choose Identity Provider Metadata to open the metadata XML file. Save the file locally.
8. Choose Done.

**Set Up ID Federation in IAM**

AWS Identity and Access Management (IAM) is the AWS service that you use to gain access to your AWS account. You gain access to AWS through an IAM account.

1. Sign in to the AWS console.
2. Choose AWS Identity and Access Management (IAM).
3. Choose Identity Providers.
4. Choose Create Provider.
5. For Configure Provider, specify the following:
   - **Provider Type** – From the dropdown menu, choose SAML.
   - **Provider Name** – Specify Okta.
   - **Metadata Document** – Upload the XML document that you've saved locally from step 7 of Add the SageMaker Canvas Application To Okta (p. 230).

7. For Roles, choose the IAM role that you're using for Okta SSO access.
8. Under Trust Relationship for the IAM role, choose Edit Trust Relationship.
9. Modify the IAM trust relationship policy by specifying the Provider ARN value that you've copied and add the following policy:

   ```json
   {
     "Version": "2012-10-17",
     "Statement": [
       {
         "Effect": "Allow",
         "Principal": {
           "Federated": "arn:aws:iam::123456789012:saml-provider/Okta"
         },
         "Action": [
           "sts:AssumeRoleWithSAML",
           "sts:SetSourceIdentity",
           "sts:TagSession"
         ],
         "Condition": {
           "StringEquals": {
             "SAML:aud": "https://signin.aws.amazon.com/saml"
           }
         }
       }
     ]
   }
   ```

10. For Permissions, add the following policy:

   ```json
   {
     "Version": "2012-10-17",
     "Statement": [
       {
         "Sid": "AmazonSageMakerPresignedUrlPolicy",
         "Effect": "Allow",
         "Action": [
           "sagemaker:CreatePresignedDomainUrl",
           "sagemaker:CreatePresignedDomainUrlWithPrincipalTag"
         ],
         "Resource": "*"
       }
     ]
   }
   ```

**Configure SageMaker Canvas in Okta**

The following procedure gives you the ability to configure Amazon SageMaker Canvas in Okta.
To configure Amazon SageMaker Canvas to use Okta, follow the steps in this section. You must specify unique user names for each `SageMakerStudioProfileName` field. For example, you can use `user.login` as a value. If the username is different from the SageMaker Canvas profile name, choose a different uniquely identifying attribute. For example, you can use an employee’s ID number for the profile name.

For an example of values that you can set for Attributes, see the code following the procedure.

2. Add a group with the following pattern: `sagemaker#canvas#IAM-role#AWS-account-id`
3. In Okta, open the AWS Account Federation app integration configuration.
4. Select Sign On for the AWS Account Federation app.
5. Choose Edit and specify the following:
   - SAML 2.0
   - Default Relay State – `https://Region.conso...onsole.aws.amazon.com/sagemaker/home?region=Region#/studio/canvas/open/StudioId`. You can find the studio ID in the console: `https://console.aws.amazon.com/sagemaker/`
6. Choose Attributes.
7. For the `SageMakerStudioProfileName` fields, specify unique values for each username. The usernames must match the usernames that you’ve created in the AWS console.

   Attribute 1:
   Name: https://aws.amazon.com/SAML/Attributes/
   PrincipalTag:SageMakerStudioUserProfileName
   Value: ${user.login}

   Attribute 2:
   Name: https://aws.amazon.com/SAML/Attributes/TransitiveTagKeys
   Value: {"SageMakerStudioUserProfileName"}

8. Select Environment Type. Choose Regular AWS.
   - If your environment type isn’t listed, you can set your ACS URL in the ACS URL field. If your environment type is listed, you don’t need to enter your ACS URL
9. For Identity Provider ARN, specify the ARN you used in step 6 of the preceding procedure.
10. Specify a Session Duration.
11. Choose Join all roles.
12. Turn on Use Group Mapping by specifying the following fields:
   - App Filter – okta
   - Group Filter – ^aws\#\$+$+\(?IAM\-role\[\w\-]+\)\(?accountid\d+\)$
13. Choose Save/Next.
14. Under Assignments, assign the application to the group that you’ve created.

**Add Optional Policies on Access Control in IAM**

In IAM, you can apply the following policy to the administrator user who creates the user profiles.

```json
{
    "Version": "2012-10-17",
```
If you choose to add the preceding policy to the admin user, you must use the following permissions from Set Up ID Federation in IAM (p. 230).

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "AmazonSageMakerPresignedUrlPolicy",
      "Effect": "Allow",
      "Action": [
        "sagemaker:CreatePresignedDomainUrl",
        "sagemaker:CreatePresignedDomainUrlWithPrincipalTag"
      ],
      "Resource": "*",
      "Condition": {
        "StringEquals": {
          "sagemaker:ResourceTag/studiouserid": "${aws:PrincipalTag/SageMakerStudioUserProfileName}"
        }
      }
    }
  ]
}
```

**Activate link sharing for models**

In order to create shareable links for importing SageMaker Canvas models into Amazon SageMaker Studio, the Amazon SageMaker Domain must turn on the notebook resource sharing option and have a valid Amazon S3 sharing location. If you delete the Amazon S3 sharing location specified in your Domain, or if you specify a nonexistent Amazon S3 location, you cannot create shareable links for SageMaker Canvas models.

If you choose the **Quick setup** when creating your Domain, SageMaker provides a default Amazon S3 location for resource sharing and automatically turns on notebook resource sharing.

If you choose the **Standard setup** when creating your Domain, configure the following options when setting up the **Notebook Sharing Configuration**:

1. For **Shareable notebook resources**, turn on **Enable notebook resource sharing**.
2. For **S3 location for shareable notebook resources**, enter either the default bucket already provided or a valid Amazon S3 path of your choice.
The Notebook Sharing Configuration for your Domain should look like the following screenshot, with Enable notebook resource sharing turned on and an Amazon S3 path entered for the S3 location for shareable notebook resources field.

### Notebook Sharing Configuration

<table>
<thead>
<tr>
<th>Shareable notebook resources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Notebook resources include artifacts such as cell output and Git Repositories</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>S3 location for shareable notebook resources</th>
</tr>
</thead>
<tbody>
<tr>
<td>Use the S3 default location or pick one</td>
</tr>
</tbody>
</table>

- s3://DOC-EXAMPLE-BUCKET/sharing

To find a path, go to Amazon S3

Make sure you update the IAM policy for the S3 bucket to have access with SageMaker Studio.

### Encryption key - optional

Encrypt your data. Choose an existing KMS key or enter a key's ARN.

- No Custom Encryption

### Notebook cell output sharing preference

When sharing notebooks, users can also share the output of cells.

- Allow users to share cell output
- Disable cell output sharing

---

**Encrypt Your SageMaker Canvas Data with AWS KMS**

You might have data that you want to encrypt while using Amazon SageMaker Canvas, such as your private company information or customer data. SageMaker Canvas uses AWS Key Management Service to protect your data. AWS KMS is a service that you can use to create and manage cryptographic keys for encrypting your data. For more information about AWS KMS, see AWS Key Management Service in the AWS KMS Developer Guide.

Amazon SageMaker Canvas provides you with several options for encrypting your data. SageMaker Canvas provides default encryption within the application for tasks such as building your model and generating insights. You can also choose to encrypt data stored in Amazon S3 to protect your data at rest. SageMaker Canvas supports importing encrypted datasets, so you can establish an encrypted end-to-end workflow. The following sections describe how you can use AWS KMS encryption to protect your data while building models with SageMaker Canvas.

**Encrypt your data in SageMaker Canvas**

With SageMaker Canvas, you can use two different AWS KMS encryption keys to encrypt your data in SageMaker Canvas, which you can specify when setting up your Domain. These two keys can be the same or different. SageMaker Canvas uses one key for temporary application storage, visualizations, or compute purposes (such as building models). You can use either the default AWS-managed key or specify your own. You can also specify an optional key that SageMaker Canvas uses for long-term storage of model objects and datasets, which are stored in the Region's default SageMaker S3 bucket for your account.

**Prerequisites**

To use your own KMS key for either of the previously described purposes, you must first give your user's IAM role permission to use the key. Then, you can specify the KMS key when setting up your Domain.
The simplest way to give your role permission to use the key is to modify the key policy. Use the following procedure to give your role the necessary permissions.

1. Open the AWS KMS console.
2. In the Key Policy section, choose Switch to policy view.
3. Modify the key's policy to grant permissions for the kms:GenerateDataKey and kms:Decrypt actions to the IAM role. You can add a statement that's similar to the following:

   ```json
   {
       "Sid": "ExampleStmt",
       "Action": [
           "kms:Decrypt",
           "kms:GenerateDataKey"
       ],
       "Effect": "Allow",
       "Principal": {
           "AWS": "<arn:aws:iam::111122223333:role/Jane>"
       },
       "Resource": "*"
   }
   ```
4. Choose Save changes.

The less preferred method is to modify the user's IAM role to give the user permissions to use or manage the KMS key. If you use this method, the KMS key's policy must also allow access management through IAM. To learn how to give permission to a KMS key through the user's IAM role, see Specifying KMS keys in IAM policy statements in the AWS KMS Developer Guide.

Encrypt your data in the SageMaker Canvas application

The first KMS key you can use in SageMaker Canvas is used for encrypting application data stored on Amazon Elastic Block Store (EBS) volumes and in the Amazon Elastic File System that SageMaker creates in your Domain. SageMaker Canvas encrypts your data with this key in the underlying application and temporary storage systems created when using compute instances for building models and generating insights. SageMaker Canvas passes the key to other AWS services, such as Autopilot, whenever SageMaker Canvas initiates jobs with them to process your data.

**Note**
For time series forecast models, SageMaker Canvas uses an AWS managed KMS key instead of a key that you specify.

You can specify this key by setting the KmsKeyId in the CreateDomain API call or while doing the Standard Domain setup in the console. If you don't specify your own KMS key, SageMaker uses a default AWS managed KMS key to encrypt your data in the SageMaker Canvas application.

To specify your own KMS key for use in the SageMaker Canvas application through the console, first set up your Amazon SageMaker Domain using the Standard setup. Use the following procedure to complete the Network and Storage Section for the Domain.

1. Fill out your desired Amazon VPC settings.
2. For Encryption key, choose Enter a KMS key ARN.
3. For KMS ARN, enter the ARN for your KMS key, which should have a format similar to the following: `arn:aws:kms:example-region-1:123456789098:key/111aa2bb-333c-4d44-5555-a11bb2c33dd`
Encrypt your SageMaker Canvas data saved in Amazon S3

The second KMS key you can specify is used for data that SageMaker Canvas stores to Amazon S3. SageMaker Canvas saves duplicates of your input datasets, application and model data, and output data to the Region’s default SageMaker S3 bucket for your account. The naming pattern for this bucket is `sagemaker-{region}-{account-ID}`, and SageMaker Canvas stores data in the `Canvas/` folder.

1. Turn on Enable notebook resource sharing.
2. For S3 location for shareable notebook resources, leave the default Amazon S3 path. Note that SageMaker Canvas does not use this S3 path; this S3 path is used for Studio notebooks.
3. For Encryption key, choose Enter a KMS key ARN.
4. For KMS ARN, enter the ARN for your KMS key, which should have a format similar to the following:
   ```
   arn:aws:kms:example-region-1:123456789098:key/111aa2bb-333c-4d44-5555-a11bb2c33dd
   ```

Import encrypted datasets from Amazon S3

Your users might have datasets that have been encrypted with a KMS key. While the preceding section shows you how to encrypt data in SageMaker Canvas and data stored to Amazon S3, you must give your user's IAM role additional permissions if you want to import data from Amazon S3 that is already encrypted with AWS KMS.

To give your user permissions to import encrypted datasets from Amazon S3 into SageMaker Canvas, add the following permissions to the IAM execution role that you've used for the user profile.

```
{kms:Encrypt},
{kms:Decrypt},
{kms:ReEncrypt*},
{kms:GenerateDataKey*},
{kms:DescribeKey}
```

To learn how to edit the IAM permissions for a role, see Adding and removing IAM identity permissions in the IAM User Guide. For more information about KMS keys, see Key policies in AWS Key Management Service in the AWS KMS Developer Guide.

FAQs

Refer to the following FAQ items for answers to commonly asked questions about SageMaker Canvas AWS KMS support.

Q: Does SageMaker Canvas retain my KMS key?

A: No. SageMaker Canvas may temporarily cache your key or pass it on to other AWS services (such as Autopilot), but SageMaker Canvas does not retain your KMS key.

Q: I specified a KMS key when setting up my Domain. Why did my dataset fail to import in SageMaker Canvas?

A: Your user’s IAM role may not have permissions to use that KMS key. To give your user permissions, see the Prerequisites (p. 234). Another possible error is that you have a bucket policy on your Amazon S3 bucket that requires the use of a specific KMS key that doesn't match the KMS key you specified in your Domain. Make sure that you specify the same KMS key for your Amazon S3 bucket and your Domain.
Q: How do I find the Region's default SageMaker S3 bucket for my account?
A: The default S3 bucket follows the naming pattern sagemaker-\{region\}-\{account-ID\}. The Canvas folder in this bucket stores your SageMaker Canvas application data.

Q: Can I change the default SageMaker S3 bucket used to store SageMaker Canvas data?
A: No, SageMaker creates this bucket for you.

Q: What does SageMaker Canvas store in the default SageMaker S3 bucket?
A: SageMaker Canvas uses the default SageMaker S3 bucket to store duplicates of your input datasets, model artifacts, and model outputs.

Q: What use cases are supported for using KMS keys with SageMaker Canvas?
A: With SageMaker Canvas, you can use your own encryption keys with AWS KMS for Regression, Multi-class classification, and Binary classification models, as well as batch inference for these models. SageMaker Canvas doesn't currently support using customer-managed encryption keys for time series forecasting models.

Give Your Users Permissions to Perform Time Series Forecasting

In order to perform time series forecasts in Amazon SageMaker Canvas, your users must have the necessary permissions. The preferred method to give your users these permissions is to enable the time series forecasting option when setting up the Amazon SageMaker Domain, or when editing the settings for a specific user profile. You can also use the manual method of attaching a policy and trust relationship for Amazon Forecast to the AWS Identity and Access Management (IAM) role.

Domain setup method

SageMaker provides you with the option to give time series forecasting permissions to users through the Domain settings. You can toggle the permissions for all of the users in your Domain, and SageMaker manages attaching the required IAM policy and trust relationship for you.

If you are setting up your Amazon SageMaker Domain for the first time and want to turn on time series forecasting permissions for all users in the Domain, then use the following procedures.

Quick setup

Use the following procedure to turn on SageMaker Canvas time series forecasting permissions when doing a Quick setup for your Domain.

1. In the Amazon SageMaker Domain Quick setup, fill out the Name and Default execution role fields in the User profile section.
2. Leave the Enable SageMaker Canvas permissions option turned on (it is turned on by default).
3. Choose Submit to finish setting up your Domain.

Standard setup

Use the following procedure to turn on SageMaker Canvas time series forecasting permissions when doing a Standard setup for your Domain.

1. In the Amazon SageMaker Domain Standard setup, fill out the General settings, Studio settings, and RStudio settings pages.
2. Choose the Canvas settings page.
3. For the **Canvas base permissions configuration**, leave the **Enable Canvas base permissions** option turned on (it is turned on by default). These permissions are required in order to turn on time series forecasting permissions.

4. For the **Time series forecasting configuration**, leave the **Enable time series forecasting** option turned on (it is turned on by default).

5. Select **Create and use a new execution role**, or select **Use an existing execution role** if you already have an IAM role with the required Amazon Forecast permissions attached (for more information, see the [IAM role setup method](#)).

6. Finish making any other changes to your Domain setup, and then choose **Submit**.

Your users should now have the necessary permissions to perform time series forecasting in SageMaker Canvas.

**User setup method**

You can configure time series forecasting permissions for individual users in an existing Domain. The user profile settings override the general Domain settings, so you can give permissions to specific users without giving permissions to all of your users. To give time series forecasting permissions to a specific user that doesn't already have permissions, use the following procedure.

2. In the **Control Panel**, in the **Users** panel, select the name of the user whose permissions you want to edit.
3. On the **User Details** page, choose **Edit**.
4. Choose the **Canvas settings** page.
5. Turn on **Enable Canvas base permissions**. These permissions are required in order to turn on time series forecasting permissions.
6. Turn on the **Enable time series forecasting** option.
7. If you want to use a different execution role for the user than the role specified in the Domain, select **Create and use a new execution role**, or **Use an existing execution role** if you already have an IAM role ready to use.

   **Note**
   If you want to use an existing IAM role, make sure that it has the IAM policy `AmazonSageMakerCanvasForecastAccess` attached and has a trust relationship that establishes Amazon Forecast as a service principal. For more information, see the section [IAM role setup method](#).

8. The **Canvas settings** page should look like the following screenshot. Finish making any other changes to your user profile, and then choose **Submit** to save your changes.
Your user should now have permission to do time series forecasting in SageMaker Canvas.

You can also remove permissions from a user by using the preceding procedure and turning off the Enable time series forecasting option.

**IAM role setup method**

You can manually give your users permissions to perform time series forecasting in Amazon SageMaker Canvas by adding additional permissions to the AWS Identity and Access Management (IAM) role specified for the user's profile. The IAM role must have a trust relationship with Amazon Forecast and an attached policy that gives permissions to Forecast.

The following section shows you how to create the trust relationship and attach the AmazonSageMakerCanvasForecastAccess managed policy to your IAM role, which grants the minimum permissions necessary for time series forecasting to work in SageMaker Canvas.

To configure an IAM role with the manual method, use the following procedure.

2. From the list of Users, select the profile of the user to whom you want to give time series forecasting permissions.

3. Under Details, copy or make a note of the name of the user's Execution role. The name of the IAM role should be similar to the following: AmazonSageMaker-ExecutionRole-1111222233334444.

4. Once you have the name of the user's IAM role, go to the IAM console.

5. Choose Roles.

6. Search for the user's IAM role by name from the list of roles and select it.

7. Under Permissions, choose Add permissions.

8. Choose Attach policies.

9. Search for the AmazonSageMakerCanvasForecastAccess managed policy and select it. Choose Attach policies to attach the policy to the role.
After attaching the policy, the role's **Permissions** section should now include `AmazonSageMakerCanvasForecastAccess`.

**10.** Return to the IAM role's page, and under **Trust relationships**, choose *Edit trust policy*.

**11.** In the *Edit trust policy* editor, update the trust policy to add Forecast as a service principal. The policy should look like the following example.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Principal": {
        "Service": [
          "sagemaker.amazonaws.com",
          "forecast.amazonaws.com"
        ]
      },
      "Action": "sts:AssumeRole"
    }
  ]
}
```

**12.** After editing the trust policy, choose *Update policy*.

You should now have an IAM role that has the policy `AmazonSageMakerCanvasForecastAccess` attached to it and a trust relationship established with Amazon Forecast, giving users permission to perform time series forecasting in SageMaker Canvas. For information about AWS managed policies, see [Managed policies and inline policies](#).

### Update SageMaker Canvas for Your Users

You can update to the latest version of Amazon SageMaker Canvas as either a user or an IT administrator. You can update Amazon SageMaker Canvas for a single user at a time.

To update the Amazon SageMaker Canvas application, you must delete the previous version.

**Important**
Deleting the previous version of Amazon SageMaker Canvas doesn't delete the data or models that the users have created.

Use the following procedure to log in to AWS, open Amazon SageMaker Domain, and update Amazon SageMaker Canvas. The users can start using the SageMaker Canvas application when they log back in.

1. Sign in to the Amazon SageMaker console at [Amazon SageMaker](#).
2. In the navigation pane, choose **Control Panel**.
3. For **Users**, choose a user name.
4. Choose **Delete app**.
5. Complete the dialog box and choose **Confirm action**.

The following images show the workflow from the preceding procedure.
Your users might use AWS resources in amounts that exceed those specified by their quotas. If your users are resource constrained, you can request a quota increase for them.

Amazon SageMaker Canvas uses the following services to process the requests of your users:

- Amazon SageMaker Autopilot
- Amazon SageMaker Studio Domain
- Amazon Forecast

For information about increasing quotas for SageMaker Canvas operations that aren’t used to forecast time series data, see Amazon SageMaker endpoints and quotas.

For information about increasing quotas for SageMaker Canvas operations that are used to forecast time series data, see Amazon Forecast endpoints and quotas.
Give Users Permissions to Import Amazon Redshift Data

Your users might have datasets stored in Amazon Redshift. Before users can import data from Amazon Redshift into SageMaker Canvas, you must add the AmazonRedshiftFullAccess managed policy to the IAM execution role that you've used for the user profile.

To add the AmazonRedshiftFullAccess policy to the user's IAM role, do the following.

1. Go to the IAM console.
2. Choose Roles.
3. In the search box, search for the user's IAM role by name and select it.
4. On the page for the user's role, under Permissions, choose Add permissions.
5. Choose Attach policies.
6. Search for the AmazonRedshiftFullAccess managed policy and select it.
7. Choose Attach policies to attach the policy to the role.

For more information about AWS managed policies, see Managed policies and inline policies in the AWS IAM User Guide.

Manage apps

The following sections describe how you can manage your SageMaker Canvas applications. You can view, delete, or relaunch your apps from the Control Panel in the SageMaker console.

Check for active apps

To check if you have any actively running SageMaker Canvas apps, use the following procedure.

1. Open the SageMaker console.
2. In the navigation pane, select Control panel.
3. Under Users, select the user profile name for the SageMaker Canvas app you want to view.
4. Under Apps, find the app that says Canvas in the App type column.

The Status column displays the status of the app, such as Ready, Pending, or Deleted. If the app is Ready, then your SageMaker Canvas session is active. You can delete the app from the console or log out from the SageMakerCanvas interface to stop the session.

Delete app

If you want to end your SageMaker Canvas session, you can either log out from the SageMaker Canvas app or delete your app from the SageMaker console. A session is the period of time from when you start using SageMaker Canvas to the point when you stop using it. Deleting the app only ends the session. Models and datasets aren't affected, but Quick build tasks are cancelled. The billing for the session also stops.

Use the following procedure to delete your SageMakerCanvas app.

1. Open the SageMaker console.
2. In the navigation pane, select Control panel.
3. Under Users, select the user profile name for the SageMaker Canvas app you want to view.
4. Under Apps, find the app that says Canvas in the App type column.
5. In the Action column, choose Delete app.
6. In the Delete app dialog box, select the Yes, delete app prompt, confirm the deletion by typing delete, and then choose Delete.
After you've successfully deleted the app, the **Status** column says **Deleted**. Otherwise, your app is still active.

You can also end the session by logging out (p. 284) from within the SageMaker Canvas app.

**Relaunch app**

If you delete or log out of your SageMaker Canvas app and want to relaunch the app, use the following procedure.

1. Open the SageMaker console.
2. In the navigation pane, select **Control panel**.
3. Under **Users**, select the user profile name for the SageMaker Canvas app you want to view.
4. Choose **Launch app** and select **Canvas** from the dropdown list.

SageMaker Canvas begins launching the app.

**Configure Amazon SageMaker Canvas in a VPC without internet access**

The Amazon SageMaker Canvas application runs in a container in an AWS managed Amazon Virtual Private Cloud (VPC). If you want to further control access to your resources or run SageMaker Canvas without public internet access, you can configure your Amazon SageMaker Domain and VPC settings. Within your own VPC, you can configure settings such as security groups (virtual firewalls that control inbound and outbound traffic from Amazon EC2 instances) and subnets (ranges of IP addresses in your VPC). To learn more about VPCs, see **How Amazon VPC works**.

When the SageMaker Canvas application is running in the AWS managed VPC, it can interact with other AWS services using either an internet connection or through VPC endpoints created in a customer-managed VPC (without public internet access). SageMaker Canvas applications can access these VPC endpoints through a Studio-created network interface that provides connectivity to the customer-managed VPC. The default behavior of the SageMaker Canvas application is to have internet access. When using an internet connection, the containers for the preceding jobs access AWS resources over the internet, such as the Amazon S3 buckets where you store training data and model artifacts.

However, if you have security requirements to control access to your data and job containers, we recommend that you configure SageMaker Canvas and your VPC so that your data and containers aren’t accessible over the internet. SageMaker uses the VPC configuration settings you specify when setting up your Domain for SageMaker Canvas.

If you want to configure your SageMaker Canvas application without internet access, you must configure your VPC settings when you onboard to Amazon SageMaker Domain (p. 35), set up VPC endpoints, and grant the necessary AWS Identity and Access Management permissions. For information about configuring a VPC in Amazon SageMaker, see **Choose a VPC** (p. 42). The following sections describe how to run SageMaker Canvas in a VPC without public internet access.

**Configure Amazon SageMaker Canvas in a VPC without internet access**

You can send traffic from SageMaker Canvas to other AWS services through your own VPC. If your own VPC doesn’t have public internet access and you’ve set up your Domain in **VPC only** mode, then SageMaker Canvas won’t have public internet access as well. This includes all requests, such as accessing datasets in Amazon S3 or training jobs for standard builds, and the requests go through VPC endpoints in your VPC instead of the public internet. When you onboard to Domain and **Choose a VPC** (p. 42), you can specify your own VPC as the default VPC for the Domain, along with your desired security group and subnet settings. Then, SageMaker creates a network interface in your VPC that SageMaker Canvas uses to access VPC endpoints in your VPC. Note that the security group and subnet settings are set after you finish onboarding to Domain.
When onboarding to Domain, if you choose Public internet only as the network access type, the VPC is SageMaker managed and allows internet access.

You can change this behavior by choosing VPC only so that SageMaker sends all traffic to a network interface that SageMaker creates in your specified VPC. When you choose this option, you must provide the subnets, security groups, and VPC endpoints that are necessary to communicate with the SageMaker API and SageMaker Runtime, and various AWS services, such as Amazon S3 and Amazon CloudWatch, that are used by SageMaker Canvas. Note that you can only import data from Amazon S3 buckets located in the same Region as your VPC.

The following procedures show how you can configure these settings to use SageMaker Canvas without the internet.

**Step 1: Onboard to Amazon SageMaker Domain**

To send SageMaker Canvas traffic to a network interface in your own VPC instead of over the internet, specify the VPC you want to use when onboarding to Amazon SageMaker Domain (p. 35). Choose Standard setup and do the following procedure when configuring the Network and Storage Section for the Domain.

1. Select your desired VPC.
2. Choose one or more Subnets. If you don’t specify a subnet, SageMaker uses all of the subnets.
3. Choose one or more Security group(s).
4. Choose VPC Only to turn off direct internet access in the AWS managed VPC where SageMaker Canvas is hosted.

After disabling internet access, finish the onboarding process to set up your Domain. For more information about the VPC settings for Amazon SageMaker Domain, see Choose a VPC (p. 42).

**Step 2: Configure VPC endpoints**

SageMaker Canvas only accesses other AWS services to manage and store data for its functionality. For example, it connects to Amazon Redshift if your users access an Amazon Redshift database. It can connect to an AWS service such as Amazon Redshift using an internet connection or a VPC endpoint. Use VPC endpoints if you want to set up connections from your VPC to AWS services that don’t use the public internet.

A VPC endpoint creates a private connection to an AWS service that uses a networking path that is isolated from the public internet. For example, if you set up access to Amazon S3 using a VPC endpoint from your own VPC, then the SageMaker Canvas application can access Amazon S3 by going through the network interface in your VPC and then through the VPC endpoint that connects to Amazon S3. The communication between SageMaker Canvas and Amazon S3 is private.

For more information about configuring VPC endpoints for your VPC, see AWS PrivateLink.

The following are the VPC endpoints for each service you can use with SageMaker Canvas:

<table>
<thead>
<tr>
<th>Service</th>
<th>Endpoint</th>
<th>Endpoint type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon Athena</td>
<td>com.amazonaws.Region.athena</td>
<td>Interface</td>
</tr>
<tr>
<td>Amazon SageMaker</td>
<td>com.amazonaws.Region.sagemaker.api</td>
<td>Interface</td>
</tr>
<tr>
<td></td>
<td>com.amazonaws.Region.sagemaker.runtime</td>
<td></td>
</tr>
<tr>
<td></td>
<td>com.amazonaws.Region.notebook</td>
<td></td>
</tr>
</tbody>
</table>
### Step 3: Grant IAM permissions

The SageMaker Canvas user must have the necessary AWS Identity and Access Management permissions to allow connection to the VPC endpoints. The IAM role to which you give permissions must be the same one you used when onboarding to Amazon SageMaker Domain. You can attach the SageMaker managed AmazonSageMakerFullAccess policy to the IAM role for the user to give the user the required permissions. If you require more restrictive IAM permissions and use custom policies instead, then give the user's role the `ec2:DescribeVpcEndpointServices` permission. SageMaker Canvas requires these permissions to verify the existence of the required VPC endpoints for standard build jobs. If it detects these VPC endpoints, then standard build jobs run by default in your VPC. Otherwise, they will run in the default AWS managed VPC.

For instructions on how to attach the AmazonSageMakerFullAccess IAM policy to your user's IAM role, see Adding and removing IAM identity permissions.

To grant your user's IAM role the granular `ec2:DescribeVpcEndpointServices` permission, use the following procedure.

1. Sign in to the AWS Management Console and open the IAM console.
2. In the navigation pane, choose Roles.
3. In the list, choose the name of the role to which you want to grant permissions.
4. Choose the Permissions tab.
5. Choose Add permissions and then choose Create inline policy.
6. Choose the JSON tab and enter the following policy, which grants the `ec2:DescribeVpcEndpointServices` permission:

```json
{
    "Version": "2012-10-17",
    "Statement": [
```
7. Choose **Review policy**, and then enter a **Name** for the policy (for example, VPCEndpointPermissions).

8. Choose **Create policy**.

The user's IAM role should now have permissions to access the VPC endpoints configured in your VPC.

(Optional) **Step 4: Override security group settings for specific users**

If you are an administrator, you might want different users to have different VPC settings, or user-specific VPC settings. When you override the default VPC's security group settings for a specific user, these settings are passed on to the SageMaker Canvas application for that user.

You can override the security groups that a specific user has access to in your VPC when you set up a new user profile in Studio. You can use the `CreateUserProfile` SageMaker API call (or `create_user_profile` with the `AWS CLI`), and then in the `UserSettings`, you can specify the `SecurityGroups` for the user.

**Importing data in Amazon SageMaker Canvas**

You can import data from different data sources into Amazon SageMaker Canvas. The data sources include Amazon S3, your local machine, and external data sources. Currently, you can only import comma delimited `.csv` files. Your `.csv` files must not have newline characters except when denoting a new row. You can use the dataset that you import to build a model and make predictions on other datasets.

You can import data from the following external data sources:

- An Amazon S3 bucket from an external account
- An Amazon Redshift database
- Snowflake

You can import data with the following data types:

- Categorical
- Numeric
- Text
- Datetime

Canvas has the following limits for importing data and building models.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum dataset file size</td>
<td>5 GB</td>
</tr>
<tr>
<td>Maximum number of columns in datasets</td>
<td>1000</td>
</tr>
<tr>
<td>Maximum number of rows for Quick builds</td>
<td>50,000</td>
</tr>
</tbody>
</table>
To import data from an external data source, create a connection. For more information, see Connect to an external data source (p. 248).

To import data from multiple files on your local machine or Amazon S3 locations, you import the data from each data source and join them into a single dataset. For information about joining datasets, see Join data that you’ve imported into SageMaker Canvas (p. 253).

SageMaker Canvas provides several sample datasets in your application to help you get started. To learn more about the SageMaker-provided sample datasets you can experiment with, see Use sample datasets (p. 255).

## Connect to an external data source

Add a connection to an external data source to import data from it. The credentials that you specify depend on the data source that you’re connecting to. For more information, see the following sections.

### Connect to an Amazon Redshift database

You can import data from Amazon Redshift, a data warehouse where your organization keeps its data. Before you can import data from Amazon Redshift, the AWS IAM role you use must have the AmazonRedshiftFullAccess managed policy attached. For instructions on how to attach this policy, see Give Users Permissions to Import Amazon Redshift Data (p. 243).

To import data from Amazon Redshift, you do the following:

1. Create a connection to Amazon Redshift database.
2. Choose the data that you're importing.
3. Import the data.

You can use the Amazon Redshift editor to drag datasets onto the import pane and import them into SageMaker Canvas. For more control over the values returned in the dataset, you can use the following:

- SQL queries
- Joins

SQL queries give you the ability to customize how you import the values in the dataset. For example, you can specify the columns returned in the dataset or the range of values for a column.

You can use joins to combine multiple datasets from Amazon Redshift into a single dataset. You can drag your datasets from Amazon Redshift into the panel that gives you the ability to join the datasets.

You can use the SQL editor to edit the dataset that you've joined and convert the joined dataset into a single node. You can join another dataset to the node. You can import the data that you've selected into SageMaker Canvas.

Use the following procedure to import data from Amazon Redshift.

You can join datasets before you import them into SageMaker Canvas using SQL or the SageMaker Canvas interface. You can consolidate the joins you make into a single node before joining them into another node.
1. Navigate to the import data screen.
2. Choose Add connection.
3. Choose Amazon Redshift.
4. Specify your Amazon Redshift credentials.
5. From the tab that has the name of your connection, drag the .csv file that you’re importing to the Drag and drop table to import pane.
6. Optional: Drag additional tables to the import pane. You can use the GUI to join the tables. For more specificity in your joins, choose **Edit in SQL**.
7. Optional: If you’re using SQL to query the data, you can choose **Context** to add context to the connection by specifying values for the following:
   - Warehouse
   - Database
   - Schema
8. Choose Import.

The following image shows an example of fields specified for an Amazon Redshift connection.

The following image shows the page used to join datasets in Amazon Redshift.

The following image shows a SQL query being used to edit a join in Amazon Redshift.
Use Snowflake with Amazon SageMaker Canvas

You can import data from your Snowflake account by doing the following:

1. Create a connection to the Snowflake database.
2. Choose the data that you're importing by dragging and dropping the table from the left navigation menu into the editor.
3. Import the data.

You can use the Snowflake editor to drag datasets onto the import pane and import them into SageMaker Canvas. For more control over the values returned in the dataset, you can use the following:

- SQL queries
- Joins

SQL queries give you the ability to customize how you import the values in the dataset. For example, you can specify the columns returned in the dataset or the range of values for a column.

You can use joins to combine multiple datasets from Snowflake into a single dataset. You can drag your datasets from Snowflake into the panel that gives you the ability to join the datasets.

You can combine the datasets that you've joined into a single node and join the nodes to a different Snowflake dataset. You can import the data that you've selected into SageMaker Canvas.

Use the following procedure to import data from Snowflake to Amazon SageMaker Canvas.

You can join datasets before you import them into SageMaker Canvas using SQL or the SageMaker Canvas interface. You can edit the joins in SQL and convert the SQL into a single node. You can join other nodes to the node that you've converted.

1. Navigate to the import data screen.
2. Choose Add connection.
3. Choose Snowflake.
4. Specify your Snowflake credentials.
5. From the tab that has the name of your connection, drag the .csv file that you're importing to the Drag and drop table to import pane.
6. Optional: Drag additional tables to the import pane. You can use the user interface to join the tables. For more specificity in your joins, choose **Edit in SQL**.

7. Optional: If you’re using SQL to query the data, you can choose **Context** to add context to the connection by specifying values for the following:
   - **Warehouse**
   - **Database**
   - **Schema**

   Adding context to a connection makes it easier to specify future queries.

8. Choose **Import**.

The following image shows an example of fields specified for a Snowflake connection.

The following image shows the page used to add context to a connection.
The following image shows the page used to join datasets in Snowflake.

The following image shows a SQL query being used to edit a join in Snowflake.
Join data that you've imported into SageMaker Canvas

You can use Amazon SageMaker Canvas to join multiple datasets into a single dataset. A join combines the two datasets. By default, SageMaker Canvas automatically joins the datasets on their matching column names. The option to combine multiple datasets might give you the ability to get more insight from the models that you build.

You can make the following joins for your datasets:

- **Inner** – Returns a dataset with matching values in both datasets.
- **Left** – Returns a dataset that has:
  - All the rows from the dataset to the left of the join.
  - All the rows from the dataset to the right of the join that have matching values with the columns to the left of the join.
- **Right** – Returns a dataset that has:
  - All the rows from the dataset to the right of the join.
  - All the rows from the dataset to the left of the join that have matching values with the columns to the right of the join.
- **Outer** – Returns all the rows when there is a match in either the left or the right dataset. The dataset from an outer join might have null values that SageMaker Canvas might impute when you build a model.

Use the following procedure to join your datasets.

To join datasets, do the following.

1. Navigate to the **Datasets** page.
2. Choose **Join data**.
3. Drag and drop the datasets that you’re joining into the **Drag and drop datasets to join** box.
4. Configure the join. Amazon SageMaker Canvas shows you a preview of the joined data after you configure it.
5. Choose **Save joined data** to save the output of the join.

The following images show the workflow of the preceding procedure.
Use sample datasets

SageMaker Canvas provides sample datasets addressing unique use cases so you can start building, training, and validating models quickly without writing any code. The use cases associated with these datasets highlight the capabilities of SageMaker Canvas, and you can leverage these datasets to get started with building models. You can find the sample datasets in the Datasets page of your SageMaker Canvas application.
Sample datasets

The following datasets are the samples that SageMaker Canvas provides by default. These datasets cover use cases such as predicting house prices, loan defaults, and readmission for diabetic patients; forecasting sales; predicting machine failures to streamline predictive maintenance in manufacturing units; and generating supply chain predictions for transportation and logistics. The datasets are stored in the sample_dataset folder in the default Amazon S3 bucket that SageMaker creates for your account in a Region.

- **canvas-sample-diabetic-readmission.csv:** This dataset contains historical data including over fifteen features with patient and hospital outcomes. You can use this dataset to predict whether high-risk diabetic patients are likely to get readmitted to the hospital within 30 days of discharge, after 30 days, or not at all. Use the **redadmitted** column as the target column, and use the 3+ category prediction model type with this dataset. To learn more about how to build a model with this dataset, see the SageMaker Canvas workshop page. This dataset was obtained from the UCI Machine Learning Repository.

- **canvas-sample-housing.csv:** This dataset contains data on the characteristics tied to a given housing price. You can use this dataset to predict housing prices. Use the **median_house_value** column as the target column, and use the Numeric prediction model type with this dataset. To learn more about building a model with this dataset, see the SageMaker Canvas workshop page. This is the California housing dataset obtained from the StatLib repository.

- **canvas-sample-loans.csv:** This dataset contains complete loan data for all loans issued from 2007–2011, including the current loan status and latest payment information. You can use this dataset to predict whether a customer will repay a loan. Use the **loan_status** column as the target column, and use the 3+ category prediction model type with this dataset. To learn more about how to build a model with this dataset, see the SageMaker Canvas workshop page. This data uses the LendingClub data obtained from Kaggle.

- **canvas-sample-maintenance.csv:** This dataset contains data on the characteristics tied to a given maintenance failure type. You can use this dataset to predict which failure will occur in the future. Use the **Failure Type** column as the target column, and use the 3+ category prediction model type with this dataset. To learn more about how to build a model with this dataset, see the SageMaker Canvas workshop page. This dataset was obtained from the UCI Machine Learning Repository.

- **canvas-sample-shipping-logs.csv:** This dataset contains complete shipping data for all products delivered, including estimated time shipping priority, carrier, and origin. You can use this dataset to predict the estimated time of arrival of the shipment in number of days. Use the **ActualShippingDays** column as the target column, and use the Numeric prediction model type with this dataset. To learn more about how to build a model with this data, see the SageMaker Canvas workshop page. This is a synthetic dataset created by Amazon.

- **canvas-sample-sales-forecasting.csv:** This dataset contains historical time series sales data for retail stores. You can use this dataset to forecast sales for a particular retail store. Use the **sales** column as the target column, and use the Time series forecasting model type with this dataset. To learn more about how to build a model with this dataset, see the SageMaker Canvas workshop page. This is a synthetic dataset created by Amazon.

Re-import a deleted sample dataset

If you no longer wish to use the sample datasets, you can delete them from the Datasets page of your SageMaker Canvas application. However, these datasets are still stored in the default SageMaker-created Amazon S3 bucket for your account, so you can always access them later.

The default Amazon S3 bucket name where the datasets are stored follows the pattern **sagemaker-{region}-{account ID}**. You can find the sample datasets in the directory path **Canvas/sample_dataset**.

If you delete a sample dataset from your SageMaker Canvas application and want to access the sample dataset again, use the following procedure.
1. Navigate to the Datasets page in your SageMaker Canvas application.
2. Choose Import data.
3. From the list of S3 buckets, select the default SageMaker S3 bucket for your account, which follows the naming pattern sagemaker-{region}-{account ID}.
4. Select the Canvas folder.
5. Select the sample_dataset folder, which contains all of the sample datasets for SageMaker Canvas.
6. Select the dataset you want to import, and then choose Import data.

Build a model

Use Amazon SageMaker Canvas to build a model on the dataset that you've imported. Use the model that you've built to make predictions on new data. SageMaker Canvas uses the information in the dataset to build up to 250 models and choose the one that performs the best.

For each model that you build, you choose the Target column. The Target column is the column that contains the information that you want to predict. For example, if you're building a model to predict whether people have cancelled their subscriptions, the Target column contains data points that are either a "yes" or a "no" about someone's cancellation status.

Amazon SageMaker Canvas uses the data in the Target column to automatically recommend one or more Model types. Model types fall into one of the following categories:

- Categorical prediction, known as classification in machine learning
- Numeric prediction, known as regression in machine learning

The following are the types of categorical prediction:

- 2 category prediction. The machine learning term for 2 category prediction is binary classification. Predicting whether someone has cancelled their subscription is an example of 2 category prediction.
- 3+ category prediction. The machine learning term for 3+ category prediction is multiclass classification.

Amazon SageMaker Canvas predicts the value of the Target column by using the information in the rest of the dataset. For categorical prediction, SageMaker Canvas puts each row into one of the categories listed in the Target column. For numeric prediction, SageMaker Canvas uses the information in the dataset to predict the numeric values in the Target column.

The Build page of SageMaker Canvas generates a preview of 100 rows taken from your dataset, or if your dataset has more than 20,000 rows, then SageMaker Canvas selects 100 rows from a random sample of your dataset. To learn more about the random sample and how you can change the sample size, see the following section Random sample (p. 259).

Before building your model, you can filter your data or prepare it using advanced transforms. For more information about preparing your data for model building, see Prepare data with advanced transformations (p. 266).

To build your model, you can choose either a Quick build or a Standard build. The Quick build usually takes 2-20 minutes to build the model, whereas the Standard build usually takes 2-4 hours and generally has a higher accuracy. For a Quick build, your input dataset can have a maximum of 50,000 rows. If you log out while running a Quick build, your build might be interrupted until you log in again. When you log in again, SageMaker Canvas restarts the Quick build.

While Amazon SageMaker Canvas builds the model, it automatically adds missing values for datasets that don't have time series data. SageMaker Canvas uses the values in your dataset to perform a
mathematical approximation for the missing values. For the highest model accuracy, we recommend adding in the missing data if you can find it.

Amazon SageMaker Canvas can make time series forecasts on your data. Time series forecasts are useful for when you make predictions over a period of time. For information about time series forecasts, see Time Series Forecasts in Amazon SageMaker Canvas (p. 284).

Preview a model

Amazon SageMaker Canvas gives you the ability to get insights from your data before you build a model by choosing Preview model. For example, you can see how the data in each column is distributed. For models built using categorical data, you can also choose Preview model to generate an Estimated accuracy prediction of how well the model might analyze your data. The accuracy of a Quick build or a Standard build represents how well the model can perform on real data and is generally higher than the Estimated accuracy.

Amazon SageMaker Canvas automatically handles missing values in your dataset while it builds the model. It infers the missing values by using adjacent values that are present in the dataset.

Validate data

Before you build your model, SageMaker Canvas checks your dataset for issues that will cause your build to fail. If SageMaker Canvas finds any issues, then it warns you on the Build page before you attempt to build a model.

You can choose Validate data to see a list of the issues with your dataset. You can then use the SageMaker Canvas data preparation features (p. 266) and tools, or your own tools, to fix your dataset before starting a build. If you don’t fix the issues with your dataset, then your build will fail.

If you make changes to your dataset to fix the issues, you have the option to re-validate your dataset before attempting a build. We recommend that you re-validate your dataset before building.

The following table shows the issues that SageMaker Canvas checks for in your dataset and how to resolve them.

<table>
<thead>
<tr>
<th>Issue</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wrong model type for your data</td>
<td>Try another model type or use a different dataset.</td>
</tr>
<tr>
<td>Missing values in your target column</td>
<td>Replace the missing values, drop rows with missing values, or use a different dataset.</td>
</tr>
<tr>
<td>Issue</td>
<td>Resolution</td>
</tr>
<tr>
<td>------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Too many unique labels in your target column</td>
<td>Verify that you've used the correct column for your target column, or use a different dataset.</td>
</tr>
<tr>
<td>Too many non-numeric values in your target column</td>
<td>Choose a different target column, select another model type, or use a different dataset.</td>
</tr>
<tr>
<td>One or more column names contain double underscores</td>
<td>Rename the columns to remove any double underscores, and try again.</td>
</tr>
<tr>
<td>None of the rows in your dataset are complete</td>
<td>Replace the missing values, or use a different dataset.</td>
</tr>
<tr>
<td>Too many unique labels for the number of rows in your data</td>
<td>Check that you're using the right target column, increase the number of rows in your dataset, consolidate similar labels, or use a different dataset.</td>
</tr>
</tbody>
</table>

### Random sample

SageMaker Canvas uses the random sampling method to sample your dataset. The random sample method means that each row has an equal chance of being picked for the sample. You can choose a column in the preview to get summary statistics for the random sample, such as the mean and the mode.

By default, SageMaker Canvas uses a random sample size of 20,000 rows from your dataset for datasets with more than 20,000 rows. For datasets smaller than 20,000 rows, the default sample size is the number of rows in your dataset. You can increase or decrease the sample size by choosing Random sample in the Build tab of the SageMaker Canvas app. You can use the slider to select your desired sample size, and then choose Update to change the sample size. The maximum sample size you can choose for a dataset is 40,000 rows, and the minimum sample size is 500 rows. If you choose a large sample size, the dataset preview and summary statistics might take a few moments to reload.

The Build page shows a preview of 100 rows from your dataset. If the sample size is the same size as your dataset, then the preview uses the first 100 rows of your dataset. Otherwise, the preview uses the first 100 rows of the random sample.

### Explore your data using visualization techniques

With Amazon SageMaker Canvas, you can explore and visualize your data, helping you to gain advanced insights into your data before building your ML models. You can visualize using scatter plots, bar charts, and box plots, which can help you understand your data and discover the relationships between features that could affect the model accuracy.

In the Build tab of the SageMaker Canvas app, choose Data visualizer to begin creating your visualizations.

You can change the visualization sample size to adjust the size of the random sample taken from your dataset. A sample size that is too large might affect the performance of your data visualizations, so we recommend that you choose an appropriate sample size. To change the sample size, use the following procedure.

1. Choose Visualization sample.
2. Use the slider to select your desired sample size.
3. Choose Update to confirm the change to your sample size.
**Note**
Certain visualization techniques require columns of a specific data type. For example, you can only use numeric columns for the x and y-axes of scatter plots.

**Scatter plot**

To create a scatter plot with your dataset, choose **Scatter plot** in the **Visualization** panel. Then, you can choose the features you want to plot on the x and y-axes from the **Columns** section. You can drag and drop the columns onto the axes, or once an axis has been dropped, you can choose a column from the list of supported columns.

You can use **Color by** to color the data points on the plot with a third feature. You can also use **Group by** to group the data into separate plots based on a fourth feature.

The following image shows a scatter plot that uses **Color by** and **Group by**. In this example, each data point is colored by the **MaritalStatus** feature, and grouping by the **Department** feature results in a scatter plot for the data points of each department.
Bar chart

To create a bar chart with your dataset, choose Bar chart in the Visualization panel. Then, you can choose the features you want to plot on the x and y-axes from the Columns section. You can drag and drop the columns onto the axes, or once an axis has been dropped, you can choose a column from the list of supported columns.

You can use Group by to group the bar chart by a third feature. You can use Stack by to vertically shade each bar based on the unique values of a fourth feature.

The following image shows a bar chart that uses Group by and Stack by. In this example, the bar chart is grouped by the MaritalStatus feature and stacked by the JobLevel feature. For each JobRole on the x axis, there is a separate bar for the unique categories in the MaritalStatus feature, and every bar is vertically stacked by the JobLevel feature.
Box plot

To create a box plot with your dataset, choose Box plot in the Visualization panel. Then, you can choose the features you want to plot on the x and y-axes from the Columns section. You can drag and drop the columns onto the axes, or once an axis has been dropped, you can choose a column from the list of supported columns.

You can use Group by to group the box plots by a third feature.

The following image shows a box plot that uses Group by. In this example, the x and y-axes show JobLevel and JobSatisfaction, respectively, and the colored box plots are grouped by the Department feature.
Prepare data with advanced transformations

Your machine learning dataset might require data preparation before you build your model. You might want to clean your data due to various issues, which might include missing values or outliers, and perform feature engineering to improve the accuracy of your model. Amazon SageMaker Canvas provides ML data transforms with which you can clean, transform, and prepare your data for model building. You can use these transforms on your datasets without any code. SageMaker Canvas adds the transforms you use to the Model recipe, which is a record of the data preparation done on your data before building the model. Any data transforms you use only modify the input data for model building and do not modify your original data source.

The following transforms are available in SageMaker Canvas for you to prepare your data for building.

**Note**
The preview of your dataset shows the first 100 rows of the dataset. If your dataset has more than 20,000 rows, Canvas takes a random sample of 20,000 rows and previews the first 100 rows from that sample. You can only search for and specify values from the previewed rows, and the filter functionality only filters the previewed rows and not the entire dataset.

Functions and operators

You can use mathematical functions and operators to explore and distribute your data. You can use the SageMaker Canvas supported functions or create your own formula with your existing data and create a new column with the result of the formula. For example, you can add the corresponding values of two columns and save the result to a new column.

You can nest statements to create more complex functions. The following are some examples of nested functions that you might use.

- To calculate BMI, you could use the function \( \frac{\text{weight}}{\text{height}^2} \).
- To classify ages, you could use the function \( \text{Case}(\text{age} < 18, \text{'child'}, \text{age} < 65, \text{'adult'}, \text{'senior'}) \).

You can specify functions in the data preparation stage before you build your model. To use a function, do the following.

- In the **Build** tab of the SageMaker Canvas app, choose **Functions** to open up the **Functions** panel.
- In the **Functions** panel, you can choose a **Formula** to add to your **Model Recipe**. Each formula is applied to all of the values in the column(s) you specify. For formulas that accept two or more columns as arguments, use columns with matching data types; otherwise, you will get an error or null values in the new column.
- After you've specified a **Formula**, add a column name in the **New Column Name** field. SageMaker Canvas uses this name for the new column that is created.
- To add the function to your Model Recipe, choose **Add**.

SageMaker Canvas saves the result of your function to a new column using the name you specified in **New Column Name**. You can view or remove functions from the **Model Recipe** panel.

SageMaker Canvas supports the following operators for functions. You can use either the text format or the in-line format to specify your function.

<table>
<thead>
<tr>
<th>Operator</th>
<th>Description</th>
<th>Supported data types</th>
<th>Text format</th>
<th>In-line format</th>
</tr>
</thead>
<tbody>
<tr>
<td>Add</td>
<td>Returns the sum of the values</td>
<td>Numeric</td>
<td>Add(sales1, sales2)</td>
<td>sales1 + sales2</td>
</tr>
<tr>
<td>Operator</td>
<td>Description</td>
<td>Supported data types</td>
<td>Text format</td>
<td>In-line format</td>
</tr>
<tr>
<td>----------</td>
<td>-------------</td>
<td>----------------------</td>
<td>-------------</td>
<td>----------------</td>
</tr>
<tr>
<td>Subtract</td>
<td>Returns the difference between the values</td>
<td>Numeric</td>
<td>Subtract(sales1, sales2)</td>
<td>sales1 - sales2</td>
</tr>
<tr>
<td>Multiply</td>
<td>Returns the product of the values</td>
<td>Numeric</td>
<td>Multiply(sales1, sales2)</td>
<td>sales1 * sales2</td>
</tr>
<tr>
<td>Divide</td>
<td>Returns the quotient of the values</td>
<td>Numeric</td>
<td>Divide(sales1, sales2)</td>
<td>sales1 / sales2</td>
</tr>
<tr>
<td>Mod</td>
<td>Returns the result of the modulo operator (the remainder after dividing the two values)</td>
<td>Numeric</td>
<td>Mod(sales1, sales2)</td>
<td>sales1 % sales2</td>
</tr>
<tr>
<td>Abs</td>
<td>Returns the absolute value of the value</td>
<td>Numeric</td>
<td>Abs(sales1)</td>
<td>N/A</td>
</tr>
<tr>
<td>Negate</td>
<td>Returns the negative of the value</td>
<td>Numeric</td>
<td>Negate(c1)</td>
<td>-c1</td>
</tr>
<tr>
<td>Exp</td>
<td>Returns e (Euler's number) raised to the power of the value</td>
<td>Numeric</td>
<td>Exp(sales1)</td>
<td>N/A</td>
</tr>
<tr>
<td>Log</td>
<td>Returns the logarithm (base 10) of the value</td>
<td>Numeric</td>
<td>Log(sales1)</td>
<td>N/A</td>
</tr>
<tr>
<td>Ln</td>
<td>Returns the natural logarithm (base e) of the value</td>
<td>Numeric</td>
<td>Ln(sales1)</td>
<td>N/A</td>
</tr>
<tr>
<td>Pow</td>
<td>Returns the value raised to a power</td>
<td>Numeric</td>
<td>Pow(sales1, 2)</td>
<td>sales1 ^ 2</td>
</tr>
<tr>
<td>If</td>
<td>Returns a true or false label based on a condition you specify</td>
<td>Boolean, Numeric, Text</td>
<td>If(sales1&gt;7000, 'truelabel', 'falselabel')</td>
<td>N/A</td>
</tr>
<tr>
<td>Or</td>
<td>Returns a boolean value of whether one of the specified values/conditions is true or not</td>
<td>Boolean</td>
<td>Or(fullprice, discount)</td>
<td>fullprice</td>
</tr>
<tr>
<td>And</td>
<td>Returns a boolean value of whether two of the specified values/conditions are true or not</td>
<td>Boolean</td>
<td>And(sales1, sales2)</td>
<td>sales1 &amp;&amp; sales2</td>
</tr>
<tr>
<td>Not</td>
<td>Returns a boolean value that is the opposite of the specified value/conditions</td>
<td>Boolean</td>
<td>Not(sales1)</td>
<td>!sales1</td>
</tr>
<tr>
<td>Case</td>
<td>Returns a boolean value based on conditional statements (returns c1 if cond1 is true, returns c2 if cond2 is true, else returns c3)</td>
<td>Boolean, Numeric, Text</td>
<td>Case(cond1, c1, cond2, c2, c3)</td>
<td>N/A</td>
</tr>
<tr>
<td>Equal</td>
<td>Returns a boolean value of whether two values are equal</td>
<td>Boolean, Numeric, Text</td>
<td>N/A</td>
<td>c1 = c2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>c1 == c2</td>
</tr>
</tbody>
</table>
### Operator

<table>
<thead>
<tr>
<th>Operator</th>
<th>Description</th>
<th>Supported data types</th>
<th>Text format</th>
<th>In-line format</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not equal</td>
<td>Returns a boolean value of whether two values are not equal</td>
<td>Boolean, Numeric, Text</td>
<td>N/A</td>
<td>c1 != c2</td>
</tr>
<tr>
<td>Less than</td>
<td>Returns a boolean value of whether c1 is less than c2</td>
<td>Boolean, Numeric, Text</td>
<td>N/A</td>
<td>c1 &lt; c2</td>
</tr>
<tr>
<td>Greater than</td>
<td>Returns a boolean value of whether c1 is greater than c2</td>
<td>Boolean, Numeric, Text</td>
<td>N/A</td>
<td>c1 &gt; c2</td>
</tr>
<tr>
<td>Less than or equal</td>
<td>Returns a boolean value of whether c1 is less than or equal to c2</td>
<td>Boolean, Numeric, Text</td>
<td>N/A</td>
<td>c1 &lt;= c2</td>
</tr>
<tr>
<td>Greater than or equal</td>
<td>Returns a boolean value of whether c1 is greater than or equal to c2</td>
<td>Boolean, Numeric, Text</td>
<td>N/A</td>
<td>c1 &gt;= c2</td>
</tr>
</tbody>
</table>

SageMaker Canvas also supports aggregate operators, which can perform operations such as calculating the sum of all the values or finding the minimum value in a column. You can use aggregate operators in combination with standard operators in your functions. For example, to calculate the difference of values from the mean, you could use the function $\text{Abs} (\text{height} - \text{avg(\text{height})})$. SageMaker Canvas supports the following aggregate operators.

<table>
<thead>
<tr>
<th>Aggregate operator</th>
<th>Description</th>
<th>Format</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>sum</td>
<td>Returns the sum of all the values in a column</td>
<td>sum</td>
<td>sum(c1)</td>
</tr>
<tr>
<td>minimum</td>
<td>Returns the minimum value of a column</td>
<td>min</td>
<td>min(c2)</td>
</tr>
<tr>
<td>maximum</td>
<td>Returns the maximum value of a column</td>
<td>max</td>
<td>max(c3)</td>
</tr>
<tr>
<td>average</td>
<td>Returns the average value of a column</td>
<td>avg</td>
<td>avg(c4)</td>
</tr>
<tr>
<td>std</td>
<td>Returns the sample standard deviation of a column</td>
<td>std</td>
<td>std(c1)</td>
</tr>
<tr>
<td>stddev</td>
<td>Returns the standard deviation of the values in a column</td>
<td>stddev</td>
<td>stddev(c1)</td>
</tr>
<tr>
<td>variance</td>
<td>Returns the unbiased variance of the values in a column</td>
<td>variance</td>
<td>variance(c1)</td>
</tr>
<tr>
<td>approx_count_distinct</td>
<td>Returns the approximate number of distinct items in a column</td>
<td>approx_count_distinct</td>
<td>approx_count_distinct(c1)</td>
</tr>
<tr>
<td>count</td>
<td>Returns the number of items in a column</td>
<td>count</td>
<td>count(c1)</td>
</tr>
<tr>
<td>first</td>
<td>Returns the first value of a column</td>
<td>first</td>
<td>first(c1)</td>
</tr>
</tbody>
</table>
### Aggregate operator

<table>
<thead>
<tr>
<th>Description</th>
<th>Format</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>last Returns the last value of a column</td>
<td>last</td>
<td>last(c1)</td>
</tr>
<tr>
<td>stddev_pop Returns the population standard</td>
<td>stddev_pop</td>
<td>stddev_pop(c1)</td>
</tr>
<tr>
<td>deviation of a column</td>
<td></td>
<td></td>
</tr>
<tr>
<td>variance_pop Returns the population variance of</td>
<td>variance_pop</td>
<td>variance_pop(c1)</td>
</tr>
<tr>
<td>the values in a column</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Datetime extraction

With the datetime extraction transform, you can extract values from a datetime column to a separate column. For example, if you have a column containing dates of purchases, you can extract the month value to a separate column and use the new column when building your model. You can also extract multiple values to separate columns with a single transform.

Your datetime column must use a supported timestamp format. For a list of the formats that SageMaker Canvas supports, see [Time Series Forecasts in Amazon SageMaker Canvas](p. 284). If your dataset does not use one of the supported formats, update your dataset to use a supported timestamp format and re-import it to Amazon SageMaker Canvas before building your model.

To perform a datetime extraction, do the following.

1. In the **Build** tab of the SageMaker Canvas application, choose **Extract**.
2. Choose the **Column** from which you want to extract values.
3. For **Value**, select one or more values to extract from the column. The values you can extract from a timestamp column are **Year**, **Month**, **Day**, **Hour**, **Week of year**, **Day of year**, and **Quarter**.
4. Choose **Add** to add the transform to the **Model recipe**.

SageMaker Canvas creates a new column in the dataset for each of the values you extract. Except for **Year** values, SageMaker Canvas uses a 0-based encoding for the extracted values. For example, if you extract the **Month** value, January is extracted as 0, and February is extracted as 1.

You can see the transform listed in the **Model recipe** section. If you remove the transform from the **Model recipe** section, the new columns are removed from the dataset.
Drop columns

You can exclude a column from your model build by dropping it in the Build tab of the SageMaker Canvas application. Deselect the column you want to drop, and it isn’t included when building the model.

**Note**

If you drop columns and then make batch predictions (p. 225) with your model, SageMaker Canvas adds the dropped columns back to the .csv file available for you to download. However, SageMaker Canvas does not add the dropped columns back for time series models.

Rename columns

With the rename columns transform, you can rename columns in your data. When you rename a column, SageMaker Canvas changes the column name in the model input.

You can rename a column in your dataset by double-clicking on the column name in the Build tab of the SageMaker Canvas application and entering a new name. Pressing the Enter key submits the change, and clicking anywhere outside the input cancels the change. You can also rename a column by clicking the **More options** icon (i), located at the end of the row in list view or at the end of the header cell in grid view, and choosing **Rename**.

Your column name can’t be longer than 32 characters or have double underscores (_), and you can’t rename a column to the same name as another column. You also can’t rename a dropped column.

The following screenshot shows how to rename a column by double-clicking the column name.

When you rename a column, SageMaker Canvas adds the transform in the **Model recipe** section. If you remove the transform from the **Model recipe** section, the column reverts to its original name.

Remove rows

This transform removes rows of data from the dataset where values in a specific column meet conditions that you specify. You can remove rows that have missing values, contain outliers, or meet custom conditions in a column you choose. These rows are not used when building your model.

Remove rows by missing values

Missing values are a common occurrence in machine learning datasets and can impact model accuracy. Use this transform if you want to drop rows with null or empty values in certain columns.

To remove rows that contain missing values in a specified column, do the following.
1. In the Build tab of the SageMaker Canvas application, choose Remove rows by.
2. Choose the Column you want to check for missing values.
3. For the Operation, choose Is missing.
4. Choose Add to add the transform to the Model recipe.

SageMaker Canvas drops rows that contain missing values in the Column you selected. After removing the rows from the dataset, SageMaker Canvas adds the transform in the Model recipe section. If you remove the transform from the Model recipe section, the rows return to your dataset.

Remove rows by outliers

Outliers, or rare values in the distribution and range of your data, can negatively impact model accuracy and lead to longer building times. With SageMaker Canvas, you can detect and remove rows that contain outliers in numeric columns. You can choose to define outliers with either standard deviations or a custom range.

To remove outliers from your data, do the following.
1. In the Build tab of the SageMaker Canvas application, choose Remove rows by.
2. Choose the Column you want to check for outliers.
3. For the Operation, choose Is outlier.
4. Set the Outlier range to either Standard deviation or Custom range.
5. If you choose Standard deviation, specify a SD (standard deviation) value from 1–3. If you choose Custom range, select either Percentile or Number, and then specify the Min and Max values.
6. Choose Add to add the transform to the Model recipe.

The Standard deviation option detects and removes outliers in numeric columns using the mean and standard deviation. You specify the number of standard deviations a value must vary from the mean to be considered an outlier. For example, if you specify 3 for SD, a value must fall more than 3 standard deviations from the mean to be considered an outlier.

The Custom range option detects and removes outliers in numeric columns using minimum and maximum values. Use this method if you know your threshold values that delimit outliers. You can set the Type of the range to either Percentile or Number. If you choose Percentile, the Min and Max values should be the minimum and maximum of the percentile range (0–100) that you want to allow. If you choose Number, the Min and Max values should be the minimum and maximum numeric values that you want to allow in the data.
After removing the rows from the dataset, SageMaker Canvas adds the transform in the **Model recipe** section. If you remove the transform from the **Model recipe** section, the rows return to your dataset.

### Remove rows by custom values

You can remove rows with values that meet custom conditions. For example, you might want to exclude all of the rows with a price value greater than 100 when building your model. With this transform, you can create a rule that removes all rows that exceed the threshold you set.

To use the custom remove transform, do the following.

1. In the **Build** tab of the SageMaker Canvas application, choose **Remove rows by**.
2. Choose the **Column** you want to check.
3. Select the type of **Operation** you want to use, and then specify the value(s) for the selected condition.
4. Choose **Add** to add the transform to the **Model recipe**.

For the **Operation**, you can choose one of the following options. Note that the available operations depend on the data type of the column you choose. For example, you cannot create a “Greater than” operation for a column containing text values.

<table>
<thead>
<tr>
<th>Operation</th>
<th>Supported column type</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is equal to</td>
<td>Binary, numeric, text, categorical</td>
<td>Removes rows where the value in <strong>Column</strong> equals the values you specify.</td>
</tr>
<tr>
<td>Is not equal to</td>
<td>Binary, numeric, text, categorical</td>
<td>Removes rows where the value in <strong>Column</strong> doesn't equal the values you specify.</td>
</tr>
<tr>
<td>Is less than</td>
<td>Numeric</td>
<td>Removes rows where the value in <strong>Column</strong> is less than the value you specify.</td>
</tr>
<tr>
<td>Is less than or equal to</td>
<td>Numeric</td>
<td>Removes rows where the value in <strong>Column</strong> is less than or equal to the value you specify.</td>
</tr>
<tr>
<td>Is greater than</td>
<td>Numeric</td>
<td>Removes rows where the value in <strong>Column</strong> is greater than the value you specify.</td>
</tr>
<tr>
<td>Is greater than or equal to</td>
<td>Numeric</td>
<td>Removes rows where the value in <strong>Column</strong> is greater than or equal to the value you specify.</td>
</tr>
</tbody>
</table>
### Replace values

This transform replaces values in your dataset where the values in a specific column meet conditions that you specify. You can replace missing values or outliers. SageMaker Canvas uses the replaced values when building your model but doesn't change your original dataset. Note that if you've dropped a column from your dataset using the *Drop columns* transform, you can't replace values in that column.

#### Replace missing values

Missing values are a common occurrence in machine learning datasets and can impact model accuracy. You can choose to drop rows that have missing values, but your model is more accurate if you choose to replace the missing values instead. With this transform, you can replace missing values in numeric columns with the mean or median of the data in a column, or you can also specify a custom value with which to replace missing values. For non-numeric columns, you can replace missing values with the mode (most common value) of the column or a custom value.

Use this transform if you want to replace the null or empty values in certain columns. To replace missing values in a specified column, do the following.

1. In the *Build* tab of the SageMaker Canvas application, choose *Replace*.
2. Choose the *Column* in which you want to replace missing values.
3. For *Values to replace*, choose *Is missing*.  

<table>
<thead>
<tr>
<th>Operation</th>
<th>Supported column type</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is between</td>
<td>Numeric</td>
<td>Remarks where the value in <em>Column</em> is between or equal to two values you specify.</td>
</tr>
<tr>
<td>Contains</td>
<td>Text, categorical</td>
<td>Remarks where the value in <em>Column</em> contains a values you specify.</td>
</tr>
<tr>
<td>Starts with</td>
<td>Text, categorical</td>
<td>Remarks where the value in <em>Column</em> begins with a value you specify.</td>
</tr>
<tr>
<td>Ends with</td>
<td>Text, categorical</td>
<td>Remarks where the value in <em>Column</em> ends with a value you specify.</td>
</tr>
</tbody>
</table>
4. Set Mode to either Automatic (default) or Manual. If you choose Automatic (default), SageMaker Canvas replaces missing values with imputed values that best fit your data. If you choose Manual, then specify the Replace with value in the next step.

5. (Optional) If you choose the Manual replacement option, set the Replace with value:
   - If your column is numeric, then select Mean, Median, or Custom. Mean replaces missing values with the mean for the column, and Median replaces missing values with the median for the column. If you choose Custom, then you must specify a custom value that you want to use to replace missing values.
   - If your column is non-numeric, then select Mode or Custom. Mode replaces missing values with the mode, or the most common value, for the column. For Custom, specify a custom value that you want to use to replace missing values.

6. Choose Add to add the transform to the Model recipe.

After replacing the missing values in the dataset, SageMaker Canvas adds the transform in the Model recipe section. If you remove the transform from the Model recipe section, the missing values return to the dataset.

Replace outliers

Outliers, or rare values in the distribution and range of your data, can negatively impact model accuracy and lead to longer building times. SageMaker Canvas enables you to detect outliers in numeric columns and replace the outliers with values that lie within an accepted range in your data. You can choose to define outliers with either standard deviations or a custom range, and you can replace outliers with the minimum and maximum values in the accepted range.

To replace outliers in your data, do the following.

1. In the Build tab of the SageMaker Canvas application, choose Replace.
2. Choose the Column in which you want to replace outliers.
3. For Values to replace, choose Is outlier.
4. For Define outliers, choose either Standard deviation or Custom Range.
5. If you choose Standard deviation, specify a SD (standard deviation) value from 1–3. If you choose Custom Range, select either Percentile or Number, and then specify the Min and Max values.
6. For Replace with, select Min/max range.
7. Choose Add to add the transform to the Model recipe.
The **Standard deviation** option detects outliers in numeric columns using the mean and standard deviation. You specify the number of standard deviations a value must vary from the mean to be considered an outlier. For example, if you specify 3 for SD, a value must fall more than 3 standard deviations from the mean to be considered an outlier. SageMaker Canvas replaces outliers with the minimum value or maximum value in the accepted range. For example, if you configure the standard deviations to only include values from 200 to 300, then SageMaker Canvas changes a value of 198 to 200 (the minimum).

The **Custom Range** option detects outliers in numeric columns using minimum and maximum values. Use this method if you know your threshold values that delimit outliers. You can set the **Type** of the custom range to either **Percentile** or **Number**. If you choose **Percentile**, the **Min** and **Max** values should be the minimum and maximum of the percentile range (0-100) that you want to allow. If you choose **Number**, the **Min** and **Max** values should be the minimum and maximum numeric values that you want to allow. SageMaker Canvas replaces any values that fall outside of the minimum and maximum to the minimum and maximum values. For example, if your range only allows values from 1 to 100, then SageMaker Canvas changes a value of 102 to 100 (the maximum).

After replacing the values in the dataset, SageMaker Canvas adds the transform in the **Model recipe** section. If you remove the transform from the **Model recipe** section, the original values return to the dataset.

### Filter rows

The filter functionality filters the previewed rows (the first 100 rows of your dataset) according to conditions that you specify. Filtering rows creates a temporary preview of the data and does not impact the model building. You can filter to preview rows that have missing values, contain outliers, or meet custom conditions in a column you choose.

#### Filter rows by missing values

Missing values are a common occurrence in machine learning datasets. If you have rows with null or empty values in certain columns, you might want to filter for and preview those rows.

To filter missing values from your previewed data, do the following.

1. In the **Build** tab of the SageMaker Canvas application, choose **Filter by rows**.
2. Choose the **Column** you want to check for missing values.
3. For the **Operation**, choose **Is missing**.

SageMaker Canvas filters for rows that contain missing values in the **Column** you selected and provides a preview of the filtered rows.
Filter rows by outliers

Outliers, or rare values in the distribution and range of your data, can negatively impact model accuracy and lead to longer building times. SageMaker Canvas enables you to detect and filter rows that contain outliers in numeric columns. You can choose to define outliers with either standard deviations or a custom range.

To filter for outliers in your data, do the following.

1. In the **Build** tab of the SageMaker Canvas application, choose **Filter by rows** (Y).
2. Choose the **Column** you want to check for outliers.
3. For the **Operation**, choose **Is outlier**.
4. Set the **Outlier range** to either **Standard deviation** or **Custom range**.
5. If you choose **Standard deviation**, specify a **SD** (standard deviation) value from 1–3. If you choose **Custom range**, select either **Percentile** or **Number**, and then specify the **Min** and **Max** values.

The **Standard deviation** option detects and filters for outliers in numeric columns using the mean and standard deviation. You specify the number of standard deviations a value must vary from the mean to be considered an outlier. For example, if you specify 3 for **SD**, a value must fall more than 3 standard deviations from the mean to be considered an outlier.

The **Custom range** option detects and filters for outliers in numeric columns using minimum and maximum values. Use this method if you know your threshold values that delimit outliers. You can set the **Type** of the range to either **Percentile** or **Number**. If you choose **Percentile**, the **Min** and **Max** values should be the minimum and maximum of the percentile range (0-100) that you want to allow. If you choose **Number**, the **Min** and **Max** values should be the minimum and maximum numeric values that you want to filter in the data.
Filter rows by custom values

You can filter for rows with values that meet custom conditions. For example, you might want to preview rows that have a price value greater than 100 before removing them. With this functionality, you can filter rows that exceed the threshold you set and preview the filtered data.

To use the custom filter functionality, do the following.

1. In the Build tab of the SageMaker Canvas application, choose Filter by rows (Y).
2. Choose the Column you want to check.
3. Select the type of Operation you want to use, and then specify the value(s) for the selected condition.

For the Operation, you can choose one of the following options. Note that the available operations depend on the data type of the column you choose. For example, you cannot create a “Greater than” operation for a column containing text values.

<table>
<thead>
<tr>
<th>Operation</th>
<th>Supported column type</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is equal to</td>
<td>Binary, numeric, text, categorical</td>
<td>Filters rows where the value in Column equals the values you specify.</td>
</tr>
<tr>
<td>Is not equal to</td>
<td>Binary, numeric, text, categorical</td>
<td>Filters rows where the value in Column doesn't equal the values you specify.</td>
</tr>
<tr>
<td>Is less than</td>
<td>Numeric</td>
<td>Filters rows where the value in Column is less than the value you specify.</td>
</tr>
<tr>
<td>Is less than or equal to</td>
<td>Numeric</td>
<td>Filters rows where the value in Column is less than or equal to the value you specify.</td>
</tr>
<tr>
<td>Is greater than</td>
<td>Numeric</td>
<td>Filters rows where the value in Column is greater than the value you specify.</td>
</tr>
<tr>
<td>Is greater than or equal to</td>
<td>Numeric</td>
<td>Filters rows where the value in Column is greater than or equal to the value you specify.</td>
</tr>
<tr>
<td>Is between</td>
<td>Numeric</td>
<td>Filters rows where the value in Column is between or equal to two values you specify.</td>
</tr>
</tbody>
</table>
Evaluating Your Model's Performance in Amazon SageMaker Canvas

You can evaluate how well your model performed on your data before you start using it to make predictions by using the following:

- **Column impact**
- **Scoring**
- **Advanced metrics**

**Column impact** is a percentage score that indicates how much weight a column has in making predictions in relation to the other columns. For a column impact of 25%, SageMaker Canvas weighs the prediction as 25% for the column and 75% for the other columns.

**Scoring** is a section that shows visualizations and figures that you can use to get more insights into your model's performance beyond the overall accuracy metric. For a categorical prediction, you can see the predicted values in contrast to the actual values.

**Advanced metrics** is a section that contains information that you can use for a deeper understanding of your model's performance.
Model Scoring

Amazon SageMaker Canvas provides different scoring information for both numeric and categorical prediction models.

The **Scoring** section for a categorical prediction model gives you the ability to visualize all the predictions. Line segments extend from the left of the page, indicating all the predictions the model has made. In the middle of the page, the line segments converge on a perpendicular segment to indicate the proportion of each prediction to a single category. From the predicted category, the segments branch out to the actual category. You can get a visual sense of how accurate the predictions were by following each line segment from the predicted category to the actual category.

The following image gives you an example **Scoring section** for a 2 category prediction model.

The following image gives you an example **Scoring section** for a 3+ category prediction model.

The **Scoring** section for numeric prediction shows a line to indicate the model's predicted value in relation to the data used to make predictions. The values of the numeric prediction are often +/- the RMSE (root mean squared error) value. The value that the model predicts is often within the range of the RMSE. The width of the purple band around the line indicates the RMSE range. The predicted values often fall within the range.

The following image shows the **Scoring** section for numeric prediction.
Use advanced metrics in your analyses

Amazon SageMaker Canvas uses different advanced performance metrics to give you a sense of how well your model performed. The advanced metrics that SageMaker Canvas shows you depend on whether your model performs numeric, categorical, or time series forecasting predictions on your data.

**Numeric prediction** refers to the mathematical concept of regression. When your **Target column** has values that can be measured, such as yearly revenue or the number of items sold by a department store, Amazon SageMaker Canvas builds a model on your data using regression. For more information about regression, see Metrics for numeric prediction (p. 281).

**Categorical prediction**, such as 2 category prediction or 3 category prediction, refers to the mathematical concept of classification. Categorical prediction can be performed on data that can be put into a category:

- The colors on a color wheel
- Instances where the data is either a 0 or 1
- Instances where the data is either a Yes or a No.
- A list of responses to a survey question.

**Time series forecasting** refers to making predictions that vary over time. You can perform time series forecasts on data with timestamps that correlate to a value you want to predict. For example, you can make a time series forecast that takes daily sales data and makes sales predictions for the next month.

SageMaker Canvas uses confusion matrices to help you visualize when a model makes predictions correctly.

The following image is an example of a confusion matrix for 2 categories.
Evaluating Your Model’s Performance in Amazon SageMaker Canvas

The following image is an example of a confusion matrix for 3+ categories.

Metrics for numeric prediction

The following defines the advanced metrics for numeric prediction in Amazon SageMaker Canvas and gives you information about how you can use them.

- **R2** – The percentage of the difference in the target column that can be explained by the input column.
- **MAE** – Mean absolute error. On average, the prediction for the target column is +/- {MAE} from the actual value.
- **MAPE** – Mean absolute percent error. On average, the prediction for the target column is +/- {MAPE} % from the actual value
- **RMSE** – Root Mean Square Error. The standard deviation of the errors.

The following image shows a graph of the residuals or errors. The horizontal line indicates an error of 0 or a perfect prediction. The blue dots are the errors. Their distance from the horizontal line indicates the magnitude of the errors.
The following image shows an error density plot.

**Metrics for categorical prediction**

The following defines the advanced metrics for categorical prediction in Amazon SageMaker Canvas and gives you information about how you can use them.

- **Missing** – A missing value contains no content or is non-existent. Missing values are automatically inferred.
- **Mismatched** – A mismatched value has a different data type from the type specified for its column. SageMaker Canvas categorizes these values as missing and infers values for them.
- **Unique** – The number and percentage of values that are unique.
- **Target correlation** – A value between -1 and 1 that represents strength of the linear relationship between a column and the target column. 0 represents no detectable relationship. 1 represents a strong positive relationship. -1 represents a strong negative relationship.
- **Column impact** – Identifies the relative impact of the column in predicting the target column.

The following is a list of available metrics for binary classification.
Making predictions on your data

- F1 – A balanced measure of accuracy that takes class balance into account.
- Accuracy – The percentage of correct predictions.
- Precision – Of all the times that {category-1} was predicted, the prediction was correct {precision}% of the time.
- Recall – The model correctly predicted {recall}% to be {category-1} when {target_column} was actually {category-1}.
- AUC – A value between 0 and 1 that indicates how well your model is able to separate the categories in your dataset. A value of 1 indicates that it was able to separate the categories perfectly.

The following is a list of available metrics for multi-classification.

- F1 – A balanced measure of accuracy that takes class balance into account.
- Accuracy – The percentage of correct predictions.
- Precision – Of all the times that {category-1} was predicted, the prediction was correct {precision}% of the time.
- Recall – The model correctly predicted {recall}% to be {category-1} when {target_column} was actually {category-1}.
- AUC – A value between 0 and 1 that indicates how well your model is able to separate the categories in your dataset. A value of 1 indicates that it was able to separate the categories perfectly.
- Average F1 – The F1 averaged for all categories.
- Average Accuracy – The percentage of correct predictions out of all the predictions that are made.
- Average Precision – The precision averaged for all categories.
- Average Recall – The recall averaged for all categories.
- Average AUC – The AUC averaged for all categories.

Metrics for time series forecasts

The following defines the advanced metrics for time series forecasts in Amazon SageMaker Canvas and gives you information about how you can use them.

- Average Weighted Quantile Loss (wQL) – Evaluates the forecast by averaging the accuracy at the P10, P50, and P90 quantiles. A lower value indicates a more accurate model.
- Weighted Absolute Percent Error (WAPE) – The sum of the absolute error normalized by the sum of the absolute target, which measure the overall deviation of forecasted values from observed values. A lower value indicates a more accurate model, where WAPE = 0 is a model with no errors.
- Root Mean Square Error (RMSE) – The square root of the average squared errors. A lower RMSE indicates a more accurate model, where RMSE = 0 is a model with no errors.
- Mean Absolute Percent Error (MAPE) – The percentage error (percent difference of the mean forecasted value versus the actual value) averaged over all time points. A lower value indicates a more accurate model, where MAPE = 0 is a model with no errors.
- Mean Absolute Scaled Error (MASE) – The mean absolute error of the forecast normalized by the mean absolute error of a simple baseline forecasting method. A lower value indicates a more accurate model, where MASE < 1 is estimated to be better than the baseline and MASE > 1 is estimated to be worse than the baseline.

Making predictions on your data

Use the model that you’ve built in Amazon SageMaker Canvas to make predictions with your model. For information about making predictions, see Step 5: Make predictions (p. 225).
Logging out of Amazon SageMaker Canvas

If you're not using Amazon SageMaker Canvas, you can log out of your session. A session starts as soon as you launch SageMaker Canvas from the console. Logging out ends the session. You are only billed for the duration of the session.

When you log out, your models and datasets aren't affected, but SageMaker Canvas cancels any Quick build tasks. If you log out of SageMaker Canvas while running a Quick build, your build might be interrupted until you log back in. When you log back in, SageMaker Canvas automatically restarts the build.

To log out, choose the Log out button (Logout) on the left panel of the SageMaker Canvas app.

You can also log out from the SageMaker Canvas app by deleting the app (p. 243) in the console.

After you log out, SageMaker Canvas tells you to start a new session in a different tab. Logging in takes between 3 minutes and 8 minutes. If you have an administrator who set up SageMaker Canvas for you, use the instructions they gave you to log back in. If don't have an administrator, see the procedure for accessing SageMaker Canvas in Prerequisites for setting up Amazon SageMaker Canvas (p. 215).

Time Series Forecasts in Amazon SageMaker Canvas

Amazon SageMaker Canvas gives you the ability to use machine learning time series forecasts. Time series forecasts give you the ability to make predictions that can vary with time.

You can make a time series forecast for the following examples:

- Forecasting your inventory in the coming months.
- The number of items sold in the next four months.
- The effect of reducing the price on sales during the holiday season.
- Item inventory in the next 12 months.
- The number of customers entering a store in the next several hours.
- Forecasting how a 10% reduction in the price of a product affects sales over a time period.

To make a time series forecast, your dataset must have the following:

- A timestamp column with all values having the datetime type.
- A target column that has the values that you're using to forecast future values.

The datetime values in the timestamp column must use one of the following formats:

- YYYY-MM-DD HH:MM:SS
- YYYY-MM-DDTHH:MM:SSZ
- YYYY-MM-DD
- MM/DD/YY
- MM/DD/YY HH:MM
- MM/DD/YYYY
- YYYY/MM/DD HH:MM:SS
- YYYY/MM/DD
• DD/MM/YYYY
• DD/MM/YY
• DD-MM-YY
• DD-MM-YYYY

You can make forecasts for the following intervals:

• 1 min
• 5 min
• 15 min
• 30 min
• 1 hour
• 1 day
• 1 week
• 1 month
• 1 year

For higher prediction accuracy, your dataset can also have additional columns that can provide data that can explain the variation in the target column. Using the additional explanatory columns might help you forecast future values in the target column more accurately.

For example, you can forecast the amount of ice cream sold by a grocery store. To make a forecast, you must have a timestamp column and a column that indicates how much ice cream the grocery store sold. For a more accurate forecast, your dataset can also include the price, the ambient temperature, the flavor of the ice cream, or a unique identifier for the ice cream.

Ice cream sales might increase when the weather is warmer. A decrease in the price of the ice cream might result in more units sold. Having a column with ambient temperature data and a column with pricing data can improve your ability to forecast the number of units of ice cream the grocery store sells.

You might have missing data for different reasons. The reason for your missing data might inform how you want Amazon SageMaker Canvas to impute it. For example, your organization might use an automatic system that only tracks when a sale happens. If you're using a dataset that comes from this type of automatic system, you have missing values in the target column.

For missing values in the dataset, SageMaker Canvas imputes the missing values for you.

**Important**

If you have missing values in the target column, we recommend using a dataset that doesn't have them. SageMaker Canvas uses the target column to forecast future values. Missing values in the target column can greatly reduce the accuracy of the forecast.

You can make one of the following types of forecasts:

• **Single item**
• **All items**

For a forecast on all the items in your dataset, SageMaker Canvas returns a forecast for the future values for each item in your dataset.

For a single item forecast, you specify the item and SageMaker Canvas returns a forecast for the future values. The forecast includes a line graph that plots the predicted values over time.
Topics

- Gain additional insights from your forecast (p. 286)
- Make a time series forecast (p. 286)

Gain additional insights from your forecast

In Amazon SageMaker Canvas, you can use the following optional methods to get more insights from your forecast:

- Group column
- Holiday schedule
- What-if scenario

You can specify a column in your dataset as a Group column. Amazon SageMaker Canvas groups the forecast by each value in the column. For example, you can group the forecast on columns containing price data or unique item identifiers. Grouping a forecast by a column lets you make more specific forecasts. For example, if you group a forecast on a column containing item identifiers, you can see the forecast for each item.

Overall sales of items might be impacted by the presence of holidays. For example, in the United States, the number of items sold in both November and December might differ greatly from the number of items sold in January. If you use the data from November and December to forecast the sales in January, your results might be inaccurate. Using a holiday schedule prevents you getting inaccurate results. You can use a holiday schedule for 66 countries.

For a forecast on a single item in your dataset, you can use what-if scenarios. A what-if scenario gives you the ability to change values in your data and change the forecast. For example, you can answer the following questions by using a what-if scenario, "What if I lowered prices? How would that affect the number of items sold?"

Make a time series forecast

To make a time series forecast, you choose a target column. The target column contains the data that you want to predict. For example, your target column might have data on the number of items sold. After you select the target column, Amazon SageMaker Canvas selects a Model type. SageMaker Canvas uses the time-series data to automatically choose a time series model that you can use to make predictions on your data. After you build the model, you can evaluate its performance and use it to make predictions on new data.

Use the following procedure to make a time series forecast.

To make a time-series forecast, do the following.

1. Import the data.
2. Choose a target column in your dataset.
3. SageMaker Canvas automatically chooses Time series forecasting as the model type. Choose Set configuration to confirm that you're performing a time series forecast.
4. Specify the following fields:
   - Item ID column – The column that contains unique identifiers for each item in your dataset. For example, an SKU number uniquely identifies an item.
   - Optional: Group column – Groups the time series forecast by values in the column. For example, you can group your forecast for an item by store.
• **Time stamp column** – The column containing the time stamps in your dataset. For a list of the supported date time formats for this column, see *Time Series Forecasts in Amazon SageMaker Canvas* (p. 284).

• **Future timestamp** – A timestamp that indicates a future forecast time. SageMaker Canvas forecasts values up to the point in time specified by the timestamp.

• Optional: **Holiday schedule** – Activate the holiday schedule to use a country's holiday schedule. Use it to make your forecasts with holiday data more accurate.

You can have one of the following types of missing values:

• Missing future values

• Missing values

Missing future values are missing values in the target column. SageMaker Canvas uses the values in the target column to forecast the values in the future. If you have missing values in the target column, your forecast might be less accurate. We highly recommend updating the dataset.

Missing values are values that are missing in any column other than the target column. With missing values that aren't in the target column, it's helpful to note the following:

• They generally don't reduce the accuracy of your forecast as much as missing future values.

• SageMaker Canvas automatically imputes the missing values.

You can evaluate the model by seeing how close the predictions are within the actual value. You can also use the **Column Impact** metric to determine the direction and magnitude of the column's impact on the model's predictions. For example, in the following image, holidays had the largest positive impact on the forecast for demand. Price had the largest negative impact on demand.

![Customer Churn Model](image)

After you've built a model, you can make the following types of forecasts:

• Single item – Make a forecast for a single item in a dataset and a line graph of the values that SageMaker Canvas forecasts. For example, you can see how sales of an item vary over time.
• All items – Make a forecast for all items in a dataset.
• What-if scenario – See how changing values in the dataset can affect the overall forecast for a single item.

The following image shows a single item forecast with a what-if scenario. In a what-if scenario, you have the ability to change values that can vary with time. You can see how changing the values affects the forecast.

The points connected by the solid blue line are the values that the model forecasts. The points connected by the dashed lines show the what-if scenario.

Updating a Model in Amazon SageMaker Canvas

Amazon SageMaker Canvas gives you the ability to update the models that you've built using new data. SageMaker Canvas shows you a model history, so that you can compare the models that you've built recently to those that you've generated in the past.

Each model that you build has a version number. The first model is Version 1.

If you have more than one version of a model, you can delete the versions that aren't useful to you.

You need to build at least one version of a model to add a new version.

Use the following procedure to add a new model version.

To add a new model version, do the following.

1. Choose the dropdown list at the top of the page. If you're on the first version of the model, it says V1 at the beginning.
2. Choose Add version.

The following image visualizes the preceding procedure.
After you choose a new version, you start the process of building another model. The process for building a new version of a model is almost the same as the process for building a model for the first time. For new versions of a model, you can only choose datasets that have the same target column as the target column in Version 1. For more information about building a model, see Step 3: Build a model (p. 221).

You can use the different versions of the model to see changes in prediction accuracy when you've used different model types or data.

**Share your models with data scientists**

You can share the models that you've built with data scientists. They can review the models and give you feedback.

- **Note**
  You can't share Quick build or time series models.

Use the following procedure to share a model.

To share a model, do the following.

1. From the screen showing the models that you've created, choose a model.
2. Choose Share.
3. Choose the versions of the model that you want to share.
4. Optional: For **Include a note with the link (optional)**, write a note giving more context on the model.
5. Choose Create SageMaker Studio Link.
6. Share the link with the data scientist.

**Manage billing and cost in SageMaker Canvas**

To track the costs associated with your SageMaker Canvas application, you can use the AWS Billing and Cost Management service. Billing and Cost Management provides tools to help you gather information related to your cost and usage, analyze your cost drivers and usage trends, and take action to budget your spending. For more information, see What is AWS Billing and Cost Management?.

Billing in SageMaker Canvas consists of the following components:
• Session charges – You are charged for the number of hours that you are logged in to or using SageMaker Canvas.
• Training charges – You are charged for training models based on the size of the dataset you use.

For more information, see SageMaker Canvas pricing.

To help you track your costs in Billing and Cost Management, you can assign custom tags to your SageMaker Canvas app and users. You can track the costs your apps incur, and by tagging individual user profiles, you can track costs based on the user profile. For more information about tags, see Using Cost Allocation Tags.

You can add tags to your SageMaker Canvas app and users by doing the following:

• If you are setting up your Amazon SageMaker Domain and SageMaker Canvas for the first time, follow the Getting Started instructions and add tags when creating your Domain or users. You can add tags either through the General settings in the Domain console setup, or through the APIs (CreateDomain or CreateUserProfile). SageMaker adds the tags specified in your Domain or UserProfile to any SageMaker Canvas apps or users you create after you create the Domain.
• If you want to add tags to apps in an existing Domain, you must add tags to either the Domain or the UserProfile. You can add tags through either the console or the AddTags API. If you add tags through the console, then you must delete and relaunch your SageMaker Canvas app in order for the tags to propagate to the app. If you use the API, the tags are added directly to the app. For more information about deleting and relaunching a SageMaker Canvas app, see Manage apps.

After you add tags to your Domain, it might take up to 24 hours for the tags to appear in the AWS Billing and Cost Management console for activation. After they appear in the console, it takes another 24 hours for the tags to activate.

On the Cost explorer page, you can group and filter your costs by tags and usage types to separate your Session charges from your Training charges. The names of the usage types are as follows:

• Session charges: REGION-Canvas:Session-Hrs (Hrs)
• Training charges:
  • REGION-Canvas:CreateModelRequest-Tier0 (CreateModelRequest)
  • REGION-Canvas:MillionCells-Tier1 (MillionCells)
Use Amazon SageMaker Notebook Instances

An Amazon SageMaker notebook instance is a machine learning (ML) compute instance running the Jupyter Notebook App. SageMaker manages creating the instance and related resources. Use Jupyter notebooks in your notebook instance to prepare and process data, write code to train models, deploy models to SageMaker hosting, and test or validate your models.

SageMaker also provides sample notebooks that contain complete code walkthroughs. These walkthroughs show how to use SageMaker to perform common machine learning tasks. For more information, see Example Notebooks (p. 306).

This video shows you how to setup and use SageMaker notebook instances. (Length: 26:04)

This video is a deep dive on how to use SageMaker notebook instances. (Length: 16:44)

Topics

- Amazon Linux 2 vs Amazon Linux notebook instances (p. 291)
- JupyterLab versioning (p. 294)
- Create a Notebook Instance (p. 296)
- Access Notebook Instances (p. 298)
- Update a Notebook Instance (p. 299)
- Customize a Notebook Instance Using a Lifecycle Configuration Script (p. 299)
- Example Notebooks (p. 306)
- Set the Notebook Kernel (p. 308)
- Associate Git Repositories with SageMaker Notebook Instances (p. 309)
- Notebook Instance Metadata (p. 316)
- Monitor Jupyter Logs in Amazon CloudWatch Logs (p. 316)

Amazon Linux 2 vs Amazon Linux notebook instances

Amazon SageMaker notebook instances currently support Amazon Linux 2 (AL2) and Amazon Linux (AL1) operating systems. You can select the operating system that your notebook instances is based on when you create the notebook instance. Notebook instances created before 08/18/2021 automatically run on AL1.

Notebook instances based on AL1 will enter a maintenance phase as of 12/01/2022. To replace AL1, you now have the option to create Amazon SageMaker notebook instances with AL2. The AL1 maintenance phase also coincides with the deprecation of Python 2 and Chainer. Notebooks based on AL2 do not have managed Python 2 and Chainer kernels.
AL1 Maintenance Phase Plan

The following table is a timeline for when AL1 enters its extended maintenance phase.

<table>
<thead>
<tr>
<th>Date</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>08/18/2021</td>
<td>Notebook instances based on AL2 are launched. Newly launched notebook instances still default to AL1. AL1 is supported with security patches and updates, but no new features. You can choose between the two operating systems when launching a new notebook instance.</td>
</tr>
<tr>
<td>10/31/2022</td>
<td>The default platform identifier for SageMaker notebook instances changes from Amazon Linux (al1-v1) to Amazon Linux 2 (al2-v2). You can choose between the two operating systems when launching a new notebook instance.</td>
</tr>
<tr>
<td>12/01/2022</td>
<td>AL1 is no longer supported with non-critical security patches and updates. AL1 still receives fixes for critical security-related issues. You can still launch instances on AL1, but assume the risks associated with using an unsupported operating system.</td>
</tr>
<tr>
<td>02/01/2023</td>
<td>AL1 is no longer an available option for new notebook instance creation. After this date, customers can create notebook instances with the AL2 platform identifiers. Existing al1-v1 notebook instances are not be affected.</td>
</tr>
</tbody>
</table>

Available Kernels

notebook-al1-v1: The following kernels are available in notebook instances based on the Amazon Linux platform. These notebook instances support JupyterLab version 1. For information about JupyterLab versions, see JupyterLab versioning (p. 294).

<table>
<thead>
<tr>
<th>Kernel Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
</tr>
<tr>
<td>Sparkmagic (PySpark)</td>
</tr>
<tr>
<td>Sparkmagic (Spark)</td>
</tr>
<tr>
<td>Sparkmagic (SparkR)</td>
</tr>
<tr>
<td>conda_amazonei_mxnet_p27</td>
</tr>
<tr>
<td>conda_amazonei_mxnet_p36</td>
</tr>
<tr>
<td>conda_amazonei_pytorch_latest_p36</td>
</tr>
<tr>
<td>conda_amazonei_tensorflow2_p27</td>
</tr>
</tbody>
</table>
### Available Kernels

<table>
<thead>
<tr>
<th>Kernel Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>conda_amazonei_tensorflow2_p36</td>
</tr>
<tr>
<td>conda_amazonei_tensorflow_p27</td>
</tr>
<tr>
<td>conda_amazonei_tensorflow_p36</td>
</tr>
<tr>
<td>conda_chainer_p27</td>
</tr>
<tr>
<td>conda_chainer_p36</td>
</tr>
<tr>
<td>conda_mxnet_latest_p37</td>
</tr>
<tr>
<td>conda_mxnet_p27</td>
</tr>
<tr>
<td>conda_mxnet_p36</td>
</tr>
<tr>
<td>conda_python2</td>
</tr>
<tr>
<td>conda_python3</td>
</tr>
<tr>
<td>conda_pytorch_latest_p36</td>
</tr>
<tr>
<td>conda_pytorch_p27</td>
</tr>
<tr>
<td>conda_pytorch_p36</td>
</tr>
<tr>
<td>conda_tensorflow2_p36</td>
</tr>
<tr>
<td>conda_tensorflow2_p36</td>
</tr>
<tr>
<td>conda_tensorflow_p27</td>
</tr>
<tr>
<td>conda_tensorflow_p36</td>
</tr>
</tbody>
</table>

**notebook-a12-v1**: The following kernels are available in notebook instances based on the Amazon Linux 2 platform. These notebook instances support JupyterLab version 1. For information about JupyterLab versions, see [JupyterLab versioning](p. 294).

<table>
<thead>
<tr>
<th>Kernel Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
</tr>
<tr>
<td>Sparkmagic (PySpark)</td>
</tr>
<tr>
<td>Sparkmagic (Spark)</td>
</tr>
<tr>
<td>Sparkmagic (SparkR)</td>
</tr>
<tr>
<td>conda_amazonei_mxnet_p36</td>
</tr>
<tr>
<td>conda_amazonei_pytorch_latest_p37</td>
</tr>
<tr>
<td>conda_amazonei_tensorflow2_p36</td>
</tr>
<tr>
<td>conda_mxnet_p37</td>
</tr>
<tr>
<td>conda_python3</td>
</tr>
<tr>
<td>conda_pytorch_p38</td>
</tr>
<tr>
<td>conda_tensorflow2_p38</td>
</tr>
</tbody>
</table>
The following kernels are available in notebook instances based on the Amazon Linux 2 platform. These notebook instances support JupyterLab version 3. For information about JupyterLab versions, see JupyterLab versioning (p. 294).

<table>
<thead>
<tr>
<th>Kernel Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>R</td>
</tr>
<tr>
<td>Sparkmagic (PySpark)</td>
</tr>
<tr>
<td>Sparkmagic (Spark)</td>
</tr>
<tr>
<td>Sparkmagic (SparkR)</td>
</tr>
<tr>
<td>conda_amazonei_pytorch_latest_p37</td>
</tr>
<tr>
<td>conda_mxnet_p37</td>
</tr>
<tr>
<td>conda_python3</td>
</tr>
<tr>
<td>conda_pytorch_p38</td>
</tr>
<tr>
<td>conda_tensorflow2_p38</td>
</tr>
</tbody>
</table>

**Migrating to Amazon Linux 2**

Your existing notebook instance is not automatically migrated to Amazon Linux 2. To upgrade your notebook instance to Amazon Linux 2, you must create a new notebook instance, replicate your code and environment, and delete your old notebook instance. For more information, see the Amazon Linux 2 migration blog.

**JupyterLab versioning**

The Amazon SageMaker notebook instance interface is based on JupyterLab, which is a web-based interactive development environment for notebooks, code, and data. Notebooks now support using either JupyterLab 1 or JupyterLab 3. A single notebook instance can run a single instance of JupyterLab (at most). You can have multiple notebook instances with different JupyterLab versions.

You can configure your notebook to run your preferred JupyterLab version by selecting the appropriate platform identifier. Use either the AWS CLI or the SageMaker console when creating your notebook instance. For more information about platform identifiers, see Amazon Linux 2 vs Amazon Linux notebook instances. If you don't explicitly configure a platform identifier, your notebook instance defaults to running JupyterLab 1.

**Topics**
- JupyterLab 3 (p. 294)
- Creating a notebook with your JupyterLab version (p. 295)
- View the JupyterLab version of a notebook from the console (p. 295)

**JupyterLab 3**

JupyterLab 3 support is available only on the Amazon Linux 2 operating system platform. JupyterLab 3 includes the following features that are not available in JupyterLab 1. For more information about these features, see JupyterLab 3.0 is released!
Important changes to JupyterLab 3

For information about important changes when using JupyterLab 3, see the following JupyterLab change logs:

- v2.0.0
- v3.0.0

Package version changes

JupyterLab 3 has the following package version changes from JupyterLab 1:

- JupyterLab has been upgraded from 1.x to 3.x.
- Jupyter notebook has been upgraded from 5.x to 6.x.
- jupyterlab-git has been updated to version 0.37.1.
- nbserverproxy 0.x (0.3.2) has been replaced with jupyter-server-proxy 3.x (3.2.1).

Creating a notebook with your JupyterLab version

You can select the JupyterLab version when creating your notebook instance from the console following the steps in Create a Notebook Instance (p. 296).

You can also select the JupyterLab version by passing the `platform-identifier` parameter when creating your notebook instance using the AWS CLI as follows:

```
create-notebook-instance --notebook-instance-name <NEW_NOTEBOOK_NAME> \
--instance-type <INSTANCE_TYPE> \
--role-arn <YOUR_ROLE_ARN> \
--platform-identifier <PLATFORM_TO_USE>
```

View the JupyterLab version of a notebook from the console

You can view the JupyterLab version of a notebook using the following procedure:

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Navigate to the Notebook instances page.
3. From the list of notebook instances, select your notebook instance name.
4. On the Notebook instance settings page, view the Platform Identifier to see the JupyterLab version of the notebook.

Create a Notebook Instance

An Amazon SageMaker notebook instance is a ML compute instance running the Jupyter Notebook App. SageMaker manages creating the instance and related resources. Use Jupyter notebooks in your notebook instance to prepare and process data, write code to train models, deploy models to SageMaker hosting, and test or validate your models.

To create a notebook instance, use either the SageMaker console or the CreateNotebookInstance API.

The notebook instance type you choose depends on how you use your notebook instance. You want to ensure that your notebook instance is not bound by memory, CPU, or IO. If you plan to load a dataset into memory on the notebook instance for exploration or preprocessing, we recommend that you choose an instance type with enough RAM memory for your dataset. This would require an instance with at least 16 GB of memory (xlarge or larger). If you plan to use the notebook for compute intensive preprocessing, we recommend you choose a compute-optimized instance such as a c4 or c5.

A best practice when using a SageMaker notebook is to use the notebook instance to orchestrate other AWS services. For example, you can use the notebook instance to manage large dataset processing by making calls to AWS Glue for ETL (extract, transform, and load) services or Amazon EMR for mapping and data reduction using Hadoop. You can use AWS services as temporary forms of computation or storage for your data.

You can store and retrieve your training and test data using an Amazon S3 bucket. You can then use SageMaker to train and build your model, so the instance type of your notebook would have no bearing on the speed of your model training and testing.

After receiving the request, SageMaker does the following:

- **Creates a network interface**—If you choose the optional VPC configuration, SageMaker creates the network interface in your VPC. It uses the subnet ID that you provide in the request to determine which Availability Zone to create the subnet in. SageMaker associates the security group that you provide in the request with the subnet. For more information, see Connect a Notebook Instance in a VPC to External Resources (p. 3633).
- **Launches an ML compute instance**—SageMaker launches an ML compute instance in a SageMaker VPC. SageMaker performs the configuration tasks that allow it to manage your notebook instance, and if you specified your VPC, it enables traffic between your VPC and the notebook instance.
- **Installs Anaconda packages and libraries for common deep learning platforms**—SageMaker installs all of the Anaconda packages that are included in the installer. For more information, see Anaconda package list. In addition, SageMaker installs the TensorFlow and Apache MXNet deep learning libraries.
- **Attaches an ML storage volume**—SageMaker attaches an ML storage volume to the ML compute instance. You can use the volume as a working area to clean up the training dataset or to temporarily store validation, test, or other data. Choose any size between 5 GB and 16384 GB, in 1 GB increments, for the volume. The default is 5 GB. ML storage volumes are encrypted, so SageMaker can't determine the amount of available free space on the volume. Because of this, you can increase the volume size when you update a notebook instance, but you can't decrease the volume size. If you want to decrease the size of the ML storage volume in use, create a new notebook instance with the desired size.

Only files and data saved within the `/home/ec2-user/SageMaker` folder persist between notebook instance sessions. Files and data that are saved outside this directory are overwritten when the notebook instance stops and restarts. Each notebook instance's `/tmp` directory provides a minimum
of 10 GB of storage in an instance store. An instance store is temporary, block-level storage that isn't persistent. When the instance is stopped or restarted, SageMaker deletes the directory's contents. This temporary storage is part of the root volume of the notebook instance.

- **Copies example Jupyter notebooks**— These Python code examples illustrate model training and hosting exercises using various algorithms and training datasets.

**To create a SageMaker notebook instance:**

2. Choose **Notebook instances**, then choose **Create notebook instance**.
3. On the **Create notebook instance** page, provide the following information:
   a. For **Notebook instance name**, type a name for your notebook instance.
   b. For **Notebook instance type**, choose an instance size suitable for your use case. For a list of supported instance types and quotas, see **Amazon SageMaker Service Quotas**.
   c. For **Elastic Inference**, choose an inference accelerator type to associate with the notebook instance if you plan to conduct inferences from the notebook instance, or choose **none**. For information about elastic inference, see **Use Amazon SageMaker Elastic Inference (EI)** (p. 3129).
   d. For **Platform Identifier**, choose a platform type to create the notebook instance on. This platform type dictates the Operating System and the JupyterLab version that your notebook instance is created with. For information about platform identifier type, see **Amazon Linux 2 vs Amazon Linux notebook instances** (p. 291). For information about JupyterLab versions, see **JupyterLab versioning** (p. 294).
   e. (Optional) **Additional configuration** lets advanced users create a shell script that can run when you create or start the instance. This script, called a lifecycle configuration script, can be used to set the environment for the notebook or to perform other functions. For information, see **Customize a Notebook Instance Using a Lifecycle Configuration Script** (p. 299).
   f. (Optional) **Additional configuration** also lets you specify the size, in GB, of the ML storage volume that is attached to the notebook instance. You can choose a size between 5 GB and 16,384 GB, in 1 GB increments. You can use the volume to clean up the training dataset or to temporarily store validation or other data.
   g. (Optional) For **Minimum IMDS Version**, select a version from the dropdown list. If this value is set to v1, both versions can be used with the notebook instance. If v2 is selected, then only IMDSv2 can be used with the notebook instance. For information about IMDSv2, see **Use IMDSv2**.

**Note**
Starting October 31, 2022, the default minimum IMDS Version for SageMaker notebook instances changes from IMDSv1 to IMDSv2. Starting February 1, 2023, IMDSv1 is no longer be available for new notebook instance creation. After this date, you can create notebook instances with a minimum IMDS version of 2.

h. For **IAM role**, choose either an existing IAM role in your account that has the necessary permissions to access SageMaker resources or choose **Create a new role**. If you choose **Create a new role**, SageMaker creates an IAM role named AmazonSageMaker-ExecutionRole-YYYYMMDDTHHnnmSS. The AWS managed policy AmazonSageMakerFullAccess is attached to the role. The role provides permissions that allow the notebook instance to call SageMaker and Amazon S3.

i. For **Root access**, to enable root access for all notebook instance users, choose **Enable**. To disable root access for users, choose **Disable**. If you enable root access, all notebook instance users have administrator privileges and can access and edit all files on it.

j. (Optional) **Encryption key** lets you encrypt data on the ML storage volume attached to the notebook instance using an AWS Key Management Service (AWS KMS) key. If you plan to store sensitive information on the ML storage volume, consider encrypting the information.
k. (Optional) **Network** lets you put your notebook instance inside a Virtual Private Cloud (VPC). A VPC provides additional security and restricts access to resources in the VPC from sources outside the VPC. For more information on VPCs, see *Amazon VPC User Guide*.

To add your notebook instance to a VPC:

i. Choose the **VPC** and a **SubnetId**.

ii. For **Security Group**, choose your VPC's default security group.

iii. If you need your notebook instance to have internet access, enable direct internet access. For **Direct internet access**, choose **Enable**. Internet access can make your notebook instance less secure. For more information, see *Connect a Notebook Instance in a VPC to External Resources* (p. 3633).

l. (Optional) To associate Git repositories with the notebook instance, choose a default repository and up to three additional repositories. For more information, see *Associate Git Repositories with SageMaker Notebook Instances* (p. 309).

m. Choose **Create notebook instance**.

   In a few minutes, Amazon SageMaker launches an ML compute instance—in this case, a notebook instance—and attaches an ML storage volume to it. The notebook instance has a preconfigured Jupyter notebook server and a set of Anaconda libraries. For more information, see the **CreateNotebookInstance** API.

4. When the status of the notebook instance is **InService**, in the console, the notebook instance is ready to use. Choose **Open Jupyter** next to the notebook name to open the classic Jupyter dashboard.

   You can choose **Open JupyterLab** to open the JupyterLab dashboard. The dashboard provides access to your notebook instance and sample SageMaker notebooks that contain complete code walkthroughs. These walkthroughs show how to use SageMaker to perform common machine learning tasks. For more information, see *Example Notebooks* (p. 306). For more information, see *Control root access to a SageMaker notebook instance* (p. 349).

   For more information about Jupyter notebooks, see *The Jupyter notebook*.

### Access Notebook Instances

To access your Amazon SageMaker notebook instances, choose one of the following options:

- Use the console.

Choose **Notebook instances**. The console displays a list of notebook instances in your account. To open a notebook instance with a standard Jupyter interface, choose **Open Jupyter** for that instance. To open a notebook instance with a JupyterLab interface, choose **Open JupyterLab** for that instance.

The console uses your sign-in credentials to send a
CreatePresignedNotebookInstanceUrl API request to SageMaker. SageMaker returns the URL for your notebook instance, and the console opens the URL in another browser tab and displays the Jupyter notebook dashboard.

**Note**
The URL that you get from a call to CreatePresignedNotebookInstanceUrl is valid only for 5 minutes. If you try to use the URL after the 5-minute limit expires, you are directed to the AWS Management Console sign-in page.

- Use the API.

To get the URL for the notebook instance, call the CreatePresignedNotebookInstanceUrl API and use the URL that the API returns to open the notebook instance.

Use the Jupyter notebook dashboard to create and manage notebooks and to write code. For more information about Jupyter notebooks, see http://jupyter.org/documentation.html.

## Update a Notebook Instance

After you create a notebook instance, you can update it using the SageMaker console and UpdateNotebookInstance API operation.

You can update the tags of a notebook instance that is InService. To update any other attribute of a notebook instance, its status must be Stopped.

**To update a notebook instance in the SageMaker console:**

2. Choose Notebook instances.
3. Choose the notebook instance that you want to update by selecting the notebook instance Name from the list.
4. If your notebook Status is not Stopped, select the Stop button to stop the notebook instance.
   - When you do this, the notebook instance status changes to Stopping. Wait until the status changes to Stopped to complete the following steps.
5. Select the Edit button to open the Edit notebook instance page. For information about the notebook properties you can update, see Create a Notebook Instance (p. 296).
6. Update your notebook instance and select the Update notebook instance button at the bottom of the page when you are done to return to the notebook instances page. Your notebook instance status changes to Updating.
   - When the notebook instance update is complete, the status changes to Stopped.

## Customize a Notebook Instance Using a Lifecycle Configuration Script

To install packages or sample notebooks on your notebook instance, configure networking and security for it, or otherwise use a shell script to customize it, use a lifecycle configuration. A lifecycle configuration provides shell scripts that run only when you create the notebook instance or whenever you start one.
When you create a notebook instance, you can create a new lifecycle configuration and the scripts it uses or apply one that you already have.

You can also use a lifecycle configuration script to access AWS services from your notebook. For example, you can create a script that lets you use your notebook to control other AWS resources, such as an Amazon EMR instance.

We maintain a public repository of notebook lifecycle configuration scripts that address common use cases for customizing notebook instances at https://github.com/aws-samples/amazon-sagemaker-notebook-instance-lifecycle-configuration-samples.

**Note**

Each script has a limit of 16384 characters.
The value of the $PATH environment variable that is available to both scripts is /usr/local/sbin:/usr/local/bin:/usr/bin:/usr/sbin:/sbin:/bin. The working directory, which is the value of the $PWD environment variable, is /.

View CloudWatch Logs for notebook instance lifecycle configurations in log group /aws/sagemaker/NotebookInstances in log stream [notebook-instance-name]/[LifecycleConfigHook].

Scripts cannot run for longer than 5 minutes. If a script runs for longer than 5 minutes, it fails and the notebook instance is not created or started. To help decrease the run time of scripts, try the following:

- Cut down on necessary steps. For example, limit which conda environments in which to install large packages.
- Run tasks in parallel processes.
- Use the nohup command in your script.

You can see a list of notebook instance lifecycle configurations you previously created by choosing Lifecycle configuration in the SageMaker console. These notebook instance lifecycle configurations are available when you create a new notebook instance.

**To create a lifecycle configuration**

2. On the left side under SageMaker dashboard, choose Lifecycle configurations.
3. From the Lifecycle configurations page, choose Create configuration.
4. For Name, type a name using alphanumeric characters and “-”, but no spaces. The name can have a maximum of 63 characters.
5. (Optional) To create a script that runs when you create the notebook and every time you start it, choose Start notebook.
6. In the Start notebook editor, type the script.
7. (Optional) To create a script that runs only once, when you create the notebook, choose Create notebook.
8. In the Create notebook editor, type the script configure networking.
9. Choose Create configuration.

**Lifecycle Configuration Best Practices**

The following are best practices for using lifecycle configurations:

**Important**

We do not recommend storing sensitive information in your lifecycle configuration script.
• Lifecycle configurations run as the root user. If your script makes any changes within the /home/ec2-user/SageMaker directory, (for example, installing a package with pip), use the command `sudo -u ec2-user` to run as the ec2-user user. This is the same user that Amazon SageMaker runs as.

• SageMaker notebook instances use conda environments to implement different kernels for Jupyter notebooks. If you want to install packages that are available to one or more notebook kernels, enclose the commands to install the packages with conda environment commands that activate the conda environment that contains the kernel where you want to install the packages.

For example, if you want to install a package only for the python3 environment, use the following code:

```bash
#!/bin/bash
sudo -u ec2-user -i <<'EOF'
# This will affect only the Jupyter kernel called "conda_python3".
source activate python3
# Replace myPackage with the name of the package you want to install.
pip install myPackage
# You can also perform "conda install" here as well.
source deactivate
EOF
```

If you want to install a package in all conda environments in the notebook instance, use the following code:

```bash
#!/bin/bash
sudo -u ec2-user -i <<'EOF'
# Note that "base" is special environment name, include it there as well.
for env in base /home/ec2-user/anaconda3/envs/*; do
  source /home/ec2-user/anaconda3/bin/activate $(basename "$env")
  # Installing packages in the Jupyter system environment can affect stability of your SageMaker Notebook Instance. You can remove this check if you'd like to install Jupyter extensions, etc.
  if [ "$env" = 'JupyterSystemEnv' ]; then
    continue
  fi

  # Replace myPackage with the name of the package you want to install.
  pip install --upgrade --quiet myPackage
  # You can also perform "conda install" here as well.
  source /home/ec2-user/anaconda3/bin/deactivate
done
EOF
```

• You must store all conda environments in the default environments folder (/home/user/anaconda3/envs).

**Important**
When you create or change a script, we recommend that you use a text editor that provides Unix-style line breaks, such as the text editor available in the console when you create a notebook. Copying text from a non-Linux operating system might introduce incompatible line breaks and result in an unexpected error.
Install External Libraries and Kernels in Notebook Instances

Amazon SageMaker notebook instances come with multiple environments already installed. These environments contain Jupyter kernels and Python packages including: scikit, Pandas, NumPy, TensorFlow, and MXNet. These environments, along with all files in the sample-notebooks folder, are refreshed when you stop and start a notebook instance. You can also install your own environments that contain your choice of packages and kernels.

The different Jupyter kernels in Amazon SageMaker notebook instances are separate conda environments. For information about conda environments, see Managing environments in the Conda documentation.

Install custom environments and kernels on the notebook instance's Amazon EBS volume. This ensures that they persist when you stop and restart the notebook instance, and that any external libraries you install are not updated by SageMaker. To do that, use a lifecycle configuration that includes both a script that runs when you create the notebook instance (on-create) and a script that runs each time you restart the notebook instance (on-start). For more information about using notebook instance lifecycle configurations, see Customize a Notebook Instance Using a Lifecycle Configuration Script (p. 299).

There is a GitHub repository that contains sample lifecycle configuration scripts at SageMaker Notebook Instance Lifecycle Config Samples. The examples at https://github.com/aws-samples/amazon-sagemaker-notebook-instance-lifecycle-config-samples/blob/master/scripts/persistent-conda-ebs/on-create.sh and https://github.com/aws-samples/amazon-sagemaker-notebook-instance-lifecycle-config-samples/blob/master/scripts/persistent-conda-ebs/on-start.sh show the best practice for installing environments and kernels on a notebook instance. The on-create script installs the ipykernel library to create custom environments as Jupyter kernels, then uses pip install and conda install to install libraries. You can adapt the script to create custom environments and install libraries that you want. SageMaker does not update these libraries when you stop and restart the notebook instance, so you can ensure that your custom environment has specific versions of libraries that you want. The on-start script installs any custom environments that you create as Jupyter kernels, so that they appear in the dropdown list in the Jupyter New menu.

Package installation tools

SageMaker notebooks support the following package installation tools:

- conda install
- pip install

You can install packages using the following methods:

- Lifecycle configuration scripts.
  
  For example scripts, see SageMaker Notebook Instance Lifecycle Config Samples. For more information on lifecycle configuration, see Customize a Notebook Instance Using a Lifecycle Configuration Script.
- Notebooks – The following commands are supported.
  
  • %conda install
  • %pip install
- The Jupyter terminal – You can install packages using pip and conda directly.

From within a notebook you can use the system command syntax (lines starting with !) to install packages, for example, !pip install and !conda install. More recently, new commands have been
added to IPython: `%pip` and `%conda`. These commands are the recommended way to install packages from a notebook as they correctly take into account the active environment or interpreter being used. For more information, see Add `%pip` and `%conda` magic functions.

**Conda**

Conda is an open source package management system and environment management system, which can install packages and their dependencies. SageMaker supports using Conda with either of the two main channels, the default channel, and the conda-forge channel. For more information, see Conda channels. The conda-forge channel is a community channel where contributors can upload packages.

**Note**

Due to how Conda resolves the dependency graph, installing packages from conda-forge can take significantly longer (in the worst cases, upwards of 10 minutes).

The Deep Learning AMI comes with many conda environments and many packages preinstalled. Due to the number of packages preinstalled, finding a set of packages that are guaranteed to be compatible is difficult. You may see a warning "The environment is inconsistent, please check the package plan carefully". Despite this warning, SageMaker ensures that all the SageMaker provided environments are correct. SageMaker cannot guarantee that any user installed packages will function correctly.

Conda has two methods for activating environments: conda activate/deactivate, and source activate/deactivate. For more information, see Should I use 'conda activate' or 'source activate' in Linux.

SageMaker supports moving Conda environments onto the Amazon EBS volume, which is persisted when the instance is stopped. The environments aren't persisted when the environments are installed to the root volume, which is the default behavior. For an example lifecycle script, see persistent-conda-ebs.

**Supported conda operations (see note at the bottom of this topic)**

- conda install of a package in a single environment
- conda install of a package in all environments
- conda install of a R package in the R environment
- Installing a package from the main conda repository
- Installing a package from conda-forge
- Changing the Conda install location to use EBS
- Supporting both conda activate and source activate

**Pip**

Pip is the de facto tool for installing and managing Python packages. Pip searches for packages on the Python Package Index (PyPI) by default. Unlike Conda, pip doesn't have built in environment support, and is not as thorough as Conda when it comes to packages with native/system library dependencies. Pip can be used to install packages in Conda environments.

You can use alternative package repositories with pip instead of the PyPI. For an example lifecycle script, see on-start.sh.

**Supported pip operations (see note at the bottom of this topic)**

- Using pip to install a package without an active conda environment (install packages system wide)
- Using pip to install a package in a conda environment
- Using pip to install a package in all conda environments
- Changing the pip install location to use EBS
- Using an alternative repository to install packages with pip
Unsupported

SageMaker aims to support as many package installation operations as possible. However, if the packages were installed by SageMaker or DLAMI, and you use the following operations on these packages, it might make your notebook instance unstable:

- Uninstalling
- Downgrading
- Upgrading

We do not provide support for installing packages via yum install or installing R packages from CRAN.

Due to potential issues with network conditions or configurations, or the availability of Conda or PyPi, we cannot guarantee that packages will install in a fixed or deterministic amount of time.

**Note**

We cannot guarantee that a package installation will be successful. Attempting to install a package in an environment with incompatible dependencies can result in a failure. In such a case you should contact the library maintainer to see if it is possible to update the package dependencies. Alternatively you can attempt to modify the environment in such a way as to allow the installation. This modification however will likely mean removing or updating existing packages, which means we can no longer guarantee stability of this environment.

Notebook Instance Software Updates

Amazon SageMaker periodically tests and releases software that is installed on notebook instances. This includes:

- Kernel updates
- Security patches
- AWS SDK updates
- Amazon SageMaker Python SDK updates
- Open source software updates

SageMaker does not update software on a notebook instance when it is in service. To ensure that you have the most recent software updates, stop and restart your notebook instance, either in the SageMaker console or by calling \texttt{StopNotebookInstance}.

You can also manually update software installed on your notebook instance while it is running by using update commands in a terminal or in a notebook.

**Note**

Updating kernels and some packages might depend on whether root access is enabled for the notebook instance. For more information, see Control root access to a SageMaker notebook instance (p. 3495).

Notebook instances do not notify you if you are running outdated software. You can check the Personal Health Dashboard or the security bulletin at Security Bulletins for updates.

Control an Amazon EMR Spark Instance Using a Notebook

You can use a notebook instance created with a custom lifecycle configuration script to access AWS services from your notebook. For example, you can create a script that lets you use your notebook with
Sparkmagic to control other AWS resources, such as an Amazon EMR instance. You can then use the Amazon EMR instance to process your data instead of running the data analysis on your notebook. This allows you to create a smaller notebook instance because you won’t use the instance to process data. This is helpful when you have large datasets that would require a large notebook instance to process the data.

The process requires three procedures using the Amazon SageMaker console:

- Create the Amazon EMR Spark instance
- Create the Jupyter Notebook
- Test the notebook-to-Amazon EMR connection

To create an Amazon EMR Spark instance that can be controlled from a notebook using Sparkmagic

1. Open the Amazon EMR console at https://console.aws.amazon.com/elasticmapreduce/.
2. In the navigation pane, choose Create cluster.
3. On the Create Cluster - Quick Options page, under Software configuration, choose Spark: Spark 2.4.4 on Hadoop 2.8.5 YARN with Ganglia 3.7.2 and Zeppelin 0.8.2.
4. Set additional parameters on the page and then choose Create cluster.
5. On the Cluster page, choose the cluster name that you created. Note the Master Public DNS, the EMR master’s security group, and the VPC name and subnet ID where the EMR cluster was created. You will use these values when you create a notebook.

To create a notebook that uses Sparkmagic to control an Amazon EMR Spark instance

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the navigation pane, under Notebook instances, choose Create notebook.
3. Enter the notebook instance name and choose the instance type.
4. Choose Additional configuration, then, under Lifecycle configuration, choose Create a new lifecycle configuration.
5. Add the following code to the lifecycle configuration script:

```bash
# OVERVIEW
# This script connects an Amazon EMR cluster to an Amazon SageMaker notebook instance that uses Sparkmagic.
#
# Note that this script will fail if the Amazon EMR cluster’s master node IP address is not reachable.
# 1. Ensure that the EMR master node IP is resolvable from the notebook instance. One way to accomplish this is to have the notebook instance and the Amazon EMR cluster in the same subnet.
# 2. Ensure the EMR master node security group provides inbound access from the notebook instance security group.
# 3. Ensure the notebook instance has internet connectivity to fetch the SparkMagic example config.
#
#
# PARAMETERS
EMR_MASTER_IP=your.emr.master.ip
```
Example Notebooks

Your notebook instance contains example notebooks provided by Amazon SageMaker. The example notebooks contain code that shows how to apply machine learning solutions by using SageMaker. Notebook instances use the nbexamples Jupyter extension, which enables you to view a read-only version of an example notebook or create a copy of it so that you can modify and run it. For more information about the nbexamples extension, see https://github.com/danielballan/nbexamples. For information about example notebooks for SageMaker Studio, see Use Amazon SageMaker Studio Notebooks (p. 129).
Note
Example notebooks typically download datasets from the internet. If you disable SageMaker-provided internet access when you create you notebook instance, example notebooks might not work. For more information, see Connect a Notebook Instance in a VPC to External Resources (p. 3653).

Use or View Example Notebooks in Jupyter Classic

To view or use the example notebooks in the classic Jupyter view, choose the SageMaker Examples tab.

To view a read-only version of an example notebook in the Jupyter classic view, on the SageMaker Examples tab, choose Preview for that notebook. To create a copy of an example notebook in the home directory of your notebook instance, choose Use. In the dialog box, you can change the notebook’s name before saving it.

Use or View Example Notebooks in Jupyterlab

To view or use the example notebooks in the Jupyterlab view, choose the examples icon in the left navigation panel.
To view a read-only version of an example notebook, choose the name of the notebook. This opens the notebook as a tab in the main area. To create a copy of an example notebook in the home directory of your notebook instance, choose Create a Copy in the top banner. In the dialog box, type a name for the notebook and then choose CREATE COPY.

For more information about the example notebooks, see the SageMaker examples GitHub repository.

Set the Notebook Kernel

Amazon SageMaker provides several kernels for Jupyter that provide support for Python 2 and 3, Apache MXNet, TensorFlow, and PySpark. To set a kernel for a new notebook in the Jupyter notebook dashboard, choose New, and then choose the kernel from the list.
You can also create a custom kernel that you can use in your notebook instance. For information, see Install External Libraries and Kernels in Notebook Instances (p. 302).

**Associate Git Repositories with SageMaker Notebook Instances**

Associate Git repositories with your notebook instance to save your notebooks in a source control environment that persists even if you stop or delete your notebook instance. You can associate one default repository and up to three additional repositories with a notebook instance. The repositories can be hosted in AWS CodeCommit, GitHub, or on any other Git server. Associating Git repositories with your notebook instance can be useful for:

- **Persistence** - Notebooks in a notebook instance are stored on durable Amazon EBS volumes, but they do not persist beyond the life of your notebook instance. Storing notebooks in a Git repository enables you to store and use notebooks even if you stop or delete your notebook instance.
- **Collaboration** - Peers on a team often work on machine learning projects together. Storing your notebooks in Git repositories allows peers working in different notebook instances to share notebooks and collaborate on them in a source-control environment.
- **Learning** - Many Jupyter notebooks that demonstrate machine learning techniques are available in publicly hosted Git repositories, such as on GitHub. You can associate your notebook instance with a repository to easily load Jupyter notebooks contained in that repository.

There are two ways to associate a Git repository with a notebook instance:

- **Add a Git repository as a resource in your Amazon SageMaker account.** Then, to access the repository, you can specify an AWS Secrets Manager secret that contains credentials. That way, you can access repositories that require authentication.
- **Associate a public Git repository that is not a resource in your account.** If you do this, you cannot specify credentials to access the repository.

**Topics**

- Add a Git Repository to Your Amazon SageMaker Account (p. 310)
- Create a Notebook Instance with an Associated Git Repository (p. 312)
- Associate a CodeCommit Repository in a Different AWS Account with a Notebook Instance (p. 313)
- Use Git Repositories in a Notebook Instance (p. 314)
Add a Git Repository to Your Amazon SageMaker Account

To manage your GitHub repositories, easily associate them with your notebook instances, and associate credentials for repositories that require authentication, add the repositories as resources in your Amazon SageMaker account. You can view a list of repositories that are stored in your account and details about each repository in the SageMaker console and by using the API.

You can add Git repositories to your SageMaker account in the SageMaker console or by using the AWS CLI.

Note
You can use the SageMaker API CreateCodeRepository to add Git repositories to your SageMaker account, but step-by-step instructions are not provided here.

Add a Git Repository to Your SageMaker Account (Console)

To add a Git repository as a resource in your SageMaker account
2. Under Notebook, choose Git repositories, then choose Add repository.
3. To add an CodeCommit repository, choose AWS CodeCommit. To add a GitHub or other Git-based repository, choose GitHub/Other Git-based repo.

To add an existing CodeCommit repository
1. Choose Use existing repository.
2. For Repository, choose a repository from the list.
3. Enter a name to use for the repository in SageMaker. The name must be 1 to 63 characters. Valid characters are a-z, A-Z, 0-9, and - (hyphen).
4. Choose Add repository.

To create a new CodeCommit repository
1. Choose Create new repository.
2. Enter a name for the repository that you can use in both CodeCommit and SageMaker. The name must be 1 to 63 characters. Valid characters are a-z, A-Z, 0-9, and - (hyphen).
3. Choose Create repository.

To add a Git repository hosted somewhere other than CodeCommit
1. Choose GitHub/Other Git-based repo.
2. Enter a name of up to 63 characters. Valid characters include alpha-numeric characters, a hyphen (-), and 0-9.
3. Enter the URL for the repository. Do not provide a user name in the URL. Add the username and password in AWS Secrets Manager as described in the next step.
4. For Git credentials, choose the credentials to use to authenticate to the repository. This is necessary only if the Git repository is private.

Note
If you have two-factor authentication enabled for your Git repository, use a personal access token generated by your Git service provider instead of a password.
a. To use an existing AWS Secrets Manager secret, choose **Use existing secret**, and then choose a secret from the list. For information about creating and storing a secret, see **Creating a Basic Secret** in the *AWS Secrets Manager User Guide*. The name of the secret you use must contain the string `sagemaker`.

**Note**
The secret must have a staging label of `AWSCURRENT` and must be in the following format:

```
{"username": Username, "password": Password}
```

For GitHub repositories, we recommend using a personal access token instead of your account password. For information, see [https://help.github.com/articles/creating-a-personal-access-token-for-the-command-line/](https://help.github.com/articles/creating-a-personal-access-token-for-the-command-line/).

b. To create a new AWS Secrets Manager secret, choose **Create secret**, enter a name for the secret, and then enter the username and password to use to authenticate to the repository. The name for the secret must contain the string `sagemaker`.

**Note**
The IAM role you use to create the secret must have the `secretsmanager:GetSecretValue` permission in its IAM policy. The secret must have a staging label of `AWSCURRENT` and must be in the following format:

```
{"username": Username, "password": Password}
```

For GitHub repositories, we recommend using a personal access token instead of your account password.

c. To not use any credentials, choose **No secret**.

5. Choose **Create secret**.

### Add a Git Repository to Your Amazon SageMaker Account (CLI)

Use the `create-code-repository` AWS CLI command. Specify a name for the repository as the value of the `code-repository-name` argument. The name must be 1 to 63 characters. Valid characters are a-z, A-Z, 0-9, and - (hyphen). Also specify the following:

- The default branch
- The URL of the Git repository

**Note**
Do not provide a user name in the URL. Add the username and password in AWS Secrets Manager as described in the next step.

- The Amazon Resource Name (ARN) of an AWS Secrets Manager secret that contains the credentials to use to authenticate the repository as the value of the `git-config` argument

For information about creating and storing a secret, see **Creating a Basic Secret** in the *AWS Secrets Manager User Guide*. The following command creates a new repository named `MyRepository` in your Amazon SageMaker account that points to a Git repository hosted at `https://github.com/myprofile/my-repo`.

For Linux, OS X, or Unix:

```
```

For Windows:

```
```
aws sagemaker create-code-repository ^
--code-repository-name "MyRepository" ^

Note
The secret must have a staging label of AWSCURRENT and must be in the following format:
{"username": UserName, "password": Password}
For GitHub repositories, we recommend using a personal access token instead of your account password.

Create a Notebook Instance with an Associated Git Repository

You can associate Git repositories with a notebook instance when you create the notebook instance by using the AWS Management Console, or the AWS CLI. If you want to use a CodeCommit repository that is in a different AWS account than the notebook instance, set up cross-account access for the repository. For information, see Associate a CodeCommit Repository in a Different AWS Account with a Notebook Instance (p. 313).

Topics
• Create a Notebook Instance with an Associated Git Repository (Console) (p. 312)
• Create a Notebook Instance with an Associated Git Repository (CLI) (p. 313)

Create a Notebook Instance with an Associated Git Repository (Console)

To create a notebook instance and associate Git repositories in the Amazon SageMaker console

1. Follow the instructions at Step 1: Create an Amazon SageMaker Notebook Instance (p. 74).
2. For Git repositories, choose Git repositories to associate with the notebook instance.
   a. For Default repository, choose a repository that you want to use as your default repository. SageMaker clones this repository as a subdirectory in the Jupyter startup directory at /home/ec2-user/SageMaker. When you open your notebook instance, it opens in this repository. To choose a repository that is stored as a resource in your account, choose its name from the list. To add a new repository as a resource in your account, choose Add a repository to SageMaker (opens the Add repository flow in a new window) and then follow the instructions at Create a Notebook Instance with an Associated Git Repository (Console) (p. 312). To clone a public repository that is not stored in your account, choose Clone a public Git repository to this notebook instance only, and then specify the URL for that repository.
   b. For Additional repository 1, choose a repository that you want to add as an additional directory. SageMaker clones this repository as a subdirectory in the Jupyter startup directory at /home/ec2-user/SageMaker. To choose a repository that is stored as a resource in your account, choose its name from the list. To add a new repository as a resource in your account, choose Add a repository to SageMaker (opens the Add repository flow in a new window) and then follow the instructions at Create a Notebook Instance with an Associated Git Repository (Console) (p. 312). To clone a repository that is not stored in your account, choose Clone a public Git repository to this notebook instance only, and then specify the URL for that repository.
Repeat this step up to three times to add up to three additional repositories to your notebook instance.

Create a Notebook Instance with an Associated Git Repository (CLI)

To create a notebook instance and associate Git repositories by using the AWS CLI, use the `create-notebook-instance` command as follows:

- Specify the repository that you want to use as your default repository as the value of the `default-code-repository` argument. Amazon SageMaker clones this repository as a subdirectory in the Jupyter startup directory at `/home/ec2-user/SageMaker`. When you open your notebook instance, it opens in this repository. To use a repository that is stored as a resource in your SageMaker account, specify the name of the repository as the value of the `default-code-repository` argument. To use a repository that is not stored in your account, specify the URL of the repository as the value of the `default-code-repository` argument.

- Specify up to three additional repositories as the value of the `additional-code-repositories` argument. SageMaker clones this repository as a subdirectory in the Jupyter startup directory at `/home/ec2-user/SageMaker`, and the repository is excluded from the default repository by adding it to the `.git/info/exclude` directory of the default repository. To use repositories that are stored as resources in your SageMaker account, specify the names of the repositories as the value of the `additional-code-repositories` argument. To use repositories that are not stored in your account, specify the URLs of the repositories as the value of the `additional-code-repositories` argument.

For example, the following command creates a notebook instance that has a repository named `MyGitRepo`, that is stored as a resource in your SageMaker account, as a default repository, and an additional repository that is hosted on GitHub:

```bash
aws sagemaker create-notebook-instance
    --notebook-instance-name "MyNotebookInstance" \
    --instance-type "ml.t2.medium" \
    --role-arn "arn:aws:iam::012345678901:role/service-role/AmazonSageMaker-ExecutionRole-20181129T121390" \
    --default-code-repository "MyGitRepo" \
    --additional-code-repositories "https://github.com/myprofile/my-other-repo"
```

**Note**

If you use an AWS CodeCommit repository that does not contain "SageMaker" in its name, add the `codecommit:GitPull` and `codecommit:GitPush` permissions to the role that you pass as the `role-arn` argument to the `create-notebook-instance` command. For information about how to add permissions to a role, see Adding and Removing IAM Policies in the AWS Identity and Access Management User Guide.

Associate a CodeCommit Repository in a Different AWS Account with a Notebook Instance

To associate a CodeCommit repository in a different AWS account with your notebook instance, set up cross-account access for the CodeCommit repository.
To set up cross-account access for a CodeCommit repository and associate it with a notebook instance:

1. In the AWS account that contains the CodeCommit repository, create an IAM policy that allows access to the repository from users in the account that contains your notebook instance. For information, see Step 1: Create a Policy for Repository Access in AccountA in the CodeCommit User Guide.

2. In the AWS account that contains the CodeCommit repository, create an IAM role, and attach the policy that you created in the previous step to that role. For information, see Step 2: Create a Role for Repository Access in AccountA in the CodeCommit User Guide.

3. Create a profile in the notebook instance that uses the role that you created in the previous step:
   a. Open the notebook instance.
   b. Open a terminal in the notebook instance.
   c. Edit a new profile by typing the following in the terminal:

   ```
   vi /home/ec2-user/.aws/config
   ```

   d. Edit the file with the following profile information:

   ```
   [profile CrossAccountAccessProfile]
   region = us-west-2
   role_arn = arn:aws:iam::CodeCommitAccount:role/CrossAccountRepositoryContributorRole
   credential_source=Ec2InstanceMetadata
   output = json
   ```

   Where CodeCommitAccount is the account that contains the CodeCommit repository, CrossAccountAccessProfile is the name of the new profile, and CrossAccountRepositoryContributorRole is the name of the role you created in the previous step.

4. On the notebook instance, configure git to use the profile you created in the previous step:
   a. Open the notebook instance.
   b. Open a terminal in the notebook instance.
   c. Edit the Git configuration file typing the following in the terminal:

   ```
   vi /home/ec2-user/.gitconfig
   ```

   d. Edit the file with the following profile information:

   ```
   [credential]
   helper = !aws codecommit credential-helper --profile CrossAccountAccessProfile @
   UseHttpPath = true
   ```

   Where CrossAccountAccessProfile is the name of the profile that you created in the previous step.

Use Git Repositories in a Notebook Instance

When you open a notebook instance that has Git repositories associated with it, it opens in the default repository, which is installed in your notebook instance directly under /home/ec2-user/SageMaker.
You can open and create notebooks, and you can manually run Git commands in a notebook cell. For example:

```
!git pull origin master
```

To open any of the additional repositories, navigate up one folder. The additional repositories are also installed as directories under `/home/ec2-user/SageMaker`.

If you open the notebook instance with a JupyterLab interface, the jupyter-git extension is installed and available to use. For information about the jupyter-git extension for JupyterLab, see https://github.com/jupyterlab/jupyterlab-git.

When you open a notebook instance in JupyterLab, you see the git repositories associated with it on the left menu:

![git repositories in JupyterLab](image)

You can use the jupyter-git extension to manage git visually, instead of using the command line:
Notebook Instance Metadata

When you create a notebook instance, Amazon SageMaker creates a JSON file on the instance at the location `/opt/ml/metadata/resource-metadata.json` that contains the ResourceName and ResourceArn of the notebook instance. You can access this metadata from anywhere within the notebook instance, including in lifecycle configurations. For information about notebook instance lifecycle configurations, see Customize a Notebook Instance Using a Lifecycle Configuration Script (p. 299).

The `resource-metadata.json` file has the following structure:

```json
{
    "ResourceArn": "NotebookInstanceArn",
    "ResourceName": "NotebookInstanceName"
}
```

You can use this metadata from within the notebook instance to get other information about the notebook instance. For example, the following commands get the tags associated with the notebook instance:

```bash
NOTEBOOK_ARN=$(jq '.ResourceArn' /opt/ml/metadata/resource-metadata.json --raw-output)
aws sagemaker list-tags --resource-arn $NOTEBOOK_ARN
```

The output looks like the following:

```json
{
    "Tags": [
        {
            "Key": "test",
            "Value": "true"
        }
    ]
}
```

Monitor Jupyter Logs in Amazon CloudWatch Logs

Jupyter logs include important information such as events, metrics, and health information that provide actionable insights when running Amazon SageMaker notebooks. By importing Jupyter logs into
CloudWatch Logs, customers can use CloudWatch Logs to detect anomalous behaviors, set alarms, and discover insights to keep the SageMaker notebooks running more smoothly. You can access the logs even when the Amazon EC2 instance that hosts the notebook is unresponsive, and use the logs to troubleshoot the unresponsive notebook. Sensitive information such as AWS account IDs, secret keys, and authentication tokens in presigned URLs are removed so that customers can share logs without leaking private information.

**To view Jupyter logs for a notebook instance:**

2. Choose Notebook instances.
3. In the list of notebook instances, choose the notebook instance for which you want to view Jupyter logs by selecting the Notebook instance Name.
   
   This will bring you to the details page for that notebook instance.
4. Under Monitor on the notebook instance details page, choose View logs.
5. In the CloudWatch console, choose the log stream for your notebook instance. Its name is in the form NotebookInstanceName/jupyter.log.

For more information about monitoring CloudWatch logs for SageMaker, see Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675).
Automate model development with Amazon SageMaker Autopilot

Amazon SageMaker Autopilot is a feature-set that automates key tasks of an automatic machine learning (AutoML) process. It explores your data, selects the algorithms relevant to your problem type, and prepares the data to facilitate model training and tuning. Autopilot applies a cross-validation resampling procedure automatically to all candidate algorithms when appropriate to test their ability to predict data they have not been trained on. It also produces metrics to assess the predictive quality of its machine learning model candidates. It simplifies your machine learning experience by automating these key tasks that constitute an AutoML process. It ranks all of the optimized models tested by their performance. It finds the best performing model that you can deploy at a fraction of the time normally required.

You can use Autopilot in different ways: on autopilot (hence the name) or with various degrees of human guidance, without code through Amazon SageMaker Studio, or with code using one of the AWS SDKs. Autopilot currently supports regression and binary and multiclass classification problem types. It supports tabular data formatted as CSV or Parquet files in which each column contains a feature with a specific data type and each row contains an observation. The column data types accepted include numerical, categorical, text, and time series that consists of strings of comma-separate numbers. Autopilot supports building machine learning models on large datasets up to hundreds of GBs.

Autopilot also helps explain how models make predictions using a feature attribution approach developed for Amazon SageMaker Clarify. Autopilot automatically generates a report that indicates the importance of each feature for the predictions made by the best candidate. This explainability functionality can make machine learning models more understandable to AWS customers. The model governance report generated can be used to inform risk and compliance teams and external regulators.

You get full visibility into how the data was wrangled and how the models were selected, trained, and tuned for each of the candidates tested. This is provided by notebooks that Autopilot generates for each trial that contains the code used to explore the data and find the best candidate. The notebooks also provide educational tools to help you learn about and conduct your own ML experiments. You can learn about the impact of various inputs and trade-offs made in experiments by examining the various data exploration and candidate definition notebooks exposed by Autopilot. You can also conduct further experiments on the higher performing candidates by making your own modifications to the notebooks and rerunning them.

The following graphic outlines the principal tasks of an AutoML process managed by Autopilot.

With Amazon SageMaker, you pay only for what you use. You pay for the underlying compute and storage resources within SageMaker or other AWS services, based on your usage. For more information about the cost of using SageMaker, see Amazon SageMaker Pricing.

Topics
- Get started with Amazon SageMaker Autopilot (p. 319)
- Create an Amazon SageMaker Autopilot experiment (p. 321)
- Amazon SageMaker Autopilot datasets and problem types (p. 323)
• Training modes and algorithm support (p. 325)
• Metrics and validation (p. 327)
• Amazon SageMaker Autopilot model deployment and prediction (p. 332)
• Amazon SageMaker Autopilot explainability (p. 344)
• Models generated by Amazon SageMaker Autopilot (p. 344)
• Amazon SageMaker Autopilot notebooks generated to manage AutoML tasks (p. 345)
• Configure inference output in generated containers (p. 359)
• Amazon SageMaker Autopilot quotas (p. 364)
• API reference guide for Amazon SageMaker Autopilot (p. 366)

Get started with Amazon SageMaker Autopilot

Amazon SageMaker Autopilot provides samples, videos, and tutorials to get started with Amazon SageMaker Autopilot

Topics
• Samples: Explore modeling with Amazon SageMaker Autopilot (p. 319)
• Videos: Use Autopilot to automate and explore the machine learning process (p. 320)
• Tutorials: Get started with Amazon SageMaker Autopilot (p. 321)

Samples: Explore modeling with Amazon SageMaker Autopilot

Amazon SageMaker Autopilot provides the following sample notebooks.

• Direct marketing with Amazon SageMaker Autopilot: This notebook demonstrates how uses the Bank Marketing Data Set to predict whether a customer will enroll for a term deposit at a bank. You can use Autopilot on this dataset to get the most accurate ML pipeline by exploring options contained in various candidate pipelines. Autopilot generates each candidate in a two-step procedure. The first step performs automated feature engineering on the dataset. The second step trains and tunes an algorithm to produce a model. The notebook contains instructions on how to train the model and how to deploy the model to perform batch inference using the best candidate.

• Customer Churn Prediction with Amazon SageMaker Autopilot: This notebook describes using machine learning for the automated identification of unhappy customers, also known as customer churn prediction. The sample shows how to analyze a publicly available dataset and perform feature engineering on it. Next it shows how to tune a model by selecting the best performing pipeline along with the optimal hyperparameters for the training algorithm. Finally, it shows how to deploy the model to a hosted endpoint and how to evaluate its predictions against ground truth. However, ML models rarely give perfect predictions. That's why this notebook also shows how to incorporate the relative costs of prediction mistakes when determining the financial outcome of using ML.

• Top Candidates Customer Churn Prediction with Amazon SageMaker Autopilot and Batch Transform (Python SDK): This notebook also describes using machine learning for the automated identification of unhappy customers, also known as customer churn prediction. This notebook demonstrates how to configure the model to obtain the inference probability, select the top N models, and make Batch Transform on a hold-out test set for evaluation.

  Note
  This notebook works with SageMaker Python SDK >= 1.65.1 released on 6/19/2020.

• Bringing your own data processing code to Amazon SageMaker Autopilot: This notebook demonstrates how to incorporate and deploy custom data processing code when using Amazon SageMaker Autopilot. It adds a custom feature selection step to remove irrelevant variables to an Autopilot job. It
then shows how to deploy both the custom processing code and models generated by Autopilot on a real-time endpoint and, alternatively, for batch processing.

Videos: Use Autopilot to automate and explore the machine learning process

Here is a video series that provides a tour of Amazon SageMaker Autopilot capabilities using Studio. They show how to start an AutoML job, analyze and preprocess data, how to do feature engineering and hyperparameter optimization on candidate models, and how to visualize and compare the resulting model metrics.

Topics
- Start an AutoML job with Amazon SageMaker Autopilot (p. 320)
- Review data exploration and feature engineering automated in Autopilot. (p. 320)
- Tune models to optimize performance (p. 320)
- Choose and deploy the best model (p. 320)
- Amazon SageMaker Autopilot tutorial (p. 320)

Start an AutoML job with Amazon SageMaker Autopilot

This video shows you to how to start an AutoML job with Autopilot. (Length: 8:41)

Amazon SageMaker Studio - AutoML with Amazon SageMaker Autopilot (part 1)

Review data exploration and feature engineering automated in Autopilot.

This video shows you how to review the data exploration and candidate definition notebooks generated by Amazon SageMaker Autopilot. (Length: 10:04)

Amazon SageMaker Studio - AutoML with Amazon SageMaker Autopilot (part 2)

Tune models to optimize performance

This video shows you how to optimize model performance during training using hyperparameter tuning. (Length: 4:59)

SageMaker Studio - AutoML with Amazon SageMaker Autopilot (part 3)

Choose and deploy the best model

This video shows you how to use job metrics to choose the best model and then how to deploy it. (Length: 5:20)

SageMaker Studio - AutoML with Amazon SageMaker Autopilot (part 4)

Amazon SageMaker Autopilot tutorial

This video walks you through an end to end demo where we first build a binary classification model automatically with Amazon SageMaker Autopilot. We see how candidate models have been built and optimized using auto-generated notebooks. We also look at the top candidates with Amazon SageMaker Experiments. Finally, we deploy the top candidate (based on XGBoost), and configure data capture with SageMaker Model Monitor.
End to end demo with AutoML on SageMaker

Tutorials: Get started with Amazon SageMaker Autopilot

Get started tutorials for Autopilot demonstrate how to create a machine learning model automatically without writing code. They show you how Autopilot simplifies the machine learning experience by helping you explore your data and try different algorithms. Autopilot builds the best machine learning model for the problem type using AutoML capabilities while allowing full control and visibility.

- Create a machine learning model automatically with Autopilot: You assume the role of a developer working at a bank in this tutorial. You have been asked to develop a machine learning model to predict if a customer will enroll for a certificate of deposit (CD). This is a binary classification problem. The model is trained on the marketing dataset that contains information on customer demographics, responses to marketing events, and external factors.

Create an Amazon SageMaker Autopilot experiment

This guide shows how to create an Amazon SageMaker Autopilot experiment, so that you can analyze data, and create a notebook with candidate model definitions. This can help you get started with machine learning quickly.

You can use a user interface (UI) to help you populate the input, output, target, and parameters to run and evaluate an Autopilot experiment. The UI has descriptions, toggle switches, drop down menus, radio buttons and more to help you navigate creating your model. You can also view statistics while the experiment is running. After it runs, you can compare trials and delve into the details.

The following instructions show how to create an Amazon SageMaker Autopilot job as a pilot experiment. You will name your experiment, provide locations for the input and output data, and specify which target data to predict. Optionally, you can also specify the type of machine learning problem that you want to solve.

To create an Autopilot experiment

2. When the SageMaker Studio console opens, choose the Launch SageMaker Studio button.
3. Next, select Launch app in the row containing your user name, and choose Studio from the dropdown list.
4. Select the Build models automatically center card from the Studio launcher tab. See the quick setup guide for more information about starting Studio for the first time.
5. A page titled Create an Autopilot experiment opens. The page includes fields for Experiment and data details such as name, Amazon S3 bucket location, split ratio, and target of the experiment.
6. In the Experiment and data details section of the Create an Autopilot experiment page, enter the following information:
   a. Experiment name – Must be unique to your account in the current AWS Region and contain a maximum of 63 alphanumeric characters. Can include hyphens (-) but not spaces.
   b. Input data – Provide the S3 bucket location of your input data. This S3 bucket must be in your current AWS Region. The URL must be in an s3:// format where Amazon SageMaker has write permissions. The file must be in CSV or parquet format and contain at least 500 rows. Select Browse to scroll through available paths and Preview to see a sample of your input data.
c. **Is your S3 input a manifest file?** – A manifest file includes metadata with your input data. The metadata specifies the location of your data in Amazon Simple Storage Service (Amazon S3). It also specifies how the data is formatted and which attributes from the dataset to use when training your model. You can use a manifest file as an alternative to preprocessing when your labeled data is being streamed in *Pipe* mode.

d. **Auto split data?** – Autopilot can split your data into an 80-20% split for training and validation data. If you prefer a custom split, you can choose the **Specify split ratio**. To use a custom dataset for validation, choose **Provide a validation set**.

e. **Output data location (S3 bucket)** – The name of the S3 bucket location where you want to store the output data. The URL for this bucket must be in an Amazon S3 format where Amazon SageMaker has write permissions. The S3 bucket must be in the current AWS Region. Autopilot can also create this for you in the same location as your input data.

7. Select **Next: Target and features**. The **Target and features** tab opens.

8. In the **Target and features** section, select a column to set as a target for model predictions. You can also select features for training and change their data type. The following data types are available: Text, Numerical, Categorical, Datetime, Sequence and Auto. All features are selected by default.


10. In the **Training method** section, select from the following training options: **Ensembling**, **Hyperparameter optimization (HPO)**, or let Autopilot choose it automatically based on the dataset size.

    For more information about these training modes, see the **Autopilot training modes** section in the **Training modes and algorithms** page.

11. Select **Next: Deployment and advanced settings** to open the **Deployment and advanced settings**. Settings include auto display endpoint name, machine learning problem type, and choices for running your experiment.

12. Currently, you are required to have at least two ml.m5.2xlarge instances.

    Automatic deployment will fail for either of these reasons:
    
    - The default resource quota for endpoint instances in a Region exceeds the limit.
    - The customer quota for endpoint instances in a Region exceeds the limit.

    If you encounter a failure related to quotas, you can request a service limit increase for SageMaker endpoint instances.

13. **Deployment settings** – Autopilot can automatically create an endpoint and deploy your model for you.

    a. To auto deploy to an automatically generated endpoint, or to provide an endpoint name for custom deployment, set the toggle to **Yes** under **Auto deploy?** If you are importing data from Amazon SageMaker Data Wrangler, you have additional options to auto deploy the best model with or without the transforms from Data Wrangler.

    **Note**
    
    If your Data Wrangler flow contains multi-row operations such as groupby, join or concatenate, you won't be able to auto deploy with these transforms. For more information see **Automatically Train Models on Your Data Flow**.

    b. **Advanced settings (optional)** – Autopilot provides additional controls to manually set experimental parameters.

    i. **Machine learning problem type** – Autopilot can automatically select the machine learning problem type. If you prefer to choose it manually, use the **Select the machine learning problem type** dropdown menu.
A. **Auto** – Autopilot infers the problem type from the values of the attribute that you want to predict. In some cases, SageMaker is unable to infer accurately. When that happens, you must provide the value for the job to succeed.

B. **Binary classification** – Binary classification is a type of supervised learning that assigns an individual to one of two predefined and mutually exclusive classes, based on their attributes. For example, medical diagnosis based on results of diagnostic tests that determine if someone has a disease.

C. **Regression** – Regression estimates the values of a dependent target variable based on one or more variables or attributes that are correlated with it. For example, house prices based on features, such as square footage and number of bathrooms.

D. **Multiclass classification** – Multiclass classification is a type of supervised learning that assigns an individual to one of several classes based on their attributes. For example, the prediction of the topic most relevant to a text document, such as politics, finance, or philosophy.

ii. Select **Next: Review and create** to get a summary of your Autopilot experiment before you create it.

14. Select **Create experiment**. Autopilot provides status on the course of the experiment, a list of generated models, and the job profile used to create them.

**Note**

To avoid incurring unnecessary charges: If you deploy a model that is no longer needed, delete the endpoints and resources that were created during that deployment. Information about pricing instances by Region is available at [Amazon SageMaker Pricing](#).

---

**Amazon SageMaker Autopilot datasets and problem types**

Amazon SageMaker Autopilot gives you the option in Studio or with the AutoML API of specifying a problem type, such as binary classification or regression, or of detecting it on your behalf based on the data you provide. Autopilot supports tabular data in which each column contains a feature with a specific data type and each row contains an observation.

**Topics**

- Autopilot datasets, data types, and formats (p. 323)
- How to specify training and validation datasets (p. 324)
- How to select features for training (p. 324)
- Amazon SageMaker Autopilot problem types (p. 325)

**Autopilot datasets, data types, and formats**

Autopilot supports tabular data formatted as CSV files or as Parquet files. For tabular data, each column contains a feature with a specific data type and each row contains an observation. The properties of these two file formats differ considerably.

- **CSV** (comma-separated-values) is a row-based file format that stores data in human readable plaintext which a popular choice for data exchange as they are supported by a wide range of applications.
- **Parquet** is a column-based file format where the data is stored and processed more efficiently than row-based file formats. This makes them a better option for big data problems.
The **data types** accepted for columns include numerical, categorical, text, and time series that consists of strings of comma-separate numbers. If Autopilot detects it is dealing with **time series** sequences, it processes them through specialized feature transformers provided by the `tsfresh` library. This library takes the time series as an input and outputs a feature such as the highest absolute value of the time series or descriptive statistics on autocorrelation. These outputted features are then used as inputs to one of the three problem types.

Autopilot supports building machine learning models on large datasets up to hundreds of GBs. For details on the default resource limits for input datasets and how to increase them, see Amazon SageMaker Autopilot quotas (p. 364)

### How to specify training and validation datasets

When using `CreateAutoMLJob` to create an AutoML job, you must use the `InputDataConfig` parameter to specify the `AutoMLChannel` objects that provide input data sources. Each `AutoMLChannel` has a `ChannelType`, which can be set to either `training` or `validation` values that specify how the data is to be used when building a machine learning model. At least one data source must be provided and a maximum of two data sources is allowed: one for training data and one for validation data.

How you split the data into training and validation datasets depends on whether you have one or two data sources.

- **If you only have one data source**, the `ChannelType` is set to `training` by default and must have this value.
  - If the `ValidationFraction` value in `AutoMLDataSplitConfig` is not set, 0.2 (20%) of the data from this source is used for validation by default.
  - If the `ValidationFraction` is set to a value between 0 and 1, the dataset is split based on the value specified, where the value specifies the fraction of the dataset used for validation.
- **If you have two data sources**, the `ChannelType` of one of the `AutoMLChannel` objects must be set to `training`, the default value. The `ChannelType` of the other data source must be set to `validation`. The two data sources must have the same format, either CSV or Parquet, and the same schema. You must not set the value for the `ValidationFraction` in this case because all of the data from each source is used for either training or validation. Setting this value will cause an error.

### How to select features for training

You can manually select the features to be used in training with the `FeatureSpecificiationS3Uri` attribute of `AutoMLCandidateGenerationConfig` within the `CreateAutoMLJob` API with the following format.

```json
{
    "AutoMLJobConfig": {
        "CandidateGenerationConfig": {
            "FeatureSpecificiationS3Uri": "string"
        }
    }
}
```

Selected features should be contained within a JSON file in the following format:

```json
[ "FeatureAttributeNames": ["col1", "col2", ...] ]
```

The values listed in ["col1", "col2", ...] are case sensitive. They should be a list of strings containing unique values that are subsets of the column names in the input data.
Note
The list of columns provided as features cannot include the target column.

Amazon SageMaker Autopilot problem types

You set the type of problem with the `CreateAutoPilot.ProblemType` parameter. This limits the kind of preprocessing and algorithms that Autopilot tries. After the job is finished, if you had set the `CreateAutoPilot.ProblemType`, then the `ResolvedAttribute.ProblemType` will match the `ProblemType` you set. If you keep it blank (or null), the `ProblemType` will be whatever Autopilot decides on your behalf.

Note
In some cases, Autopilot is unable to infer the `ProblemType` with high enough confidence, in which case you must provide the value for the job to succeed.

Your problem type options are as follows:

Regression

Regression estimates the values of a dependent target variable based on one or more other variables or attributes that are correlated with it. An example is the prediction of house prices using features like the number of bathrooms and bedrooms, square footage of the house and garden. Regression analysis can create a model that takes one or more of these features as an input and predicts the price of a house.

Binary classification

Binary classification is a type of supervised learning that assigns an individual to one of two predefined and mutually exclusive classes based on their attributes. It is supervised because the models are trained using examples where the attributes are provided with correctly labelled objects. A medical diagnosis for whether an individual has a disease or not based on the results of diagnostic tests is an example of binary classification.

Multiclass classification

Multiclass classification is a type of supervised learning that assigns an individual to one of several classes based on their attributes. It is supervised because the models are trained using examples where the attributes are provided with correctly labelled objects. An example is the prediction of the topic most relevant to a text document. A document may be classified as being about, say, religion or politics or finance, or about one of several other predefined topic classes.

Training modes and algorithm support

Amazon SageMaker Autopilot supports different training modes and algorithms to address machine learning problems, report on quality and objective metrics, and to use cross-validation automatically, when needed.

Training modes

SageMaker Autopilot can automatically select the training method based on the dataset size, or you can select it manually. The choices are as follows:

- **Ensembling** – Autopilot uses the AutoGluon library to train several base models. To find the best combination for your dataset, ensemble mode runs 10 trials with different model and meta parameter
settings. Then Autopilot combines these models using a stacking ensemble method to create an optimal predictive model. For a list of algorithms that Autopilot supports in ensembling mode, see the following Algorithm support section.

- **Hyperparameter optimization (HPO)** – Autopilot finds the best version of a model by tuning hyperparameters using Bayesian optimization or multi-fidelity optimization while running training jobs on your dataset. HPO mode selects the algorithms that are most relevant to your dataset and selects the best range of hyperparameters to tune your models. To tune your models, HPO mode runs up to 100 trials (default) to find the optimal hyperparameters settings within the selected range. If your dataset size is less than 100 MB, Autopilot uses Bayesian optimization. Autopilot chooses multi-fidelity optimization if your dataset is larger than 100 MB.

In multi-fidelity optimization, metrics are continuously emitted from the training containers. A trial that is performing poorly against a selected objective metric is stopped early. A trial that is performing well is allocated more resources.

For a list of algorithms that Autopilot supports in HPO mode, see the following Algorithm support section.

- **Auto** – Autopilot automatically chooses either ensembling mode or HPO mode based on your dataset size. If your dataset is larger than 100 MB, Autopilot chooses HPO. Otherwise, it chooses ensembling mode. Autopilot can fail to read the size of your dataset in the following cases.
  - If you enable Virtual Private Cloud (VPC) mode, for an AutoML job but the S3 bucket containing the dataset only allows access from the VPC.
  - The input S3DataType of your dataset is a ManifestFile.
  - The input S3Uri contains more than 1000 items.

If Autopilot is unable to read your dataset size, it defaults to choosing HPO mode.

**Note**
For optimal runtime and performance, use ensemble training mode for datasets that are smaller than 100 MB.

## Algorithm support

In **HPO mode**, Autopilot supports the following types of machine learning algorithms:

- **Linear learner** – A supervised learning algorithm that can solve either classification or regression problems.
- **XGBoost** – A supervised learning algorithm that attempts to accurately predict a target variable by combining an ensemble of estimates from a set of simpler and weaker models.
- **Deep learning algorithm** – A multilayer perceptron (MLP) and feedforward artificial neural network. This algorithm can handle data that is not linearly separable.

**Note**
You don’t need to specify an algorithm to use for your machine learning problem. Autopilot automatically selects the appropriate algorithm to train.

In **ensembling mode**, the following are types of machine learning algorithms that Autopilot supports:

- **LightGBM** – An optimized framework that uses tree-based algorithms with gradient boosting. This algorithm uses trees that grow in breadth, rather than depth, and is highly optimized for speed.
- **CatBoost** – A framework that uses tree-based algorithms with gradient boosting. Optimized for handling categorical variables.
- **XGBoost** – A framework that uses tree-based algorithms with gradient boosting that grows in depth, rather than breadth.
• Random Forest – A tree-based algorithm that uses several decision trees on random sub-samples of the data with replacement. The trees are split into optimal nodes at each level. The decisions of each tree are averaged together to prevent overfitting and improve predictions.

• Extra Trees – A tree-based algorithm that uses several decision trees on the entire dataset. The trees are split randomly at each level. The decisions of each tree are averaged to prevent overfitting and to improve predictions. Extra trees add a degree of randomization in comparison to the random forest algorithm.

• Linear Models – A framework that uses a linear equation to model the relationship between two variables in observed data.

• Neural network torch – A neural network model that's implemented using Pytorch.

• Neural network fast.ai – A neural network model that's implemented using fast.ai.

Metrics and validation

This guide shows metrics and validation techniques that you can use to measure machine learning model performance. Amazon SageMaker Autopilot produces metrics that measure the predictive quality of machine learning model candidates. The metrics calculated for candidates are specified using an array of MetricDatum types.

Autopilot Metrics

The following list contains the names of the metrics that are currently available to measure model performance within Autopilot.

Accuracy

The ratio of the number of correctly classified items to the total number of (correctly and incorrectly) classified items. It is used for both binary and multiclass classification. Accuracy measures how close the predicted class values are to the actual values. Values for accuracy metrics vary between zero (0) and one (1). A value of 1 indicates perfect accuracy, and 0 indicates perfect inaccuracy.

AUC

The area under the curve (AUC) metric is used to compare and evaluate binary classification by algorithms that return probabilities, such as logistic regression. To map the probabilities into classifications, these are compared against a threshold value.

The relevant curve is the receiver operating characteristic curve (ROC curve). The ROC curve plots the true positive rate (TPR) of predictions (or recall) against the false positive rate (FPR) as a function of the threshold value, above which a prediction is considered positive. Increasing the threshold results in fewer false positives, but more false negatives.

AUC is the area under this ROC curve. Therefore, AUC provides an aggregated measure of the model performance across all possible classification thresholds. AUC scores vary between 0 and 1. A score of 1 indicates perfect accuracy, and a score of one half (0.5) indicates that the prediction is not better than a random classifier.

BalancedAccuracy

BalancedAccuracy is a metric that measures the ratio of accurate predictions to all predictions. This ratio is calculated after normalizing true positives (TP) and true negatives (TN) by the total number of positive (P) and negative (N) values. It is used in both binary and multiclass classification and is defined as follows: 0.5*((TP/P)+(TN/N)), with values ranging from 0 to 1. BalancedAccuracy
gives a better measure of accuracy when the number of positives or negatives differ greatly from each other in an imbalanced dataset. For example, when only 1% of email is spam.

**F1**

The F1 score is the harmonic mean of the precision and recall, defined as follows: $F1 = 2 \times (\text{precision} \times \text{recall}) / (\text{precision} + \text{recall})$. It is used for binary classification into classes traditionally referred to as positive and negative. Predictions are said to be true when they match their actual (correct) class, and false when they do not.

Precision is the ratio of the true positive predictions to all positive predictions, and it includes the false positives in a dataset. Precision measures the quality of the prediction when it predicts the positive class.

Recall (or sensitivity) is the ratio of the true positive predictions to all actual positive instances. Recall measures how completely a model predicts the actual class members in a dataset.

F1 scores vary between 0 and 1. A score of 1 indicates the best possible performance, and 0 indicates the worst.

**F1macro**

The F1macro score applies F1 scoring to multiclass classification problems. It does this by calculating the precision and recall, and then taking their harmonic mean to calculate the F1 score for each class. Lastly, the F1macro averages the individual scores to obtain the F1macro score. F1macro scores vary between 0 and 1. A score of 1 indicates the best possible performance, and 0 indicates the worst.

**LogLoss**

Log loss, also known as cross-entropy loss, is a metric used to evaluate the quality of the probability outputs, rather than the outputs themselves. It is used in both binary and multiclass classification, neural nets, and is also the cost function for logistic regression. Log loss is an important metric to indicate when a model makes incorrect predictions with high probabilities. Values range from 0 to infinity. A value of 0 represents a model that perfectly predicts the data.

**MAE**

The mean absolute error (MAE) is a measure of how different the predicted and actual values are, when they're averaged over all values. MAE is commonly used in regression analysis to understand model prediction error. If there is linear regression, MAE represents the average distance from a predicted line to the actual value. MAE is defined as the sum of absolute errors divided by the number of observations. Values range from 0 to infinity, with smaller numbers indicating a better model fit to the data.

**MSE**

The mean squared error (MSE) is the average of the squared differences between the predicted and actual values. It is used for regression. MSE values are always positive. The better a model is at predicting the actual values, the smaller the MSE value is.

**Precision**

Precision measures how well an algorithm predicts the true positives (TP) out of all of the positives that it identifies. It is defined as follows: Precision = TP/(TP+FP), with values ranging from zero (0) to one (1), and is used in binary classification. Precision is an important metric when the cost of a false positive is high. For example, the cost of a false positive is very high if an airplane safety system is falsely deemed safe to fly. A false positive (FP) reflects a positive prediction that is actually negative in the data.

**PrecisionMacro**

The precision macro computes precision for multiclass classification problems. It does this by calculating precision for each class and averaging scores to obtain precision for several classes.
PrecisionMacro scores range from zero (0) to one (1). Higher scores reflect the model's ability to predict true positives (TP) out of all of the positives that it identifies, averaged across multiple classes.

**R2**

R², also known as the coefficient of determination, is used in regression to quantify how much a model can explain the variance of a dependent variable. Values range from one (1) to negative one (-1). Higher numbers indicate a higher fraction of explained variability. R2 values close to zero (0) indicate that very little of the dependent variable can be explained by the model. Negative values indicate a poor fit and that the model is outperformed by a constant function. For linear regression, this is a horizontal line.

**Recall**

Recall measures how well an algorithm correctly predicts all of the true positives (TP) in a dataset. A true positive is a positive prediction that is also an actual positive value in the data. Recall is defined as follows: \( \text{Recall} = \frac{TP}{TP+FN} \), with values ranging from 0 to 1. Higher scores reflect a better ability of the model to predict true positives (TP) in the data, and is used in binary classification.

Recall is important when testing for cancer because it's used to find all of the true positives. A false positive (FP) reflects a positive prediction that is actually negative in the data. It is often insufficient to measure only recall, because predicting every output as a true positive will yield a perfect recall score.

**RecallMacro**

The RecallMacro computes recall for multiclass classification problems by calculating recall for each class and averaging scores to obtain recall for several classes. RecallMacro scores range from 0 to 1. Higher scores reflect the model's ability to predict true positives (TP) in a dataset. Whereas, a true positive reflects a positive prediction that is also an actual positive value in the data. It is often insufficient to measure only recall, because predicting every output as a true positive will yield a perfect recall score.

**RMSE**

Root mean squared error (RMSE) measures the square root of the squared difference between predicted and actual values, and it's averaged over all values. It is used in regression analysis to understand model prediction error. It's an important metric to indicate the presence of large model errors and outliers. Values range from zero (0) to infinity, with smaller numbers indicating a better model fit to the data. RMSE is dependent on scale, and should not be used to compare datasets of different sizes.

Metrics that are automatically calculated for a candidate model are determined by the type of problem being addressed.

- **Regression**: MAE, MSE, R2, RMSE
- **Binary classification**: Accuracy, AUC, BalancedAccuracy, F1, LogLoss, Precision, Recall
- **Multiclass classification**: Accuracy, BalancedAccuracy, F1macro, LogLoss, PrecisionMacro, RecallMacro

**Cross-validation in Autopilot**

Cross-validation is used in to reduce overfitting and bias in model selection. It is also used to assess how well a model can predict the values of an unseen validation dataset, if the validation dataset is drawn from the same population. This method is especially important when training on datasets that have a limited number of training instances.
Autopilot uses cross-validation to build models in hyperparameter optimization (HPO) and ensemble training mode. The first step in the Autopilot cross-validation process is to split the data into k-folds.

**K-fold splitting**

K-fold splitting is a method that separates an input training dataset into multiple training and validation datasets. The dataset is split into \( k \) equally-sized sub-samples called folds. Models are then trained on \( k-1 \) folds and tested against the remaining \( k^{\text{th}} \) fold, which is the validation dataset. The process is repeated \( k \) times using a different data set for validation.

The following image depicts k-fold splitting with \( k = 4 \) folds. Each fold is represented as a row. The dark-toned boxes represent the parts of the data used in training. The remaining light-toned boxes indicate the validation datasets.

![4-fold splitting](image)

Autopilot uses k-fold cross-validation for both hyperparameter optimization (HPO) mode and ensembling mode.

You can deploy Autopilot models that are built using cross-validation like you would with any other Autopilot or SageMaker model.

**HPO mode**

K-fold cross-validation uses the k-fold splitting method for cross-validation. In HPO mode, Autopilot automatically implements k-fold cross-validation for small datasets with 50,000 or fewer training instances. Performing cross-validation is especially important when training on small datasets because it protects against overfitting and selection bias.

HPO mode uses a \( k \) value of 5 on each of the candidate algorithms that are used to model the dataset. Multiple models are trained on different splits, and the models are stored separately. When training is complete, validation metrics for each of the models are averaged to produce a single estimation metric. Lastly, Autopilot combines the models from the trial with the best validation metric into an ensemble model. Autopilot uses this ensemble model to make predictions.

The validation metric for the models trained by Autopilot is presented as the objective metric in the model leaderboard. Autopilot uses the default validation metric for each problem type that it handles, unless you specify otherwise. For more information about the metrics that Autopilot uses, see [AutoMLJobObjective](#).

For example, the Boston Housing dataset contains only 861 samples. If you build a model to predict house sale prices using this dataset without cross-validation, you risk training on a dataset that is not representative of the Boston housing stock. If you split the data only once into training and validation subsets, the training fold may only contain data mainly from the suburbs. As a result, you would train on data that isn't representative of the rest of the city. In this example, your model would likely overfit on
Cross-validation in Autopilot

this biased selection. K-fold cross-validation can reduce the risk of this kind of error by making full and randomized use of the available data for both training and validation.

Cross-validation can increase training times by an average of 20%. Training times may also increase significantly for complex datasets.

**Note**

In HPO mode, you can see the training and validation metrics from each fold in your /aws/sagemaker/TrainingJobs CloudWatch Logs. For more information about CloudWatch Logs, see *Log Amazon SageMaker Events with Amazon CloudWatch* (p. 3675).

**Ensembling mode**

In ensemble mode, cross-validation is performed regardless of dataset size. Customers can either provide their own validation dataset and custom data split ratio, or let Autopilot split the dataset automatically into an 80-20% split ratio. The training data is then split into k-folds for cross-validation, where the value of k is determined by the AutoGluon engine. An ensemble consists of multiple machine learning models, where each model is known as the base model. A single base model is trained on (k-1) folds and makes out-of-fold predictions on the remaining fold. This process is repeated for all k folds, and the out-of-fold (OOF) predictions are concatenated to form a single set of predictions. All base models in the ensemble follow this same process of generating OOF predictions.

The following image depicts k-fold validation with k = 4 folds. Each fold is represented as a row. The dark-toned boxes represent the parts of the data used in training. The remaining light-toned boxes indicate the validation datasets.

In the upper part of the image, in each fold, the first base model makes predictions on the validation dataset after training on the training datasets. At each subsequent fold, the datasets change roles. A dataset that was previously used for training is now used for validation, and this also applies in reverse. At the end of k folds, all of the predictions are concatenated to form a single set of predictions called an out-of-fold (OOF) prediction. This process is repeated for each n base models.

The OOF predictions for each base model are then used as features to train a stacking model. The stacking model learns the importance weights for each base model. These weights are used to combine the OOF predictions to form the final prediction. Performance on the validation dataset determines which base or stacking model is the best, and this model is returned as the final model.

In ensemble mode, you can either provide your own validation dataset or let Autopilot split the input dataset automatically into 80% train and 20% validation datasets. The training data is then split into k-folds for cross-validation and produces an OOF prediction and a base model for each fold.

These OOF predictions are used as features to train a stacking model, which simultaneously learns weights for each base model. These weights are used to combine the OOF predictions to form the final prediction. The validation datasets for each fold are used for hyperparameter tuning of all base models and the stacking model. Performance on the validation datasets determines which base or stacking model is the best model, and this model is returned as the final model.
Amazon SageMaker Autopilot model deployment and prediction

This Amazon SageMaker Autopilot guide includes steps for model deployment, setting up real-time inference, and running inference with batch jobs.

After you train your SageMaker Autopilot models, you can deploy them to get predictions in one of two ways:

1. Use Real-time inferencing (p. 332) to set up an endpoint and obtain predictions interactively.
2. Use Batch inferencing (p. 339) to make predictions in parallel on batches of observations on an entire dataset.

Note
To avoid incurring unnecessary charges: After the endpoints and resources that were created from model deployment are longer needed, you can delete them. For information about pricing of instances by Region, see Amazon SageMaker Pricing.

Real-time inferencing

Real-time inference is ideal for inference workloads where you have real-time, interactive, low latency requirements. This section shows how you can use real-time inferencing to obtain predictions interactively from your model.

To deploy the model that produced the best validation metric in an Autopilot experiment, you have several options. For example, when using Autopilot in SageMaker Studio, you can deploy the model automatically or manually. You can also use SageMaker APIs to manually deploy an Autopilot model.

The following tabs show three options for deploying your model. To see the code examples for each option, open each tab.

Deploy using the Autopilot User Interface (UI)

The Autopilot UI contains helpful dropdown menus, toggles, tooltips, and more to help you navigate through model deployment.

- **Automatically**: To automatically deploy the best model from an Autopilot experiment to an endpoint, toggle the Auto deploy value to Yes when creating the experiment in SageMaker Studio.

  Note
  Automatic deployment will fail if either the default resource quota or your customer quota for endpoint instances in a Region is too limited. In hyperparameter optimization (HPO) mode, you are required to have at least two ml.m5.2xlarge instances. In ensembling mode, you are required to have at least one ml.m5.12xlarge instance. If you encounter a failure related to quotas, you can request a service limit increase for SageMaker endpoint instances.

- **Manually**: To manually deploy the best model from an Autopilot experiment to an endpoint, toggle the Auto deploy value to No when creating the experiment in SageMaker Studio.

  After your Autopilot experiment has been created, select the model that you want to deploy under Model name. Then select the orange Deployment and advanced settings button located on the right of the leaderboard. This opens a new tab.

  Configure the endpoint name, instance type, and other optional information. Select the orange Deploy model to deploy to an endpoint.
Check the progress of the endpoint creation process in the https://console.aws.amazon.com/sagemaker/ by navigating to the Endpoints section. That section is located in the Inference dropdown menu in the navigation panel.

After the endpoint status changes from Creating to In Service, return to Studio and invoke the endpoint.

### Deploy using SageMaker APIs

You can also obtain real-time inference by deploying your model using API calls. This section shows the five general steps of this process using AWS Command Line Interface (AWS CLI) code snippets.

For complete code examples for both AWS CLI commands and AWS SDK for Python (Boto3), open the tabs directly following these steps.

1. **Obtain candidate definitions**

   Obtain the candidate container definitions from `InferenceContainers`. These candidate definitions are used to create a SageMaker model.

   The following example uses the `DescribeAutoMLJob` API to obtain candidate definitions for the best model candidate. See the following AWS CLI command as an example.

   ```bash
   aws sagemaker describe-auto-ml-job --auto-ml-job-name <job-name> --region <region>
   ```

2. **List candidates**

   The following example uses the `ListCandidatesForAutoMLJob` API to list all candidates. See the following AWS CLI command as an example.

   ```bash
   aws sagemaker list-candidates-for-auto-ml-job --auto-ml-job-name <job-name> --region <region>
   ```

3. **Create a SageMaker model**

   Use the container definitions from the previous steps to create a SageMaker model by using the `CreateModel` API. See the following AWS CLI command as an example.

   ```bash
   aws sagemaker create-model --model-name '<your-custom-model-name>'
   --containers [<container-definition1>, <container-definition2>, <container-definition3>]
   --execution-role-arn '<execution-role-arn>' --region '<region>'
   ```

4. **Create an endpoint configuration**

   The following example uses the `CreateEndpointConfig` API to create an endpoint configuration. See the following AWS CLI command as an example.

   ```bash
   aws sagemaker create-endpoint-config --endpoint-config-name '<your-custom-endpoint-config-name>'
   --production-variants '<list-of-production-variants>'
   ```
5. Create the endpoint

The following AWS CLI example uses the CreateEndpoint API to create the endpoint.

```
aws sagemaker create-endpoint --endpoint-name '<your-custom-endpoint-name>' \
    --endpoint-config-name '<endpoint-config-name-you-just-created>' \
    --region '<region>
```

Check the progress of your endpoint deployment by using the DescribeEndpoint API. See the following AWS CLI command as an example.

```
aws sagemaker describe-endpoint --endpoint-name '<endpoint-name>' --region '<region>
```

After the EndpointStatus changes to InService, the endpoint is ready to use for real-time inference.

6. Invoke the endpoint

The following command structure invokes the endpoint for real-time inferencing.

```
aws sagemaker invoke-endpoint --endpoint-name '<endpoint-name>' \
    --region '<region>' --body '<your-data>' [--content-type] '<content-type>' <outfile>
```

The following tabs contain complete code examples for deploying a model with AWS SDK for Python (Boto3) or the AWS CLI.

AWS SDK for Python (Boto3)

1. **Obtain the candidate definitions** by using the following code example.

```
import sagemaker
import boto3

session = sagemaker.session.Session()

sagemaker_client = boto3.client('sagemaker', region_name='us-west-2')
job_name = 'test-auto-ml-job'

describe_response = sm_client.describe_auto_ml_job(AutoMLJobName=job_name)
# extract the best candidate definition from DescribeAutoMLJob response
best_candidate = describe_response['BestCandidate']
# extract the InferenceContainers definition from the candidate definition
inference_containers = best_candidate['InferenceContainers']
```

2. **Create the model** by using the following the code example.

```
# Create Model
model_name = 'test-model'
sagemaker_role = 'arn:aws:iam::444455556666:role/sagemaker-execution-role'
create_model_response = sagemaker_client.create_model(
    ModelName = model_name,
    ExecutionRoleArn = sagemaker_role,
    Containers = inference_containers
)
```

3. **Create the endpoint configuration** by using the following the code example.
4. Create the endpoint and deploy the model with the following code example.

```python
# create endpoint and deploy the model
deployment_name = 'test-endpoint'
create_endpoint_response = sagemaker_client.create_endpoint(
    EndpointName=deployment_name,
    EndpointConfigName=endpoint_config_name)
print(create_endpoint_response)
```

Check the status of creating the endpoint by using the following the code example.

```python
# describe endpoint creation status
status = sagemaker_client.describe_endpoint(EndpointName=deployment_name)
status["EndpointStatus"]
```

5. Invoke the endpoint for real-time inferencing by using the following command structure.

```python
# once endpoint status is InService, you can invoke the endpoint for inferencing
if status == "InService":
    sm_runtime = boto3.Session().client('sagemaker-runtime')
    inference_result = sm_runtime.invoke_endpoint(EndpointName='test-endpoint',
                                                ContentType='text/csv', Body='1,2,3,4,class')
```

AWS Command Line Interface (AWS CLI)

1. Obtain the candidate definitions by using the following code example.

```bash
aws sagemaker describe-auto-ml-job --auto-ml-job-name 'test-automl-job' --region us-west-2
```

2. Create the model by using the following code example.

```bash
aws sagemaker create-model --model-name 'test-sagemaker-model'
```

```bash
--containers '{[""
```
Real-time inferencing

3. Create an endpoint configuration by using the following code example.

```bash
aws sagemaker create-endpoint-config --endpoint-config-name 'test-endpoint-config' \
--production-variants '[["VariantName": "variant1", 
  "ModelName": "test-sagemaker-model", 
  "InitialInstanceCount": 1, 
  "InstanceType": "ml.m5.2xlarge" 
  ]]' \
  --region us-west-2
```

The create endpoint configuration command will return a response in the following format.

```json
{
}
```
4. **Create an endpoint** by using the following code example.

```bash
aws sagemaker create-endpoint --endpoint-name 'test-endpoint' \
--endpoint-config-name 'test-endpoint-config' \
--region us-west-2
```

The `create_endpoint` command will return a response in the following format.

```json
{
}
```

Check the progress of the endpoint deployment by using the following `describe-endpoint` CLI code example.

```bash
aws sagemaker describe-endpoint --endpoint-name 'test-endpoint' --region us-west-2
```

The previous progress check will return a response in the following format.

```json
{
   "EndpointName": "test-endpoint",
   "EndpointConfigName": "test-endpoint-config",
   "EndpointStatus": "Creating",
   "CreationTime": 1660251167.595,
   "LastModifiedTime": 1660251167.595
}
```

After the `EndpointStatus` changes to `InService`, the endpoint is ready for use in real-time inference.

5. **Invoke the endpoint** for real-time inferencing by using the following command structure.

```bash
aws sagemaker-runtime invoke-endpoint --endpoint-name 'test-endpoint' \
--region 'us-west-2' \
--body '1,51,3.5,1.4,0.2' \
--content-type 'text/csv' \
/tmp/inference_output
```

For more options, see *invoking an endpoint*.

### Deploy models from different accounts

You can deploy an Autopilot model from a different account than the original account that a model was generated in. To implement cross-account model deployment, this section shows how to do the following:

1. **Grant permission to the deploying account**

   To assume the role in the generating account, you must grant permission to the deploying account. This allows the deploying account to describe Autopilot jobs in the generating account.

   The following example uses a generating account with a trusted `sagemaker-role` entity. The example shows how to give a deploying account with the ID `111122223333` permission to assume the role of the generating account.
"Statement": [
    {
        "Effect": "Allow",
        "Principal": {
            "Service": [
                "sagemaker.amazonaws.com"
            ],
            "AWS": [ "111122223333"
          ],
        "Action": "sts:AssumeRole"
    }

The new account with the ID 111122223333 can now assume the role for the generating account.

Next, call the DescribeAutoMLJob API from the deploying account to obtain a description of the job created by the generating account.

The following code example describes the model from the deploying account.

```python
import sagemaker
import boto3
session = sagemaker.session.Session()
sts_client = boto3.client('sts')
sts_client.assume_role

role = 'arn:aws:iam::111122223333:role/sagemaker-role'
role_session_name = 'role-session-name'
_assumed_role = sts_client.assume_role(RoleArn=role, RoleSessionName=role_session_name)
credentials = _assumed_role["Credentials"]
access_key = credentials["AccessKeyId"]
secret_key = credentials["SecretAccessKey"]
session_token = credentials["SessionToken"]

session = boto3.session.Session()

sm_client = session.client('sagemaker', region_name='us-west-2',
                           aws_access_key_id=access_key,
                           aws_secret_access_key=secret_key,
                           aws_session_token=session_token)

# now you can call describe automl job created in account A

job_name = "test-job"
response= sm_client.describe_auto_ml_job(AutoMLJobName=job_name)
```

2. **Grant access to the deploying account** to the model artifacts in the generating account.

The deploying account only needs access to the model artifacts in the generating account to deploy it. These are located in the **S3OutputPath** that was specified in the original CreateAutoMLJob API call during model generation.

To give the deploying account access to the model artifacts, choose one of the following options:

a. Give access to the ModelDataUrl from the generating account to the deploying account.

    Next, you need to give the deploying account permission to assume the role. follow the real-time inferencing steps to deploy.

b. Copy model artifacts from the generating account's original S3OutputPath to the generating account.
To grant access to the model artifacts, you must define a best_candidate model and reassign model containers to the new account.

The following example shows how to define a best_candidate model and reassign the ModelDataUrl.

```python
best_candidate = automl.describe_auto_ml_job()['BestCandidate']

# reassigning ModelDataUrl for best_candidate containers below
new_model_locations = ['new-container-1-ModelDataUrl', 'new-container-2-ModelDataUrl', 'new-container-3-ModelDataUrl']
new_model_locations_index = 0
for container in best_candidate['InferenceContainers']:
    container['ModelDataUrl'] = new_model_locations[new_model_locations_index++]
```

After this assignment of containers, follow the steps in Deploy using SageMaker APIs (p. 333) to deploy.

**Batch inferencing**

Batch inferencing, also known as offline inferencing, generates model predictions on a batch of observations. Batch inference is a good option if you don’t need an immediate response to a model prediction request.

Offline predictions are suitable for large datasets or when you need to wait a long time for a response. By contrast, online inference, or real-time inferencing, generates predictions in real time.

You can make batch inferences from an Autopilot model using the SageMaker Python SDK, the AWS SDK for Python (Boto3) or AWS CLI.

**Batch inferencing steps**

To use the SageMaker APIs for batch inferencing, there are three general steps:

1. **Obtain candidate definitions**

   Candidate definitions from InferenceContainers are used to create a SageMaker model.

   The following example shows how to use the DescribeAutoMLJob API to obtain candidate definitions for the best model candidate. See the following AWS CLI command as an example.

   ```bash
   aws sagemaker describe-auto-ml-job --auto-ml-job-name <job-name> --region <region>
   ```

   Use the ListCandidatesForAutoMLJob API to list all candidates. See the following AWS CLI command as an example.

   ```bash
   aws sagemaker list-candidates-for-auto-ml-job --auto-ml-job-name <job-name> --region <region>
   ```

2. **Create a SageMaker model**

   Use the container definitions from the previous steps to create a SageMaker model using the CreateModel API. See the following AWS CLI command as an example.

   ```bash
   aws sagemaker create-model --model-name '"<your-custom-model-name>"'
   ```
3. Create a SageMaker transform job

The following example creates a SageMaker transform job with the `CreateTransformJob` API. See the following AWS CLI command as an example.

```bash
aws sagemaker create-transform-job --transform-job-name '<your-custom-transform-job-name>' --model-name '<your-custom-model-name-from-last-step>'
  --transform-input '{
    "DataSource": {
      "S3DataSource": {
        "S3DataType": "S3Prefix",
        "S3Uri": "<your-input-data>"
      }
    },
    "ContentType": "text/csv",
    "SplitType": "Line"
  }
  --transform-output '{
    "S3OutputPath": "<your-output-path>",
    "AssembleWith": "Line"
  }
  --transform-resources '{
    "InstanceType": "<instance-type>",
    "InstanceCount": 1
  }' --region '<region>'
```

Check the progress of your transform job using the `DescribeTransformJob` API. See the following AWS CLI command as an example.

```bash
aws sagemaker describe-transform-job --transform-job-name '<your-custom-transform-job-name>' --region <region>
```

After the job is finished, the predicted result will be available in `<your-output-path>`.

The output file name has the following format: `<input_data_file_name>.out`. As an example, if your input file is `text_x.csv`, the output name will be `text_x.csv.out`.

The following tabs show code examples for SageMaker Python SDK, AWS SDK for Python (Boto3), and AWS CLI.

### SageMaker Python SDK

The following example uses the **SageMaker Python SDK** to make predictions in batches.

```python
from sagemaker import AutoML
sagemaker_session = sagemaker.session.Session()

job_name = 'test-auto-ml-job' # your autopilot job name
automl = AutoML.attach(auto_ml_job_name=job_name)
output_path = 's3://test-auto-ml-job/output'
input_data = 's3://test-auto-ml-job/test_X.csv'

# call DescribeAutoMLJob API to get the best candidate definition
best_candidate = automl.describe_auto_ml_job()['BestCandidate']
best_candidate_name = best_candidate['CandidateName']
```
# create model
model = automl.create_model(name=best_candidate_name,
                           candidate=best_candidate)

# create transformer
transformer = model.transformer(instance_count=1,
                                 instance_type='ml.m5.2xlarge',
                                 assemble_with='Line',
                                 output_path=output_path)

# do batch transform
transformer.transform(data=input_data,
                      split_type='Line',
                      content_type='text/csv',
                      wait=True)

AWS SDK for Python (Boto3)

The following example uses AWS SDK for Python (Boto3) to make predictions in batches.

```python
import sagemaker
import boto3

session = sagemaker.session.Session()

sm_client = boto3.client('sagemaker', region_name='us-west-2')
role = 'arn:aws:iam::1234567890:role/sagemaker-execution-role'
output_path = 's3://test-auto-ml-job/output'
input_data = 's3://test-auto-ml-job/test_X.csv'

best_candidate = sm_client.describe_auto_ml_job(AutoMLJobName=job_name)["BestCandidate"]
best_candidate_containers = best_candidate['InferenceContainers']
best_candidate_name = best_candidate['CandidateName']

# create model
response = sm_client.create_model(
    ModelName = best_candidate_name,
    ExecutionRoleArn = role,
    Containers = best_candidate_containers
)

# Launch Transform Job
response = sm_client.create_transform_job(
    TransformJobName=f'{best_candidate_name}-transform-job',
    ModelName=model_name,
    TransformInput={
        'DataSource': {
            'S3DataSource': {
                'S3DataType': 'S3Prefix',
                'S3Uri': input_data
            }
        },
        'ContentType': "text/csv",
        'SplitType': 'Line'
    },
    TransformOutput={
        'S3OutputPath': output_path,
        'AssembleWith': 'Line'
    },
    TransformResources={
        'InstanceType': 'ml.m5.2xlarge',
        'InstanceCount': 1
    }
)
The batch inference job returns a response in the following format.

```json
'ResponseMetadata': {
'RequestId': '659f97fc-28c4-400b-b957-a49733f7c2f2',
'HTTPStatusCode': 200,
'HTTPHeaders': {'x-amzn-requestid': '659f97fc-28c4-400b-b957-a49733f7c2f2',
'content-type': 'application/x-amz-json-1.1',
'content-length': '96',
'date': 'Thu, 11 Aug 2022 22:23:49 GMT'},
'RetryAttempts': 0}}
```

AWS Command Line Interface (AWS CLI)

1. **Obtain the candidate definitions** by using the following code example.

   ```bash
   aws sagemaker describe-auto-ml-job --auto-ml-job-name 'test-automl-job' --region us-west-2
   ```

2. **Create the model** by using the following code example.

   ```bash
   aws sagemaker create-model --model-name 'test-sagemaker-model' --containers ['{
    "Image": "348316444620.dkr.ecr.us-west-2.amazonaws.com/sagemaker-sklearn-automl:2.5-1-cpu-py3",
    "ModelDataUrl": "s3://test-bucket/out/test-job1/data-processor-models/test-job1-dpp0-1-e569f7ad77f4e55a7e549a/output/model.tar.gz",
    "Environment": {
      "AUTOML_SPARSE_ENCODE_RECORDIO_PROTOBUF": "1",
      "AUTOML_TRANSFORM_MODE": "feature-transform",
      "SAGEMAKER_DEFAULT_INVOCATIONS_ACCEPT": "application/x-recordio-protobuf",
      "SAGEMAKER_PROGRAM": "sagemaker_serve",
      "SAGEMAKER_SUBMIT_DIRECTORY": "/opt/ml/model/code"
    }
  }, {
    "Image": "348316444620.dkr.ecr.us-west-2.amazonaws.com/sagemaker-xgboost:1.3-1-cpu-py3",
    "ModelDataUrl": "s3://test-bucket/out/test-job1/tuning/flicdf10v2-dpp0-xgb/test-job1E9-244-7490a1c0/output/model.tar.gz",
    "Environment": {
      "MAX_CONTENT_LENGTH": "20971520",
      "SAGEMAKER_DEFAULT_INVOCATIONS_ACCEPT": "text/csv",
      "SAGEMAKER_INFERENCE_OUTPUT": "predicted_label",
      "SAGEMAKER_INFERENCE_SUPPORTED": "predicted_label,probability,probabilities"
    }
  }, {
    "Image": "348316444620.dkr.ecr.us-west-2.amazonaws.com/sagemaker-sklearn-automl:2.5-1-cpu-py3",
    "ModelDataUrl": "s3://test-bucket/out/test-job1/data-processor-models/test-job1-dpp0-1-e569f7ad77f4e55a7e549a/output/model.tar.gz",
    "Environment": {
      "AUTOML_TRANSFORM_MODE": "inverse-label-transform",
      "SAGEMAKER_DEFAULT_INVOCATIONS_ACCEPT": "text/csv",
      "SAGEMAKER_INFERENCE_INPUT": "predicted_label",
      "SAGEMAKER_INFERENCE_OUTPUT": "predicted_label",
      "SAGEMAKER_INFERENCE_SUPPORTED": "predicted_label,probability,labels,probabilities",
      "SAGEMAKER_PROGRAM": "sagemaker_serve",
      "SAGEMAKER_SUBMIT_DIRECTORY": "/opt/ml/model/code"
    }
  }]'
   ```
3. Create the transform job by using the following code example.

```bash
code example:
aws sagemaker create-transform-job --transform-job-name 'test-tranform-job'\
  --model-name 'test-sagemaker-model'\n  --transform-input '{
    "DataSource": {
      "S3DataSource": {
        "S3DataType": "S3Prefix",
        "S3Uri": "s3://test-bucket/data.csv"
      }
    },
    "ContentType": "text/csv",
    "SplitType": "Line"
  }'
  --transform-output '{
    "S3OutputPath": "s3://test-bucket/output/",
    "AssembleWith": "Line"
  }'
  --transform-resources '{
    "InstanceType": "ml.m5.2xlarge",
    "InstanceCount": 1
  }'
  --region 'us-west-2'
```

4. Check the progress of the transform job by using the following code example.

```bash
code example:
aws sagemaker describe-transform-job --transform-job-name 'test-tranform-job' --region us-west-2
```

The following is the response from the transform job.

```json
{  
  "TransformJobName": "test-tranform-job",
  "TransformJobStatus": "InProgress",
  "ModelName": "test-model",
  "TransformInput": {
    "DataSource": {
      "S3DataSource": {
        "S3DataType": "S3Prefix",
        "S3Uri": "s3://test-bucket/data.csv"
      }
    },
    "ContentType": "text/csv",
    "CompressionType": "None",
    "SplitType": "Line"
  },
  "TransformOutput": {
    "S3OutputPath": "s3://test-bucket/output/",
    "AssembleWith": "Line",
    "KmsKeyId": ""
  },
  "TransformResources": {
    "InstanceType": "ml.m5.2xlarge",
    "InstanceCount": 1
  },
  "CreationTime": 1662495635.679,
  "TransformStartTimestamp": 1662495847.496,
  "DataProcessing": {
```

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Batch inferencing across accounts

To create a batch inferencing job in a different account than the one that the model was generated in, follow the instructions in Deploy models from different accounts (p. 337). Then you can create models and transform jobs by following the Batch inferencing steps (p. 339).

Amazon SageMaker Autopilot explainability

Amazon SageMaker Autopilot uses tools provided by Amazon SageMaker Clarify to help explain how machine learning (ML) models make predictions. These tools can help ML modelers, developers, and other internal stakeholders understand model characteristics before deployment. You can also use tools to debug predictions provided by a model after it's deployed. Transparency about how ML models arrive at their predictions is also critical to consumers and regulators, who must trust the model predictions so they can accept the decisions based on them. The Autopilot explanatory functionality uses a model-agnostic feature attribution approach. You can use this to understand why a model made a prediction after training, and use it to provide per-instance explanation during inference. The implementation includes a scalable and efficient implementation of SHAP. This is based on the concept of a Shapley value from the field of cooperative game theory that assigns each feature an importance value for a particular prediction.

You can use explanations for auditing and meeting regulatory requirements, building trust in the model, supporting human decision-making, and debugging and improving model performance.

For additional information on Shapley values and baselines, see Feature Attributions that Use Shapley Values (p. 2653) and SHAP Baselines for Explainability (p. 2654).

For a guide to the Amazon SageMaker Clarify documentation, see Guide to the SageMaker Clarify Documentation (p. 8).

Models generated by Amazon SageMaker Autopilot

This procedure describes how to view details about Amazon SageMaker Autopilot jobs that you have run. Details provided about the candidate models generated by Autopilot include:

- A plot of the aggregated SHAP values that indicate the importance of each feature to help explain your models predictions.
- The summary statistics for various training and validation metrics, including the objective metric.
- A list of the hyperparameters used to train and tune the model.
Note
This topic assumes that you have already created and run an Autopilot experiment. For information on how to create an Autopilot experiment, see Create an Amazon SageMaker Autopilot experiment (p. 321)

Note
To access the feature importance metrics in this procedure, you must first select File > Shut down, and then restart Studio from the console.

1. To view model details after running an Amazon SageMaker Autopilot job, choose the SageMaker resources icon \( \text{\textdm{\textbullet}} \) from the left sidebar to open the SageMaker resources panel.
2. Select Experiments and trials from the dropdown menu located underneath SageMaker resources.
3. Locate the Autopilot job whose details that you want to examine in the Unassigned trial components list. Right-click over the name of the job and select Describe AutoML Job from the pop-up menu. This opens a new Autopilot job tab.
4. The Autopilot job panel lists the Objective metric values for each model in the job with the Best model at the top of the Trials tab. To review model details, right click over the model that you are interested in and select Open in model details. This opens a new Model Details tab.
5. In Model Details, the top of the Explainability tab contains a plot of aggregated SHAP values that indicate the importance of each feature, followed by hyper parameter values for this model. The Performance tab contains metrics statistics and a confusion matrix. The Artifacts tab contains information about model inputs, outputs and intermediate results. The Network tab summarizes your network isolation and encryption choices.

Note
Feature importance and information in the Performance tab is only generated for the Best model.

For more information about how the SHAP values help explain predictions based on feature importance, scroll down to see the link to the Understanding the model explainability whitepaper in the Explainability tab. Additional information is also available in the Amazon SageMaker Clarify Model Explainability (p. 2652) topic in the SageMaker Developer Guide.

Amazon SageMaker Autopilot notebooks generated to manage AutoML tasks

Amazon SageMaker Autopilot generates the key tasks in an automatic machine learning (AutoML) process. They are implemented by Autopilot with an AutoML job. The AutoML job creates three notebook-based reports that describe the plan that Autopilot follows to generate candidate models. A candidate model consists of a (pipeline, algorithm) pair. First, there’s a data exploration notebook, that describes what Autopilot learned about the data that you provided. Second, there’s a candidate definition notebook, which uses the information about the data to generate candidates. Third, a model insights report that can help detail the performance characteristics of the best model in the leaderboard of an Autopilot experiment.

Topics
- Amazon SageMaker Autopilot Data exploration report (p. 346)
- Candidate definition notebook (p. 353)
- Autopilot Model Insights (p. 354)

You can run these notebooks in Amazon SageMaker or locally if you have installed the Amazon SageMaker Python SDK. You can share the notebooks just like any other SageMaker Studio
notebook. The notebooks are created for you to conduct experiments. For example, you could edit the following items in the notebooks:

- Preprocessors used on the data
- Amount of hyperparameter optimization (HPO) runs and their parallelism
- Algorithms to try
- Instance types used for the HPO jobs
- Hyperparameter ranges

Modifications to the candidate definition notebook are encouraged as a learning tool. With this capability, you learn how the decisions made during the machine learning process impact your results.

**Note**

When you run the notebooks in your default instance, you incur baseline costs. However, when you run HPO jobs from the candidate notebook, these jobs use additional compute resources that incur additional costs.

### Amazon SageMaker Autopilot Data exploration report

Amazon SageMaker Autopilot cleans and pre-processes your dataset automatically. High data quality enables more efficient machine learning and produces models that make more accurate predictions. There are issues with customer-provided datasets that cannot be fixed automatically without the benefit of some domain knowledge. Large outlier values in the target column for regression problems, for example, may cause suboptimal predictions for the non-outlier values. Outliers may need to be removed depending on the modeling objective. If a target column is included by accident as one of the input features, the final model will validate well, but be of little value for future predictions. To help customers discover these sorts of issues, Autopilot provides a data exploration report that contains insights into potential issues with their data and suggests how to handle them.

A data exploration notebook containing the report is generated for every Autopilot job that completes the pipeline recommendation step. The report is stored in an S3 bucket and can be accessed from your output path. The path of the data exploration report usually adheres to the following pattern:

```
[s3 output path]/[name of the automl job]/sagemaker-automl-candidates/[name of processing job used for data analysis]/notebooks/SageMakerAutopilotDataExplorationNotebook.ipynb
```

The location of the data exploration notebook can be obtained from the Autopilot API using the DescribeAutoMLJob operation response, stored in DataExplorationNotebookLocation.

When running Autopilot from SageMaker Studio, you can open the data exploration report by opening UI that describes the Autopilot job, and then selecting Open data exploration notebook from the Autopilot job description page.
The data exploration report is generated from your data before the training process begins. This allows you to stop Autopilot jobs that might lead to meaningless results and address any issues or improvements with your dataset before rerunning Autopilot. This gives you an opportunity to leverage your domain expertise to improve the data quality manually before training a model on a better curated dataset.

The data report generated contains only static markdown and can be opened in any Jupyter environment. The notebook that contains the report can be converted to other formats, such as PDF or HTML. For more information on conversions, see Using the nbconvert script to convert Jupyter notebooks to other formats.

Topics
- Dataset Summary (p. 347)
- Target Analysis (p. 348)
- Data Sample (p. 350)
- Duplicate rows (p. 351)
- Cross column correlations (p. 351)
- Anomalous Rows (p. 352)
- Missing values, cardinality, and descriptive statistics (p. 352)

Dataset Summary

This **Dataset Summary** provides key statistics characterizing your dataset. It is intended to provide you with a quick alert when there are issue with your dataset that Amazon SageMaker Autopilot has detected and that are likely to require your intervention. The insights are surfaced as warnings that are classified as being of either “high” or “low” severity. The classification depends on the level of confidence that the issue will adversely impact the performance of the model.

The high and low severity insights appear in the summary as pop-ups. For most of the insights, recommendations are offered for how to confirm that there is an issue with the dataset that requires your attention. Proposals are also provided for how to resolve the issues.
Autopilot provides additional statistics about missing or not valid target values in our dataset to help you detect other issues that may not be captured by high severity insights. An unexpected number of columns of a particular type might indicate that some columns that you want to use may be missing from the dataset. It could also indicate that there was an issue with how the data was prepared or stored. Fixing these data problems brought to your attention by Autopilot can improve the performance of the machine learning models trained on your data.

### Dataset Summary

<table>
<thead>
<tr>
<th>Dataset Properties</th>
<th>Rows</th>
<th>Columns</th>
<th>Duplicate rows</th>
<th>Target column (%)</th>
<th>Missing target values (%)</th>
<th>Invalid target values (%)</th>
<th>Detected problem type</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>150454</td>
<td>132</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>Regression</td>
<td></td>
</tr>
</tbody>
</table>

#### Detected Column Types

<table>
<thead>
<tr>
<th>Column Type</th>
<th>Numerics</th>
<th>Categorical</th>
<th>Text</th>
<th>DateTime</th>
<th>Sequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Count</td>
<td>15</td>
<td>116</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Percentage</td>
<td>11.45%</td>
<td>88.55%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
</tbody>
</table>

High severity insights are shown in the summary section and in other relevant sections in the report. Examples of high and low-severity insights are usually given depending on the section of the data report.

### Target Analysis

Various high and low-severity insights are shown in this section related to the distribution of values in the target column. You should check that target column contains the correct values. Incorrect values in target column will likely result in a machine learning model that doesn't serve the intended business purpose. Several data insights of high and low severity are present in this section. Here are several examples.

- **Outlier target values** - Skewed or unusual target distribution for regression, such as heavy tailed targets.

- **High or low target cardinality** - Infrequent number of class labels or a large number of unique classes for classification.

For both regression and classification problem types, not valid values such as numeric infinity, NaN or empty space in target column are surfaced. Depending on the problem type, different dataset statistics are presented. A distribution of target column values for a regression problem allows you to verify if the distribution is what you expected.

The following example shows an Autopilot data report on the distribution of target column values.
Multiple statistics are shown regarding target values and their distribution. If any of the outliers, not valid values, or missing percentages are greater than zero, these values are surfaced so you can investigate why your data contains unusable target values. Some unusable target values are highlighted as a low severity insight warning. In the following example, a ` symbol was added accidentally to the target column, which prevented the numeric value of the target from being parsed.

To help you identify the problematic values and some impacted rows, Autopilot provides examples of rows that contain unusable or outlier target values. Distribution of labels for classification are tabulated and plotted so that you can analyze them as well.
Note
You can find definitions of all the terms presented in this and other sections in Definitions section at the bottom of the report notebook.

Data Sample

To further help you spot issues with your dataset, an actual sample of your data is presented for you to inspect by Amazon SageMaker Autopilot. The sample table scrolls horizontally. It can be used to verify that all the necessary columns are present in the dataset used. If data columns are missing, there may be a preprocessing issue that occurred before importing the dataset that you need to investigate.

A measure of predictive power is calculated by Amazon SageMaker Autopilot and can be used to identify target columns disguised as input columns. It helps focus your attention on the columns that might be important because they have high prediction power. For more information on prediction power, see the Definitions section.

Note
It is not recommended that you use prediction power as a substitute for feature importance, unless you're certain that prediction power is an appropriate measure for your use case.
Duplicate rows

If duplicate rows are present in the dataset, Amazon SageMaker Autopilot displays a sample of them.

**Note**
It is not recommended to balance a dataset by up-sampling before providing it to Autopilot. This may result in inaccurate validation scores for the models trained by Autopilot, and the models that are produced may be unusable.

Cross column correlations

Numeric column correlation is also presented using a standard cross-correlation matrix graphic. You can use this to reduce the number of features in the dataset. A smaller number of features reduces chances of overfitting a model and can reduce the costs of production in two ways. It lessens the Autopilot runtime needed and, for some applications, can make data collection procedures cheaper.

**Note**
Values close to +1 and values close to -1 indicate that two features are highly correlated, positively and negatively, respectively.
Anomalous Rows

Amazon SageMaker Autopilot detects which rows in your dataset might be anomalous. It then assigns an anomaly score to each row. Rows with negative anomaly scores are considered anomalous.

Anomalous Rows

Anomalous rows are detected using the isolation forest algorithm on a sample of 1380 randomly chosen rows after basic preprocessing. The isolation forest algorithm associates an anomaly score to each row of the dataset it is trained on. Rows with negative anomaly scores are usually considered anomalous and rows with positive anomaly scores are considered non-anomalous. When investigating an anomalous row, look for any unusual values - in particular any that might have resulted from errors in the gathering and processing of data. Dissecting whether a row is indeed anomalous, contains errors, or is in fact valid requires domain knowledge and application of business logic.

Inspect the rows below, to see if any of those are anomalous. A subset of rows is presented below. Anomaly score is presented as the leftmost column; Smaller values indicate a higher chance that the row is anomalous.

<table>
<thead>
<tr>
<th>Anomaly Scores</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>1337</td>
<td>0.211202</td>
<td>0.8</td>
<td>0.65</td>
<td>0.195</td>
<td>2.526</td>
<td>0.533</td>
<td>0.59</td>
<td>0.62</td>
</tr>
<tr>
<td>405</td>
<td>-0.200237</td>
<td>0.815</td>
<td>0.65</td>
<td>0.25</td>
<td>2.255</td>
<td>0.8905</td>
<td>0.42</td>
<td>0.7975</td>
</tr>
<tr>
<td>861</td>
<td>-0.194812</td>
<td>0.75</td>
<td>0.61</td>
<td>0.235</td>
<td>2.5085</td>
<td>1.232</td>
<td>0.519</td>
<td>0.612</td>
</tr>
<tr>
<td>1519</td>
<td>-0.195176</td>
<td>0.73</td>
<td>0.595</td>
<td>0.23</td>
<td>2.8255</td>
<td>1.1465</td>
<td>0.419</td>
<td>0.897</td>
</tr>
<tr>
<td>403</td>
<td>-0.194518</td>
<td>0.77</td>
<td>0.62</td>
<td>0.195</td>
<td>2.5155</td>
<td>1.1555</td>
<td>0.6415</td>
<td>0.642</td>
</tr>
<tr>
<td>229</td>
<td>-0.182169</td>
<td>0.735</td>
<td>0.6</td>
<td>0.22</td>
<td>2.555</td>
<td>1.3335</td>
<td>0.44</td>
<td>0.6</td>
</tr>
<tr>
<td>981</td>
<td>-0.171010</td>
<td>0.11</td>
<td>0.09</td>
<td>0.05</td>
<td>0.008</td>
<td>0.0025</td>
<td>0.002</td>
<td>0.003</td>
</tr>
<tr>
<td>5966</td>
<td>-0.160171</td>
<td>0.465</td>
<td>0.535</td>
<td>0.325</td>
<td>2.1935</td>
<td>0.7935</td>
<td>0.191</td>
<td>0.809</td>
</tr>
<tr>
<td>5956</td>
<td>-0.173547</td>
<td>0.14</td>
<td>0.105</td>
<td>0.035</td>
<td>0.014</td>
<td>0.0005</td>
<td>0.0025</td>
<td>0.006</td>
</tr>
<tr>
<td>627</td>
<td>-0.154224</td>
<td>0.175</td>
<td>0.125</td>
<td>0.04</td>
<td>0.024</td>
<td>0.0025</td>
<td>0.006</td>
<td>0.005</td>
</tr>
</tbody>
</table>

Missing values, cardinality, and descriptive statistics

Amazon SageMaker Autopilot examines and reports on properties of the individual columns of your dataset. In each section of the data report that presents this analysis, the content is arranged in order, so that you can check the most "suspicious" values first. Using these statistics you can improve contents of individual columns, and improve the quality of the model produced by Autopilot.
Autopilot calculates several statistics on the categorical values in columns that contain them. These include the number of unique entries and, for text, the number of unique words. These are presented in a table for your inspection.

<table>
<thead>
<tr>
<th>Number of Unique Entries</th>
<th>Number of Unique Words (if Text)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>n/a</td>
</tr>
<tr>
<td>1</td>
<td>n/a</td>
</tr>
<tr>
<td>2</td>
<td>n/a</td>
</tr>
<tr>
<td>3</td>
<td>n/a</td>
</tr>
<tr>
<td>4</td>
<td>n/a</td>
</tr>
<tr>
<td>5</td>
<td>n/a</td>
</tr>
<tr>
<td>6</td>
<td>n/a</td>
</tr>
<tr>
<td>7</td>
<td>n/a</td>
</tr>
</tbody>
</table>

Autopilot calculates several standard statistics on the numerical values in columns that contain them. These include the mean, median, minimum and maximum values, and the percentages of numerical types and of outlier values. These are presented in a table for your inspection.

<table>
<thead>
<tr>
<th>% of Numerical Values</th>
<th>Mean</th>
<th>Median</th>
<th>Min</th>
<th>Max</th>
<th>% of Outlier Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>y 100.0%</td>
<td>9.93957</td>
<td>9.0</td>
<td>3.0</td>
<td>27.0</td>
<td>nan</td>
</tr>
<tr>
<td>1 100.0%</td>
<td>0.523612</td>
<td>0.545</td>
<td>0.11</td>
<td>0.815</td>
<td>0.0</td>
</tr>
<tr>
<td>2 100.0%</td>
<td>0.407799</td>
<td>0.425</td>
<td>0.09</td>
<td>0.65</td>
<td>0.0</td>
</tr>
<tr>
<td>3 100.0%</td>
<td>0.13995</td>
<td>0.145</td>
<td>0.015</td>
<td>0.515</td>
<td>0.1</td>
</tr>
<tr>
<td>4 100.0%</td>
<td>0.828266</td>
<td>0.81</td>
<td>0.008</td>
<td>2.8255</td>
<td>0.0</td>
</tr>
<tr>
<td>5 100.0%</td>
<td>0.358844</td>
<td>0.339</td>
<td>0.0025</td>
<td>1.2395</td>
<td>0.0</td>
</tr>
<tr>
<td>6 100.0%</td>
<td>0.180348</td>
<td>0.1725</td>
<td>0.002</td>
<td>0.6415</td>
<td>0.0</td>
</tr>
<tr>
<td>7 100.0%</td>
<td>0.238783</td>
<td>0.235</td>
<td>0.003</td>
<td>1.005</td>
<td>0.2</td>
</tr>
</tbody>
</table>

**Candidate definition notebook**

The candidate definition notebook contains each suggested preprocessing step, algorithm, and hyperparameter ranges.

After you produce the notebook, you can choose which candidates to train and tune. Choose these candidates by running sections of the automatic machine learning (AutoML) job that contain them inside of the notebook. These candidates are optimized automatically to identify a final, best candidate.

When you run all sections of the AutoML job directly, only the best candidate is displayed after job completion.

**Note**

Candidate definition notebooks are not available for ensembling mode.
Autopilot Model Insights

Amazon SageMaker Model Monitor report provides insights and quality information for the model candidates generated in the leaderboard of an Autopilot experiment by an AutoML job. The report provides the model insights charts only for the best classification model candidate. This includes understanding false positives/false negatives, tradeoffs between true positives and false positives, and tradeoffs between precision and recall.

Autopilot also provides scalar metrics for all of your candidate models used to measure their predictive quality. The leaderboard view includes these metrics by default. The metrics automatically calculated for a candidate model are determined by the type of problem being addressed.

- Regression: MSE
- Binary classification: Accuracy, F1, AUC
- Multiclass classification: Accuracy, F1macro

You can sort your model candidates with the relevant metric to help you select and deploy the model that addresses your business needs. For definitions of these metrics, see the Autopilot candidate metrics topic.

The SageMaker model monitor report contains details characterizing the Autopilot job, a metrics table, and several model insights. These include model charts that are relevant to the type of classification problem. You access these reports in SageMaker Studio from the Performance tab on the page that opens to confirm that your AutoML job has completed. For instructions on how to create and run an AutoML job in SageMaker Studio, see Create an Amazon SageMaker Autopilot experiment (p. 321).

Topics
- Model details and metrics tables (p. 354)
- Confusion matrix (p. 355)
- The area under the receiver operating characteristic curve (p. 357)
- Precision-recall curve (p. 358)

Model details and metrics tables

Model details include the following information.

- Autopilot Candidate Name
- Autopilot Job Name
- Problem Type
- Objective Metric
- Optimization Direction

The model quality information is generated by the prebuilt SageMaker Model Monitor container. The contents of the report generated depends on the problem type addressed: regression, binary classification, or multiclass classification. The report specifies the number of rows that were included in the evaluation dataset and the time at which the evaluation occurred.

Here is an example of a metrics table in a Model Monitor report generated by AutoML job for a regression problem.
Here is an example of a metrics table in a Model Monitor report generated by AutoML job for a binary classification problem.

### Metrics table

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Value</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>recall</td>
<td>0.725</td>
<td>0.012</td>
</tr>
<tr>
<td>precision</td>
<td>0.918</td>
<td>0.009</td>
</tr>
<tr>
<td>accuracy</td>
<td>0.811</td>
<td>0.007</td>
</tr>
<tr>
<td>recall_best_constant_classifier</td>
<td>0.725</td>
<td>0.012</td>
</tr>
<tr>
<td>precision_best_constant_classifier</td>
<td>0.918</td>
<td>0.009</td>
</tr>
<tr>
<td>accuracy_best_constant_classifier</td>
<td>0.811</td>
<td>0.007</td>
</tr>
<tr>
<td>true_positive_rate</td>
<td>0.686</td>
<td>0.052</td>
</tr>
<tr>
<td>true_negative_rate</td>
<td>0.314</td>
<td>0.052</td>
</tr>
<tr>
<td>false_positive_rate</td>
<td>0.113</td>
<td>0.052</td>
</tr>
<tr>
<td>false_negative_rate</td>
<td>0.887</td>
<td>0.052</td>
</tr>
<tr>
<td>auc</td>
<td>0.913</td>
<td>0.007</td>
</tr>
<tr>
<td>au_pr</td>
<td>0.657</td>
<td>0.052</td>
</tr>
<tr>
<td>f1</td>
<td>0.814</td>
<td>0.007</td>
</tr>
<tr>
<td>f2</td>
<td>0.763</td>
<td>0.007</td>
</tr>
<tr>
<td>f1_best_constant_classifier</td>
<td>0.814</td>
<td>0.007</td>
</tr>
<tr>
<td>f2_best_constant_classifier</td>
<td>0.763</td>
<td>0.007</td>
</tr>
</tbody>
</table>

### Model monitor report

Model quality information is generated by the prebuilt SageMaker Model Monitor container. This report is for a **MulticlassClassification** problem. 1599 rows were included in the evaluation dataset. The evaluation time occurred at 2022-01-29T01:45:58.1452Z.

### Metrics table

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Value</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>accuracy</td>
<td>0.91834</td>
<td>0.0092</td>
</tr>
<tr>
<td>weighted_recall</td>
<td>0.91834</td>
<td>0.0092</td>
</tr>
<tr>
<td>weighted_precision</td>
<td>0.91834</td>
<td>0.0092</td>
</tr>
<tr>
<td>weighted_f1</td>
<td>0.91834</td>
<td>0.0092</td>
</tr>
<tr>
<td>weighted_f2</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
<tr>
<td>accuracy_best_constant_classifier</td>
<td>0.91834</td>
<td>0.0092</td>
</tr>
<tr>
<td>weighted_recall_best_constant_classifier</td>
<td>0.91834</td>
<td>0.0092</td>
</tr>
<tr>
<td>weighted_precision_best_constant_classifier</td>
<td>0.91834</td>
<td>0.0092</td>
</tr>
<tr>
<td>weighted_f1_best_constant_classifier</td>
<td>0.91834</td>
<td>0.0092</td>
</tr>
<tr>
<td>weighted_f2_best_constant_classifier</td>
<td>0.00000</td>
<td>0.00000</td>
</tr>
</tbody>
</table>

### Confusion matrix

The confusion matrix provides a way to visualize the accuracy of the predictions made by binary and multiclass classification for different classes. The confusion matrix is a table that contains the percentages of correct and incorrect predictions for the actual labels. Each row in the confusion matrix indicates how an actual label was classified by the label predicted by the model. The percentage of accurate predictions is on the diagonal, from the upper-left to the lower-right corner. The off-
diagonal percentages indicate the types of misclassification that the model is predicting. These incorrect predictions are the confusion values.

Here is an example of a confusion matrix for a binary classification problem.

Here is an example of a confusion matrix for a multi-class classification problem.
This report provides a confusion matrix that can accommodate a maximum 15 labels for multiclass classification problem types. The labels are listed in order, from those predicted least accurately to those predicted most accurately. If a row shows Nan, it means that the validation dataset doesn't have a row for that label.

The area under the receiver operating characteristic curve

The area under the receiver operating characteristic curve (AUC ROC curve) represents the trade-off between true positive and false positive rates. The AUC ROC curve is an industry-standard accuracy metric used for binary classification models. AUC measures the ability the model to predict a higher score for positive examples, as compared to negative examples. The AUC metric provides an aggregated measure of the model performance across all possible classification thresholds.

The AUC metric returns a decimal value from zero (0) to one (1). AUC values near 1 indicate an ML model that is highly accurate. Values near 0.5 indicate an ML model that is no better than guessing at random. Values near 0 are unusual to see, and these typically indicate a problem with the data. Essentially, an AUC near 0 says that the ML model has learned the correct patterns, but is using them to make predictions that are as inaccurate as possible. For example, 0s are predicted as 1s, and 1s as 0s. For more information about the AUC metric, see the Receiver operating characteristic article on Wikipedia.

A binary model that classifies no-better-than-random guessing, with equal rates of true and false positives, has an AUC score of 0.5. The curve representing a random binary classifier is a diagonal dotted red line in a receiver operating characteristic graph. The curves of more accurate classification models lie above this random baseline, where the rate of true positives exceeds the rate of false positives.

The false positive rate (FPR) measures the false alarm rate or the fraction of actual negatives that were falsely predicted as positives. The range is 0 to 1. A smaller value indicates better predictive accuracy.

- \( \text{FPR} = \frac{FP}{FP+TN} \)

The true positive rate (TPR) measures the fraction actual positives that were predicted as positives. The range is 0 to 1. A larger value (1 being the largest) indicates better predictive accuracy.

- \( \text{TPR} = \frac{TP}{TP+FN} \)
Where these rates are defined as follows.

- **Correct predictions**
  - **True positive** (TP): The predicted the value is 1, and the true value is 1.
  - **True negative** (TN): The predicted the value is 0, and the true value is 0.

- **Erroneous predictions**
  - **False positive** (FP): The predicted the value is 1, but the true value is 0.
  - **False negative** (FN): The predicted the value is 0, but the true value is 1.

### Precision-recall curve

The precision-recall curve represents the tradeoff between precision and recall for different thresholds used in a binary classification problem. The objective of a binary classification problem is to correctly classify as many of the relevant elements that labeled positive in a training dataset as possible. A system with high recall but low precision returns lots of relevant results, but a high percentage of its predicted labels is of its labels are incorrect when compared to the training labels. A system with high precision but low recall returns fewer relevant results, but a high percentage of predicted is of its labels are correct when compared to the training labels. A perfect system that has both high precision and high recall produces many correctly-labeled results. For more information, see [Precision and recall](https://en.wikipedia.org/wiki/Precision_and_recall) article in Wikipedia.

**Precision** measures the fraction of actual positives that are predicted as positive out of all those predicted as positive. The range is 0 to 1. A larger value indicates better accuracy in the values predicted.

- Precision = $\frac{TP}{TP+FP}$

**Recall** measures the fraction of actual positives that are predicted as positive out of all the actual positives in the sample. This is also known as the sensitivity and as the true positive rate. The range is 0 to 1. A larger value indicates better detection of positive values from the sample.

- Recall = $\frac{TP}{TP+FN}$

Amazon SageMaker Autopilot reports the area under the precision-recall curve (AUPRC). The AUPRC metric provides an aggregated measure of the model performance across all possible classification thresholds.

Here is an example that compares the precision-recall curves and their AUPRC values from four different models trained on the same dataset.
Configure inference output in generated containers

Amazon SageMaker Autopilot generates an ordered `ContainerDefinition` list. This can be used to build a model to deploy in a machine learning pipeline. This model can be used for online hosting and inference.

Customers can access the list of inference container definitions with the `ListCandidateForAutoMLJob` API. The list of inference container definitions that represent the best candidate is also available in the `DescribeAutoMLJob` response.

Topics
- Inference container definitions for regression and classification problem types (p. 359)

Inference container definitions for regression and classification problem types

This section provides details about container definitions for hyperparameter optimization (HPO) mode.

Autopilot generates inference containers specific to the problem type of the job.

- **Regression**: HPO generates two containers:
  1. A feature engineering container that transforms the original features into features that the regression algorithms can train on.
  2. An algorithm container that transforms features and generates a regression score for the dataset.

- **Classification**: HPO generates three containers:
  1. A feature engineering container that transforms the original features into features that the classification algorithms can train on.
2. An algorithm container that generates the `predicted_label` with the highest probability. This container can also produce the various probabilities associated with the classification outcomes in the inference response.

3. A feature engineering container that performs post-processing of the algorithm prediction. For example, it can perform an inverse transform on the predicted label and change it to the original label.

**Container definitions for ensembling mode**

In **ensembling mode**, both regression and classification problem types have only one inference container. This inference container transforms the features and generates the predictions based on problem type.

**Inference responses for classification models**

In this section, you'll learn to select inference responses for Autopilot classification models in ensembling mode.

For classification inference containers, you can select the content of the inference response by using four predefined keys:

- `predicted_label`: The label with the highest probability of predicting the correct label, as determined by Autopilot.
- `probability`: The probability of the `True` class for binary classification. The probability of the `predicted_label` for multiclass classification.
- `probabilities`: The list of probabilities for all corresponding classes.
- `labels`: The list of all labels.

By default, inference containers are configured to generate only the `predicted_label`. To select additional inference content, you can update the `inference_response_keys` parameter to include up to these three environment variables:

- `SAGEMAKER_INFERENCE_SUPPORTED`: This is set to provide hints to you about what content each container supports.
- `SAGEMAKER_INFERENCE_INPUT`: This should be set to the keys that the container expects in input payload.
- `SAGEMAKER_INFERENCE_OUTPUT`: This should be populated with the set of keys that the container outputs.

**Inference responses for classification models in HPO mode**

This section shows how to configure the inference response from classification models using hyperparameter optimization (HPO) mode.

To choose the inference response content in HPO mode: Add the `SAGEMAKER_INFERENCE_INPUT` and `SAGEMAKER_INFERENCE_OUTPUT` variables to the second and third containers that are generated in HPO mode for classification problems.

The keys supported by the second container (algorithm) are `predicted_label`, `probability`, and `probabilities`. Note that `labels` is deliberately not added to `SAGEMAKER_INFERENCE_SUPPORTED`.

The keys supported by the third classification model container are `predicted_label`, `labels`, `probability`, and `probabilities`. Therefore, the `SAGEMAKER_INFERENCE_SUPPORTED` environment includes the names of these keys.
To update the definition of the inference containers to receive predicted_label and probability, use the following code example.

```python
containers[1]['Environment'].update({'SAGEMAKER_INFERENCE_OUTPUT': 'predicted_label, probability'})
containers[2]['Environment'].update({'SAGEMAKER_INFERENCE_INPUT': 'predicted_label, probability'})
containers[2]['Environment'].update({'SAGEMAKER_INFERENCE_OUTPUT': 'predicted_label, probability'})
```

The following code example updates the definition of the inference containers to receive predicted_label, probabilities, and labels. Do not pass the labels to the second container (the algorithm container), because it is generated by the third container independently.

```python
containers[1]['Environment'].update({'SAGEMAKER_INFERENCE_OUTPUT': 'predicted_label, probability'})
containers[2]['Environment'].update({'SAGEMAKER_INFERENCE_INPUT': 'predicted_label, probability'})
containers[2]['Environment'].update({'SAGEMAKER_INFERENCE_OUTPUT': 'predicted_label, probabilities, labels'})
```

The following collapsible sections provide code examples for AWS SDK for Python (Boto3) and for SageMaker SDK for Python. Each section shows how to select the content of the inference responses in HPO mode for the respective code example.

**AWS SDK for Python (Boto3)**

```python
import boto3

sm_client = boto3.client('sagemaker', region_name='<Region>')
role = '<IAM role>'
input_data = '<S3 input uri>'
output_path = '<S3 output uri>'

best_candidate = sm_client.describe_auto_ml_job(AutoMLJobName='<AutoML Job Name>')['BestCandidate']
best_candidate_containers = best_candidate['InferenceContainers']
best_candidate_name = best_candidate['CandidateName']

best_candidate_containers[1]['Environment'].update({'SAGEMAKER_INFERENCE_OUTPUT': 'predicted_label, probability'})
best_candidate_containers[2]['Environment'].update({'SAGEMAKER_INFERENCE_INPUT': 'predicted_label, probability'})
best_candidate_containers[2]['Environment'].update({'SAGEMAKER_INFERENCE_OUTPUT': 'predicted_label, probability'})

# create model
response = sm_client.create_model(
    ModelName = '<Model Name>',
    ExecutionRoleArn = role,
    Containers = best_candidate_containers
)

# Launch Transform Job
response = sm_client.create_transform_job(
    TransformJobName='<Transform Job Name>',
    ModelName = '<Model Name>',
    TransformInput={
        'DataSource': {
            'S3DataSource': {
                'S3DataType': '<S3Prefix>'
            }
        }
    }
)```
Inference container definitions for regression and classification problem types

Inference responses for classification models in ensembling mode

This section shows how to configure the inference response from classification models using ensembling mode.

In **ensembling mode**, to choose the content of the inference response, update the SAGEMAKER_INFERENCE_OUTPUT environment variable.

The keys supported by the classification model container are predicted_label, labels, probability, and probabilities. These keys are included in the SAGEMAKER_INFERENCE_SUPPORTED environment.

To update the inference container definition to receive predicted_label and probability, refer to the following code example.

```
containers[0]['Environment'].update({'SAGEMAKER_INFERENCE_OUTPUT': 'predicted_label, probability'})
```

The following collapsible section provides a code example for selecting the content of the inference responses in ensembling mode. The example uses AWS SDK for Python (Boto3).

**AWS SDK for Python (Boto3)**

```python
import boto3
```
Inference container definitions for regression and classification problem types

```python
sm_client = boto3.client('sagemaker', region_name='Region')
role = IAM_role
input_data = '<S3 input uri>'
output_path = '<S3 output uri>'

best_candidate = sm_client.describe_auto_ml_job(AutoMLJobName='AutoML Job Name')
best_candidate_containers = best_candidate['InferenceContainers']
best_candidate_name = best_candidate['CandidateName']

best_candidate_containers[0]['Environment'].update({"SAGEMAKER_INFERENCE_OUTPUT": 'predicted_label, probability'})

# create model
response = sm_client.create_model(
    ModelName = '<Model Name>',
    ExecutionRoleArn = role,
    Containers = best_candidate_containers
)

# Launch Transform Job
response = sm_client.create_transform_job(
    TransformJobName='Transform Job Name',
    ModelName='<Model Name>',
    TransformInput={
        'DataSource': {
            'S3DataSource': {
                'S3DataType': 'S3Prefix',
                'S3Uri': input_data
            }
        },
        'ContentType': 'text/CSV',
        'SplitType': 'Line'
    },
    TransformOutput={
        'S3OutputPath': output_path,
        'AssembleWith': 'Line',
    },
    TransformResources={
        'InstanceType': 'ml.m4.xlarge',
        'InstanceCount': 1,
    },
)
```

The following collapsible section provides a code example that is identical to the SageMaker SDK for Python example for HPO. It is included for your convenience.

### SageMaker SDK for Python

The following HPO code example uses SageMaker SDK for Python.

```python
from sagemaker import AutoML

aml = AutoML.attach(auto_ml_job_name='AutoML Job Name')
aml_best_model = aml.create_model(name='<Model Name>',
                                   candidate=None,
                                   *inference_response_keys*=['probabilities', 'labels']*)

aml_transformer = aml_best_model.transformer(accept='text/csv',
                                             assemble_with='Line',
                                             instance_type='ml.m5.xlarge',
                                             instance_count=1,)
```

The following collapsible section provides a code example that is identical to the SageMaker SDK for Python example for HPO. It is included for your convenience.

### SageMaker SDK for Python

The following HPO code example uses SageMaker SDK for Python.
Amazon SageMaker Autopilot quotas

There are quotas that limit the resources available to you when using Amazon SageMaker Autopilot. Some of these limits are increasable and some are not.

**Note**
The resource quotas documented in the following sections are valid for versions of Amazon SageMaker Studio 3.22.2 and higher. For information on updating your version of SageMaker Studio, see [Shut Down and Update SageMaker Studio and Studio Apps](#) (p. 179).

**Topics**
- Quotas that you can increase (p. 364)
- Resource quotas (p. 365)

### Quotas that you can increase

There are default limits for the size of the input datasets: file size of a single Parquet file (*), the target dataset size subsampling (**), and the number of concurrent jobs you can run with Amazon SageMaker Autopilot for each AWS account, per AWS Region.

#### Resource limits

<table>
<thead>
<tr>
<th>Resource</th>
<th>Regions</th>
<th>Default limits</th>
<th>Can be increased up to</th>
</tr>
</thead>
<tbody>
<tr>
<td>Size of input dataset</td>
<td>All</td>
<td>100 GB</td>
<td>Hundreds of GBs</td>
</tr>
<tr>
<td>Size of a single Parquet file*</td>
<td>All</td>
<td>2 GB</td>
<td>Tens of GBs</td>
</tr>
<tr>
<td>Target dataset size for subsampling**</td>
<td>All</td>
<td>5 GB</td>
<td>Hundreds of GBs</td>
</tr>
<tr>
<td>Number of concurrent Autopilot jobs</td>
<td>us-east-1, us-east-2, us-west-2, ap-northeast-1, eu-west-1, eu-central-1</td>
<td>4</td>
<td>Hundreds</td>
</tr>
<tr>
<td></td>
<td>ap-northeast-2, ap-southeast-2, eu-west-2, ap-southeast-1</td>
<td>2</td>
<td>Hundreds</td>
</tr>
<tr>
<td></td>
<td>All other Regions</td>
<td>1</td>
<td>Tens</td>
</tr>
</tbody>
</table>

**Note**
*This 2 GB size limit is for a single compressed Parquet file. You can provide a Parquet dataset that includes multiple compressed Parquet files. After the files are decompressed, they may each expand to a larger size.
**Autopilot automatically subsamples input datasets that are larger than the target dataset size while accounting for class imbalance and preserving rare class labels.
You can increase these limits by contacting Support.

To request a quota increase:

1. Open the AWS Support Center page, sign in if necessary, and then choose Create case.
2. On the Create case page, choose Service limit increase.
3. In the Case details panel, select SageMaker AutoML for the Limit Type.
4. On the Requests panel for Request 1, select the Region, the resource Limit to increase and the New Limit value you are requesting. Select Add another request if you have additional requests for quota increases.
5. Provide your preferred Contact options and choose Submit.

Resource quotas

The following table contains the runtime resource limits for an Amazon SageMaker Autopilot job in an AWS Region.

<table>
<thead>
<tr>
<th>Resource</th>
<th>Limit per Autopilot job</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum runtime for an Autopilot job</td>
<td>30 days</td>
</tr>
</tbody>
</table>
Amazon SageMaker provides API reference documentation that describes all of the REST operations and data types used by Autopilot and a higher-level level Amazon SageMaker Python SDK that you can use to create and manage AutoML jobs. It also provides a command line interface (CLI), an AWS SDK for Python (Boto) for clients of SageMaker services, and SDKs for .NET, C++, Go, Java, JavaScript, PHP V3, and Ruby V3. The following sections describe these Autopilot programming interfaces.

Topics
- SageMaker API reference (p. 366)
- Amazon SageMaker Python SDK (p. 367)
- AWS Command Line Interface (CLI) (p. 367)
- AWS SDK for Python (Boto) (p. 367)
- AWS SDK for .NET (p. 368)
- AWS SDK for C++ (p. 368)
- AWS SDK for Go (p. 368)
- AWS SDK for Java (p. 368)
- AWS SDK for JavaScript (p. 369)
- AWS SDK for PHP V3 (p. 369)
- AWS SDK for Ruby V3 (p. 369)

SageMaker API reference

This API provides HTTP service APIs for creating and managing Amazon SageMaker Autopilot resources.

Actions
- CreateAutoMLJob
- DescribeAutoMLJob
- ListAutoMLJobs
- ListCandidatesForAutoMLJob
- StopAutoMLJob

Data Types
- AutoMLCandidate
- AutoMLCandidateStep
- AutoMLChannel
- AutoMLContainerDefinition
- AutoMLDataSource
- AutoMLJobArtifacts
- AutoMLJobCompletionCriteria
- AutoMLJobConfig
- AutoMLJobObjective
For more information on the entire SageMaker REST API, see API and SDK Reference.

Amazon SageMaker Python SDK

This Python library provides several high-level abstractions for working with SageMaker. The following classes can be used to manage AutoML jobs.

- AutoML
- AutoMLInput
- AutoMLJob
- CandidateEstimator
- CandidateStep

For more information how this Python SDK simplifies model training and deployment, see Using the Amazon SageMaker Python SDK.

AWS Command Line Interface (CLI)

The AWS CLI provides APIs for creating and managing SageMaker resources. Here are the AWS CLI for Amazon SageMaker Autopilot commands.

- create-auto-ml-job
- describe-auto-ml-job
- list-auto-ml-jobs
- list-candidates-for-auto-ml-job
- stop-auto-ml-job

AWS SDK for Python (Boto)

Boto is the Amazon Web Services (AWS) SDK for Python. It enables Python developers to create, configure, and manage AWS services such as SageMaker. Boto provides a low-level Client API that maps to the underlying SageMaker service API. Here is a list of the methods used to manage AutoML jobs with the Client class.
• `create_auto_ml_job()`
• `describe_auto_ml_job()`
• `list_auto_ml_jobs()`
• `list_candidates_for_auto_ml_job()`
• `stop_auto_ml_job()`

**AWS SDK for .NET**

The .NET SDK enables developers to create, configure, and manage AWS services such as SageMaker. The API maps to the underlying SageMaker service API. Here is a list of the methods used to manage AutoML jobs with the Client class.

• `CreateAutoMLJob`
• `DescribeAutoMLJob`
• `ListAutoMLJobs`
• `ListCandidatesForAutoMLJob`
• `StopAutoMLJob`

**AWS SDK for C++**

The C++ SDK enables developers to create, configure, and manage AWS services such as SageMaker. The API maps to the underlying SageMaker service API. For information on the methods used to manage AutoML jobs with the Client class, see `Aws::SageMaker::SageMakerClient Class Reference`.

**AWS SDK for Go**

The Go SDK enables developers to create, configure, and manage AWS services such as SageMaker. The API maps to the underlying SageMaker service API. Here is a list of the methods used to manage AutoML jobs with the Client class.

• `CreateAutoMLJob`
• `DescribeAutoMLJob`
• `ListAutoMLJobs`
• `ListCandidatesForAutoMLJob`
• `StopAutoMLJob`

**AWS SDK for Java**

The Java SDK enables developers to create, configure, and manage AWS services such as SageMaker. The API maps to the underlying SageMaker service API. Here is a list of the methods used to manage AutoML jobs with the Client class.

• `createAutoMLJob`
• `describeAutoMLJob`
• `listAutoMLJobs`
• `listCandidatesForAutoMLJob`
• `stopAutoMLJob`
**AWS SDK for JavaScript**

The JavaScript SDK enables developers to create, configure, and manage AWS services such as SageMaker. The API maps to the underlying SageMaker service API. Here is a list of the methods used to manage AutoML jobs with the Client class.

- `createAutoMLJob`
- `describeAutoMLJob`
- `listAutoMLJobs`
- `listCandidatesForAutoMLJob`
- `stopAutoMLJob`

**AWS SDK for PHP V3**

The PHP V3 SDK enables developers to create, configure, and manage AWS services such as SageMaker. The API maps to the underlying SageMaker service API. Here is a list of the methods used to manage AutoML jobs with the Client class.

- `CreateAutoMLJob`
- `DescribeAutoMLJob`
- `ListAutoMLJobs`
- `ListCandidatesForAutoMLJob`
- `StopAutoMLJob`

**AWS SDK for Ruby V3**

The Ruby V3 SDK enables developers to create, configure, and manage AWS services such as SageMaker. The API maps to the underlying SageMaker service API. Here is a list of the methods used to manage AutoML jobs with the Client class.

- `create_auto_ml_job()`
- `describe_auto_ml_job()`
- `list_auto_ml_jobs()`
- `list_candidates_for_auto_ml_job()`
- `stop_auto_ml_job()`
Label Data

To train a machine learning model, you need a large, high-quality, labeled dataset. You can label your
data using Amazon SageMaker Ground Truth. Choose from one of the Ground Truth built-in task types or
create your own custom labeling workflow. To improve the accuracy of your data labels and reduce the
total cost of labeling your data, use Ground Truth enhanced data labeling features like automated data
labeling and annotation consolidation.

Topics
- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Use Amazon SageMaker Ground Truth Plus to Label Data (p. 677)
- Use Amazon SageMaker Ground Truth Synthetic Data to Generate and Label Data (p. 687)
- Create and Manage Workforces (p. 694)
- Crowd HTML Elements Reference (p. 720)

Use Amazon SageMaker Ground Truth to Label Data

To train a machine learning model, you need a large, high-quality, labeled dataset. Ground Truth helps
you build high-quality training datasets for your machine learning models. With Ground Truth, you can
use workers from either Amazon Mechanical Turk, a vendor company that you choose, or an internal,
private workforce along with machine learning to enable you to create a labeled dataset. You can use the
labeled dataset output from Ground Truth to train your own models. You can also use the output as a
training dataset for an Amazon SageMaker model.

Depending on your ML application, you can choose from one of the Ground Truth built-in task types
to have workers generate specific types of labels for your data. You can also build a custom labeling
workflow to provide your own UI and tools to workers labeling your data. To learn more about the
Ground Truth built in task types, see Built-in Task Types (p. 542). To learn how to create a custom
labeling workflow, see Creating Custom Labeling Workflows (p. 509).

In order to automate labeling your training dataset, you can optionally use automated data labeling,
a Ground Truth process that uses machine learning to decide which data needs to be labeled by
humans. Automated data labeling may reduce the labeling time and manual effort required. For more
information, see Automate Data Labeling (p. 640). To create a custom labeling workflow, see Creating
Custom Labeling Workflows (p. 509).

Use either pre-built or custom tools to assign the labeling tasks for your training dataset. A labeling UI
template is a webpage that Ground Truth uses to present tasks and instructions to your workers. The
SageMaker console provides built-in templates for labeling data. You can use these templates to get
started, or you can build your own tasks and instructions by using our HTML 2.0 components. For more
information, see Creating Custom Labeling Workflows (p. 509).

Use the workforce of your choice to label your dataset. You can choose your workforce from:
- The Amazon Mechanical Turk workforce of over 500,000 independent contractors worldwide.
• A private workforce that you create from your employees or contractors for handling data within your organization.
• A vendor company that you can find in the AWS Marketplace that specializes in data labeling services.

For more information, see Create and Manage Workforces (p. 694).

You store your datasets in Amazon S3 buckets. The buckets contain three things: The data to be labeled, an input manifest file that Ground Truth uses to read the data files, and an output manifest file. The output file contains the results of the labeling job. For more information, see Use Input and Output Data (p. 572).

Events from your labeling jobs appear in Amazon CloudWatch under the /aws/sagemaker/LabelingJobs group. CloudWatch uses the labeling job name as the name for the log stream.

Are You a First-time User of Ground Truth?

If you are a first-time user of Ground Truth, we recommend that you do the following:

1. Read Getting started (p. 371)—This section walks you through setting up your first Ground Truth labeling job.
2. Explore other topics—Depending on your needs, do the following:
   • Explore built-in task types—Use built-in task types to streamline the process of creating a labeling job. See Built-in Task Types (p. 542) to learn more about Ground Truth built-in task types.
   • Manage your labeling workforce—Create new work teams and manage your existing workforce. For more information, see Create and Manage Workforces (p. 694).
   • Learn about streaming labeling jobs—Create a streaming labeling job and send new dataset objects to workers in real time using a perpetually running labeling job. Workers continuously receive new data objects to label as long as the labeling job is active and new objects are being sent to it. To learn more, see Ground Truth Streaming Labeling Jobs (p. 576).
3. See the Reference—This section describes operations to automate Ground Truth operations.

Getting started

This video shows you how to setup and use Amazon SageMaker Ground Truth. (Length: 9:37)

To get started using Amazon SageMaker Ground Truth, follow the instructions in the following sections. The sections here explain how to use the console to create a labeling job, assign a public or private workforce, and send the labeling job to your workforce. You can also learn how to monitor the progress of a labeling job.

If you want to create a custom labeling workflow, see Creating Custom Labeling Workflows (p. 509) for instructions.

Before you create a labeling job, you must upload your dataset to an Amazon S3 bucket. For more information, see Use Input and Output Data (p. 572).

Topics
• Step 1: Before You Begin (p. 372)
• Step 2: Create a Labeling Job (p. 372)
• Step 3: Select Workers (p. 373)
• Step 4: Configure the Bounding Box Tool (p. 375)
Step 1: Before You Begin

Before you begin using the SageMaker console to create a labeling job, you must set up the dataset for use. Do this:

1. Save two images at publicly available HTTP URLs. The images are used when creating instructions for completing a labeling task. The images should have an aspect ratio of around 2:1. For this exercise, the content of the images is not important.
2. Create an Amazon S3 bucket to hold the input and output files. The bucket must be in the same Region where you are running Ground Truth. Make a note of the bucket name because you use it during step 2.

Ground Truth requires all S3 buckets that contain labeling job input image data have a CORS policy attached. To learn more about this change, see CORS Permission Requirement (p. 649).
3. You can create an IAM role or let SageMaker create a role with the AmazonSageMakerFullAccess IAM policy. Refer to Creating IAM roles and assign the following permissions policy to the user that is creating the labeling job:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "sagemakergroundtruth",
            "Effect": "Allow",
            "Action": [
                "cognito-idp:CreateGroup",
                "cognito-idp:CreateUserPool",
                "cognito-idp:CreateUserPoolDomain",
                "cognito-idp:AdminCreateUser",
                "cognito-idp:CreateUserPoolClient",
                "cognito-idp:AdminAddUserToGroup",
                "cognito-idp:DescribeUserPoolClient",
                "cognito-idp:DescribeUserPool",
                "cognito-idp:UpdateUserPool"
            ],
            "Resource": "*"
        }
    ]
}
```

Next

Step 2: Create a Labeling Job (p. 372)

Step 2: Create a Labeling Job

In this step you use the console to create a labeling job. You tell Amazon SageMaker Ground Truth the Amazon S3 bucket where the manifest file is stored and configure the parameters for the job. For more information about storing data in an Amazon S3 bucket, see Use Input and Output Data (p. 572).

To create a labeling job

2. From the left navigation, choose Labeling jobs.
3. Choose **Create labeling job** to start the job creation process.
4. In the **Job overview** section, provide the following information:
   - **Job name** – Give the labeling job a name that describes the job. This name is shown in your job list. The name must be unique in your account in an AWS Region.
   - **Label attribute name** – Leave this unchecked as the default value is the best option for this introductory job.
   - **Input data setup** – Select **Automated data setup**. This option allows you to automatically connect to your input data in S3.
   - **S3 location for input datasets** – Enter the S3 location where you added the images in step 1.
   - **S3 location for output datasets** – The location where your output data is written in S3.
   - **Data type** – Use the drop down menu to select **Image**. Ground Truth will use all images found in the S3 location for input datasets as input for your labeling job.
   - **IAM role** – Create or choose an IAM role with the AmazonSageMakerFullAccess IAM policy attached.
5. In the **Task type** section, for the **Task category** field, choose **Image**.
6. In the **Task selection** choose **Bounding box**.
7. Choose **Next** to move on to configuring your labeling job.

**Next**

**Step 3: Select Workers (p. 373)**

**Step 3: Select Workers**

In this step you choose a workforce for labeling your dataset. It is recommended that you create a private workforce to test Amazon SageMaker Ground Truth. Use email addresses to invite the members of your workforce. If you create a private workforce in this step you won't be able to import your Amazon Cognito user pool later. If you want to create a private workforce using an Amazon Cognito user pool, see **Manage a Private Workforce (Amazon Cognito) (p. 703)** and use the Mechanical Turk workforce instead in this tutorial.

**Tip**

To learn about the other workforce options you can use with Ground Truth, see **Create and Manage Workforces (p. 694)**.

**To create a private workforce:**

1. In the **Workers** section, choose **Private**.
2. If this is your first time using a private workforce, in the **Email addresses** field, enter up to 100 email addresses. The addresses must be separated by a comma. You should include your own email address so that you are part of the workforce and can see data object labeling tasks.
3. In the **Organization name** field, enter the name of your organization. This information is used to customize the email sent to invite a person to your private workforce. You can change the organization name after the user pool is created through the console.
4. In the **Contact email** field enter an email address that members of the workforce use to report problems with the task.

If you add yourself to the private workforce, you will receive an email that looks similar to the following. **Amazon, Inc.** is replaced by the organization you enter in step 3 of the preceding procedure. Select the link in the email to log in using the temporary password provided. If prompted, change your password. When you successfully log in, you see the worker portal where your labeling tasks appear.
Tip
You can find the link to your private workforce's worker portal in the Labeling workforces section of the Ground Truth area of the SageMaker console. To see the link, select the Private tab. The link is under the Labeling portal sign-in URL header in Private workforce summary.

If you choose to use the Amazon Mechanical Turk workforce to label the dataset, you are charged for labeling tasks completed on the dataset.

To use the Amazon Mechanical Turk workforce:

1. In the Workers section, choose Public.
2. Set a Price per task.
3. If applicable, choose The dataset does not contain adult content to acknowledge that the sample dataset has no adult content. This information enables Amazon SageMaker Ground Truth to warn external workers on Mechanical Turk that they might encounter potentially offensive content in your dataset.
4. Choose the check box next to the following statement to acknowledge that the sample dataset does not contain any personally identifiable information (PII). This is a requirement to use Mechanical Turk with Ground Truth. If your input data does contain PII, use the private workforce for this tutorial.

You understand and agree that the Amazon Mechanical Turk workforce consists of independent contractors located worldwide and that you should not share confidential information, personal information or protected health information with this workforce.

Next
Step 4: Configure the Bounding Box Tool (p. 375)
Step 4: Configure the Bounding Box Tool

Finally you configure the bounding box tool to give instructions to your workers. You can configure a task title that describes the task and provides high-level instructions for the workers. You can provide both quick instructions and full instructions. Quick instructions are displayed next to the image to be labeled. Full instructions contain detailed instructions for completing the task. In this example, you only provide quick instructions. You can see an example of full instructions by choosing Full instructions at the bottom of the section.

To configure the bounding box tool

1. In the Task description field type in brief instructions for the task. For example:

   Draw a box around any objects in the image.

   Replace objects with the name of an object that appears in your images.

2. In the Labels field, type a category name for the objects that the worker should draw a bounding box around. For example, if you are asking the worker to draw boxes around football players, you could use "Football Player" in this field.

3. The Short instructions section enables you to create instructions that are displayed on the page with the image that your workers are labeling. We suggest that you include an example of a correctly drawn bounding box and an example of an incorrectly drawn box. To create your own instructions, use these steps:
   a. Select the text between GOOD EXAMPLE and the image placeholder. Replace it with the following text:

      Draw the box around the object with a small border.

   b. Select the first image placeholder and delete it.

   c. Choose the image button and then enter the HTTPS URL of one of the images that you created in step 1. It is also possible to embed images directly in the short instructions section, however this section has a quota of 100 kilobytes (including text). If your images and text exceed 100 kilobytes, you receive an error.

   d. Select the text between BAD EXAMPLE and the image placeholder. Replace it with the following text:

      Don’t make the bounding box too large or cut into the object.

   e. Select the second image placeholder and delete it.

   f. Choose the image button and then enter the HTTPS URL of the other image that you created in step 1.

4. Select Preview to preview the worker UI. The preview opens in a new tab, and so if your browser blocks pop ups you may need to manually enable the tab to open. When you add one or more annotations to the preview and then select Submit you can see a preview of the output data your annotation would created.

5. After you have configured and verified your instructions, select Create to create the labeling job.

If you used a private workforce, you can navigate to the worker portal that you logged into in Step 3: Select Workers (p. 373) of this tutorial to see your labeling tasks. The tasks may take a few minutes to appear.

Next

Step 5: Monitoring Your Labeling Job (p. 376)
Step 5: Monitoring Your Labeling Job

After you create your labeling job, you see a list of all the jobs that you have created. You can use this list to monitor that status of your labeling jobs. The list has the following fields:

- **Name** – The name that you assigned the job when you created it.
- **Status** – The completion status of the job. The status can be one of Complete, Failed, In progress, or Stopped.
- **Labeled objects/total** – Shows the total number of objects in the labeling job and how many of them have been labeled.
- **Creation time** – The date and time that you created the job.

You can also clone, chain, or stop a job. Select a job and then select one of the following from the Actions menu:

- **Clone** – Creates a new labeling job with the configuration copied from the selected job. You can clone a job when you want to change to the job and run it again. For example, you can clone a job that was sent to a private workforce so that you can send it to the Amazon Mechanical Turk workforce. Or you can clone a job to rerun it against a new dataset stored in the same location as the original job.
- **Chain** – Creates a new labeling job that can build upon the data and models (if any) of a stopped, failed, or completed job. For more information about the use cases and how to use it, see Chaining Labeling Jobs (p. 646).
- **Stop** – Stops a running job. You cannot restart a stopped job. You can clone a job to start over or chain the job to continue from where it left off. Labels for any already labeled objects are written to the output file location. For more information, see Output Data (p. 614).

Label Images

Use Ground Truth to label images. Select one of the following built in task types to learn more about that task type. Each page includes instructions to help you create a labeling job using that task type.

**Tip**
To learn more about supported file types and input data quotas, see Input Data (p. 572).

**Topics**
- Bounding Box (p. 376)
- Image Semantic Segmentation (p. 382)
- Auto-Segmentation Tool (p. 385)
- Image Classification (Single Label) (p. 389)
- Image Classification (Multi-label) (p. 391)
- Image Label Verification (p. 395)

Bounding Box

The images used to train a machine learning model often contain more than one object. To classify and localize one or more objects within images, use the Amazon SageMaker Ground Truth bounding box labeling job task type. In this context, localization means the pixel-location of the bounding box.

You create a bounding box labeling job using the Ground Truth section of the Amazon SageMaker console or the CreateLabelingJob operation.
Important
For this task type, if you create your own manifest file, use "source-ref" to identify the location of each image file in Amazon S3 that you want labeled. For more information, see Input Data (p. 57).

Creating a Bounding Box Labeling Job (Console)

You can follow the instructions Create a Labeling Job (Console) (p. 544) to learn how to create a bounding box labeling job in the SageMaker console. In Step 10, choose Image from the Task category drop down menu, and choose Bounding box as the task type.

Ground Truth provides a worker UI similar to the following for labeling tasks. When you create the labeling job with the console, you specify instructions to help workers complete the job and up to 50 labels that workers can choose from.
Good example

Fit each box tightly around the boundaries of the object.

Bad example

Boxes should not overlap with the boundaries of objects.
Create a Bounding Box Labeling Job (API)

To create a bounding box labeling job, use the SageMaker API operation `CreateLabelingJob`. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of `CreateLabelingJob`.

Follow the instructions on Create a Labeling Job (API) (p. 547) and do the following while you configure your request:

- Pre-annotation Lambda functions for this task type end with `PRE-BoundingBox`. To find the pre-annotation Lambda ARN for your Region, see `PreHumanTaskLambdaArn`.
- Annotation-consolidation Lambda functions for this task type end with `ACS-BoundingBox`. To find the annotation-consolidation Lambda ARN for your Region, see `AnnotationConsolidationLambdaArn`.

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region. All parameters in red should be replaced with your specifications and resources.

```python
response = client.create_labeling_job(
    LabelingJobName='example-bounding-box-labeling-job,
    LabelAttributeName='label',
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json'
            }
        },
        'DataAttributes': {
            'ContentClassifiers': [
                'FreeOfPersonallyIdentifiableInformation'|'FreeOfAdultContent'
            ]
        }
    },
    OutputConfig={
        'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
        'KmsKeyId': 'string'
    },
    RoleArn='arn:aws:iam::*:role/*',
    LabelCategoryConfigS3Uri='s3://bucket/path/label-categories.json',
    StoppingConditions={
        'MaxHumanLabeledObjectCount': 123,
        'MaxPercentageOfInputDatasetLabeled': 123
    },
    HumanTaskConfig={
        'WorkteamArn': 'arn:aws:sagemaker:region:*:workteam/private-crowd/*',
        'UiConfig': {
            'UiTemplateS3Uri': 's3://bucket/path/worker-task-template.html'
        },
        'PreHumanTaskLambdaArn': 'arn:aws:lambda:us-east-1:432418664414:function:PRE-BoundingBox',
        'TaskKeywords': ['Bounding Box'],
        'TaskTitle': 'Bounding Box task',
        'TaskDescription': 'Draw bounding boxes around objects in an image',
        'NumberOfHumanWorkersPerDataObject': 123,
        'TaskTimeLimitInSeconds': 123,
        'TaskAvailabilityLifetimeInSeconds': 123,
        'MaxConcurrentTaskCount': 123,
        'AnnotationConsolidationConfig': {
            'AnnotationConsolidationLambdaArn': 'arn:aws:lambda:us-east-1:432418664414:function:ACS-BoundingBox'
        }
    }
)
```
Provide a Template for Bounding Box Labeling Jobs

If you create a labeling job using the API, you must supply a worker task template in `UiTemplateS3Uri`. Copy and modify the following template. Only modify the `short-instructions`, `full-instructions`, and `header`. Upload this template to S3, and provide the S3 URI for this file in `UiTemplateS3Uri`.

```html
<crowd-form>
  <crowd-bounding-box
    name="boundingBox"
    src="{{ task.input.taskObject | grant_read_access }}"
    header="please draw box"
    labels="{{ task.input.labels | to_json | escape }}"
  >

  <full-instructions header="Bounding box instructions">
    <ol>
      <li><strong>Inspect</strong> the image</li>
      <li><strong>Determine</strong> if the specified label is/are visible in the picture.</li>
      <li><strong>Outline</strong> each instance of the specified label in the image using the provided "Box" tool.</li>
      <li>Boxes should fit tight around each object</li>
      <li>Do not include parts of the object are overlapping or that cannot be seen, even though you think you can interpolate the whole shape.</li>
      <li>Avoid including shadows.</li>
      <li>If the target is off screen, draw the box up to the edge of the image.</li>
    </ol>

  </full-instructions>

  <short-instructions>
    <h3><span style="color: rgb(0, 138, 0);">Good example</span></h3>
    <p>Enter description of a correct bounding box label and add images</p>

    <h3><span style="color: rgb(230, 0, 0);">Bad example</span></h3>
    <p>Enter description of an incorrect bounding box label and add images</p>
  </short-instructions>

</crowd-bounding-box>
</crowd-form>
```

Bounding Box Output Data

Once you have created a bounding box labeling job, your output data will be located in the Amazon S3 bucket specified in the `S3OutputPath` parameter when using the API or in the `Output dataset location` field of the `Job overview` section of the console.

For example, the output manifest file of a successfully completed single-class bounding box task will contain the following:

```json
[{
    "boundingBox": {
        "boundingBoxes": [
            {
                "height": 2832,
                "label": "bird",
            }
        ]
    }
}]
```
The `boundingBoxes` parameter identifies the location of the bounding box drawn around an object identified as a "bird" relative to the top-left corner of the image which is taken to be the (0,0) pixel-coordinate. In the previous example, `left` and `top` identify the location of the pixel in the top-left corner of the bounding box relative to the top-left corner of the image. The dimensions of the bounding box are identified with `height` and `width`. The `inputImageProperties` parameter gives the pixel-dimensions of the original input image.

When you use the bounding box task type, you can create single- and multi-class bounding box labeling jobs. The output manifest file of a successfully completed multi-class bounding box will contain the following:

```json
[
  {
    "boundingBox": {
      "boundingBoxes": [
        {
          "height": 938,
          "label": "squirrel",
          "left": 316,
          "top": 218,
          "width": 785
        },
        {
          "height": 825,
          "label": "rabbit",
          "left": 1930,
          "top": 2265,
          "width": 540
        },
        {
          "height": 1174,
          "label": "bird",
          "left": 748,
          "top": 2113,
          "width": 927
        },
        {
          "height": 893,
          "label": "bird",
          "left": 1333,
          "top": 847,
          "width": 736
        }
      ],
      "inputImageProperties": {
        "height": 3726,
        "width": 2662
      }
    }
  }
]
To learn more about the output manifest file that results from a bounding box labeling job, see Bounding Box Job Output (p. 620).

To learn more about the output manifest file generated by Ground Truth and the file structure the Ground Truth uses to store your output data, see Output Data (p. 614).

Image Semantic Segmentation

To identify the contents of an image at the pixel level, use an Amazon SageMaker Ground Truth semantic segmentation labeling task. When assigned a semantic segmentation labeling job, workers classify pixels in the image into a set of predefined labels or classes. Ground Truth supports single and multi-class semantic segmentation labeling jobs.

Images that contain large numbers of objects that need to be segmented require more time. To help workers (from a private or vendor workforce) label these objects in less time and with greater accuracy, Ground Truth provides an AI-assisted auto-segmentation tool. For information, see Auto-Segmentation Tool (p. 385).

You create a semantic segmentation labeling job using the Ground Truth section of the Amazon SageMaker console or the CreateLabelingJob operation.

Important
For this task type, if you create your own manifest file, use "source-ref" to identify the location of each image file in Amazon S3 that you want labeled. For more information, see Input Data (p. 572).

Creating a Semantic Segmentation Labeling Job (Console)

You can follow the instructions Create a Labeling Job (Console) (p. 544) to learn how to create a semantic segmentation labeling job in the SageMaker console. In Step 10, choose Image from the Task category drop down menu, and choose Semantic segmentation as the task type.

Ground Truth provides a worker UI similar to the following for labeling tasks. When you create the labeling job with the console, you specify instructions to help workers complete the job and labels that workers can choose from.
Instructions

View full instructions
View tool guide
How to use the Auto-segment tool

Good example

All pixels in the image that are part of an animal have been colors with the appropriate label color.

Bad example

Some animals in the image have not been colored in completely.

The color for a given animal extends beyond the boundaries of the animal.
Create a Semantic Segmentation Labeling Job (API)

To create a semantic segmentation labeling job, use the SageMaker API operation CreateLabelingJob. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of CreateLabelingJob.

Follow the instructions on Create a Labeling Job (API) (p. 547) and do the following while you configure your request:

- Pre-annotation Lambda functions for this task type end with PRE-SemanticSegmentation. To find the pre-annotation Lambda ARN for your Region, see PreHumanTaskLambdaArn.
- Annotation-consolidation Lambda functions for this task type end with ACS-SemanticSegmentation. To find the annotation-consolidation Lambda ARN for your Region, see AnnotationConsolidationLambdaArn.

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region. All parameters in red should be replaced with your specifications and resources.

```python
response = client.create_labeling_job(
    LabelingJobName='example-semantic-segmentation-labeling-job',
    LabelAttributeName='label',
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json'
            }
        },
        'DataAttributes': {
            'ContentClassifiers': [
                'FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent'
            ]
        }
    },
    OutputConfig={
        'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
        'KmsKeyId': 'string'
    },
    RoleArn='arn:aws:iam::*:role/*',
    LabelCategoryConfigS3Uri='s3://bucket/path/label-categories.json',
    StoppingConditions={
        'MaxHumanLabeledObjectCount': 123,
        'MaxPercentageOfInputDatasetLabeled': 123
    },
    HumanTaskConfig={
        'WorkteamArn': 'arn:aws:sagemaker:region:*:workteam/private-crowd/*',
        'UiConfig': {
            'UiTemplateS3Uri': 's3://bucket/path/worker-task-template.html'
        },
        'TaskKeywords': ['Semantic Segmentation'],
        'TaskTitle': 'Semantic segmentation task',
        'TaskDescription': 'For each category provided, segment out each relevant object using the color associated with that category',
        'NumberOfHumanWorkersPerDataObject': 123,
        'TaskTimeLimitInSeconds': 123,
        'TaskAvailabilityLifetimeInSeconds': 123,
        'MaxConcurrentTaskCount': 123,
        'AnnotationConsolidationConfig': {
```
Provide a Template for Semantic Segmentation Labeling Jobs

If you create a labeling job using the API, you must supply a worker task template in UiTemplateS3Uri. Copy and modify the following template. Only modify the short-instructions, full-instructions, and header.

Upload this template to S3, and provide the S3 URI for this file in UiTemplateS3Uri.

Semantic Segmentation Output Data

Once you have created a semantic segmentation labeling job, your output data will be located in the Amazon S3 bucket specified in the S3OutputPath parameter when using the API or in the Output dataset location field of the Job overview section of the console.

To learn more about the output manifest file generated by Ground Truth and the file structure the Ground Truth uses to store your output data, see Output Data (p. 614).

To see an example of an output manifest file for a semantic segmentation labeling job, see 3D Point Cloud Semantic Segmentation Output (p. 630).

Auto-Segmentation Tool

Image segmentation is the process of dividing an image into multiple segments, or sets of labeled pixels. In Amazon SageMaker Ground Truth, the process of identifying all pixels that fall under a given
label involves applying a colored filler, or "mask", over those pixels. Some labeling job tasks contain images with large numbers of objects that need to be segmented. To help workers label these objects in less time and with greater accuracy, Ground Truth provides an auto-segmentation tool for segmentation tasks assigned to private and vendor workforces. This tool uses a machine learning model to automatically segment individual objects in the image with minimal worker input. Workers can refine the mask generated by the auto-segmentation tool using other tools found in the worker console. This helps workers complete image segmentation tasks faster and more accurately, resulting in lower cost and higher label quality.

**Note**
The auto-segmentation tool is available for segmentation tasks that are sent to a private workforce or vendor workforce. It isn't available for tasks sent to the public workforce (Amazon Mechanical Turk).

**Tool Preview**

When workers are assigned a labeling job that provides the auto-segmentation tool, they are provided with detailed instructions on how to use the tool. For example, a worker might see the following in the worker console:
Use paint brush to paint a mask on each bird in the image.
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Workers can use View full instructions to learn how to use the tool. Workers will need to place a point
on four extreme-points ( top-most, bottom-most, left-most, and right-most points ) of the object of
interest, and the tool will automatically generate a mask for the object. Workers can further-reﬁne the
mask using the other tools provided, or by using the auto-segment tool on smaller portions of the object
that were missed.

Tool Availability
The auto-segmentation tool automatically appears in your workers' consoles if you create a semantic
segmentation labeling job using the Amazon SageMaker console. While creating a semantic
segmentation job in the SageMaker console, you will be able to preview the tool while creating worker
instructions. To learn how to create a semantic segmentation labeling job in the SageMaker console, see
Getting started (p. 371).
If you are creating a custom instance segmentation labeling job in the SageMaker console or creating
an instance- or semantic-segmentation labeling job using the Ground Truth API, you need to create a
custom task template to design your worker console and instructions. To include the auto-segmentation
tool in your worker console, ensure that the following conditions are met in your custom task template:
• For semantic segmentation labeling jobs created using the API, the <crowd-semanticsegmentation> is present in the task template. For custom instance segmentation labeling jobs, the
<crowd-instance-segmentation> tag is present in the task template.
• The task is assigned to a private workforce or vendor workforce.
• The images to be labeled are Amazon Simple Storage Service Amazon S3) objects that have been
pre-signed for the Worker so that they can access it. This is true if the task template includes the
grant_read_access ﬁlter. For information about the grant_read_access ﬁlter, see Adding
automation with Liquid (p. 513).
The following is an example of a custom task template for a custom instance segmentation labeling job,
which includes the <crowd-instance-segmentation/> tag and the grant_read_access Liquid
ﬁlter.
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
<crowd-instance-segmentation
name="crowd-instance-segmentation"
src="{{ task.input.taskObject | grant_read_access }}"
labels="['Car','Road']"
<full-instructions header="Segmentation instructions">
Segment each instance of each class of objects in the image.
</full-instructions>
<short-instructions>
<p>Segment each instance of each class of objects in the image.</p>
<h3 style="color: green">GOOD EXAMPLES</h3>
<img src="path/to/image.jpg" style="width: 100%">
<p>Good because A, B, C.</p>
<h3 style="color: red">BAD EXAMPLES</h3>
<img src="path/to/image.jpg" style="width: 100%">
<p>Bad because X, Y, Z.</p>
</short-instructions>
</crowd-instance-segmentation>
</crowd-form>

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Image Classification (Single Label)

Use an Amazon SageMaker Ground Truth image classification labeling task when you need workers to classify images using predefined labels that you specify. Workers are shown images and are asked to choose one label for each image.

You can create an image classification labeling job using the Ground Truth section of the Amazon SageMaker console or the `CreateLabelingJob` operation.

**Important**
For this task type, if you create your own manifest file, use "source-ref" to identify the location of each image file in Amazon S3 that you want labeled. For more information, see Input Data (p. 572).

Create an Image Classification Labeling Job (Console)

You can follow the instructions Create a Labeling Job (Console) (p. 544) to learn how to create a image classification labeling job in the SageMaker console. In Step 10, choose Image from the Task category drop down menu, and choose Image Classification (Single Label) as the task type.

Ground Truth provides a worker UI similar to the following for labeling tasks. When you create the labeling job with the console, you specify instructions to help workers complete the job and labels that workers can choose from.

Create an Image Classification Labeling Job (API)

To create an image classification labeling job, use the SageMaker API operation `CreateLabelingJob`. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of `CreateLabelingJob`. 
Follow the instructions on Create a Labeling Job (API) (p. 547) and do the following while you configure your request:

- Pre-annotation Lambda functions for this task type end with PRE-ImageMultiClass. To find the pre-annotation Lambda ARN for your Region, see PreHumanTaskLambdaArn.
- Annotation-consolidation Lambda functions for this task type end with ACS-ImageMultiClass. To find the annotation-consolidation Lambda ARN for your Region, see AnnotationConsolidationLambdaArn.

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region. All parameters in red should be replaced with your specifications and resources.

```python
response = client.create_labeling_job(
    LabelingJobName='example-image-classification-labeling-job',
    LabelAttributeName='label',
    InputConfig={
        'DataSource': { 'S3DataSource': { 'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json' } },
        'DataAttributes': { 'ContentClassifiers': ['FreeOfPersonallyIdentifiableInformation','FreeOfAdultContent'],
    } },
    OutputConfig={
        'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
        'KmsKeyId': 'string'
    },
    RoleArn='arn:aws:iam::*:role/*',
    LabelCategoryConfigS3Uri='s3://bucket/path/label-categories.json',
    StoppingConditions={
        'MaxHumanLabeledObjectCount': 123,
        'MaxPercentageOfInputDatasetLabeled': 123,
    },
    HumanTaskConfig={
        'WorkteamArn': 'arn:aws:sagemaker:region::workteam/private-crowd/*',
        'UiConfig': { 'UiTemplateS3Uri': 's3://bucket/path/worker-task-template.html' },
        'TaskKeywords': ['Image classification'],
        'TaskTitle': 'Image classification task',
        'TaskDescription': 'Carefully inspect the image and classify it by selecting one label from the categories provided.',
        'NumberOfHumanWorkersPerDataObject': 123,
        'TaskTimeLimitInSeconds': 123,
        'TaskAvailabilityLifetimeInSeconds': 123,
        'MaxConcurrentTaskCount': 123,
        'AnnotationConsolidationConfig': { 'AnnotationConsolidationLambdaArn': 'arn:aws:lambda:us-east-1:432418664414:function:ACS-ImageMultiClass' },
    },
    Tags=[
        { 'Key': 'string', 'Value': 'string' }
    ],
)```
Provide a Template for Image Classification Labeling Jobs

If you create a labeling job using the API, you must supply a worker task template in UiTemplateS3Uri. Copy and modify the following template. Only modify the short-instructions, full-instructions, and header.

Upload this template to S3, and provide the S3 URI for this file in UiTemplateS3Uri.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-image-classifier
    name="crowd-image-classifier"
    src="{{ task.input.taskObject | grant_read_access }}"
    header="please classify"
    categories="{{ task.input.labels | to_json | escape }}"
  >
    <full-instructions header="Image classification instructions">
      <ol>
        <li><strong>Read</strong> the task carefully and inspect the image.</li>
        <li><strong>Read</strong> the options and review the examples provided to understand more about the labels.</li>
        <li><strong>Choose</strong> the appropriate label that best suits the image.</li>
      </ol>
    </full-instructions>
    <short-instructions>
      <h3><span style="color: rgb(0, 138, 0);">Good example</span></h3>
      <p>Enter description to explain the correct label to the workers</p>
      <h3><span style="color: rgb(230, 0, 0);">Bad example</span></h3>
      <p>Enter description of an incorrect label</p>
    </short-instructions>
  </crowd-image-classifier>
</crowd-form>

Image Classification Output Data

Once you have created an image classification labeling job, your output data will be located in the Amazon S3 bucket specified in the S3OutputPath parameter when using the API or in the Output dataset location field of the Job overview section of the console.

To learn more about the output manifest file generated by Ground Truth and the file structure the Ground Truth uses to store your output data, see Output Data (p. 614).

To see an example of an output manifest file from an image classification labeling job, see Classification Job Output (p. 618).

Image Classification (Multi-label)

Use an Amazon SageMaker Ground Truth multi-label image classification labeling task when you need workers to classify multiple objects in an image. For example, the following image features a dog and a cat. You can use multi-label image classification to associate the labels "dog" and "cat" with this image.
When working on a multi-label image classification task, workers should choose all applicable labels, but must choose at least one. When creating a job using this task type, you can provide up to 50 label-categories.

When creating a labeling job in the console, Ground Truth doesn't provide a "none" category for when none of the labels applies to an image. To provide this option to workers, include a label similar to "none" or "other" when you create a multi-label image classification job.

To restrict workers to choosing a single label for each image, use the Image Classification (Single Label) (p. 389) task type.

Important
For this task type, if you create your own manifest file, use "source-ref" to identify the location of each image file in Amazon S3 that you want labeled. For more information, see Input Data (p. 572).

Create a Multi-Label Image Classification Labeling Job (Console)

You can follow the instructions Create a Labeling Job (Console) (p. 544) to learn how to create a multi-label image classification labeling job in the SageMaker console. In Step 10, choose Image from the Task category drop down menu, and choose Image Classification (Multi-label) as the task type.

Ground Truth provides a worker UI similar to the following for labeling tasks. When you create a labeling job in the console, you specify instructions to help workers complete the job and labels that workers can choose from.
Create a Multi-Label Image Classification Labeling Job (API)

To create a multi-label image classification labeling job, use the SageMaker API operation CreateLabelingJob. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of CreateLabelingJob.

Follow the instructions on Create a Labeling Job (API) (p. 547) and do the following while you configure your request:

- Pre-annotation Lambda functions for this task type end with PRE-ImageMultiClassMultiLabel. To find the pre-annotation Lambda ARN for your Region, see PreHumanTaskLambdaArn.
- Annotation-consolidation Lambda functions for this task type end with ACS-ImageMultiClassMultiLabel. To find the annotation-consolidation Lambda ARN for your Region, see AnnotationConsolidationLambdaArn.

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region. All parameters in red should be replaced with your specifications and resources.

```python
response = client.create_labeling_job(
    LabelingJobName='example-multi-label-image-classification-labeling-job',
    LabelAttributeName='label',
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json'
            }
        },
        'DataAttributes': {
            'ContentClassifiers': [
                'FreeOfPersonallyIdentifiableInformation',
                'FreeOfAdultContent',
            ]
        }
    }
)
```
OutputConfig={
    'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
    'KmsKeyId': 'string'
},
RoleArn='arn:aws:iam::*:role/*,
LabelCategoryConfigS3Uri='s3://bucket/path/label-categories.json',
StoppingConditions={
    'MaxHumanLabeledObjectCount': 123,
    'MaxPercentageOfInputDatasetLabeled': 123
},
HumanTaskConfig={
    'WorkteamArn': 'arn:aws:sagemaker:region:::workteam/private-crowd/*',
    'UiConfig': {
        'UiTemplateS3Uri': 's3://bucket/path/worker-task-template.html'
    },
    'TaskKeywords': ['Image Classification'],
    'TaskTitle': 'Multi-label image classification task',
    'TaskDescription': 'Select all labels that apply to the images shown',
    'NumberOfHumanWorkersPerDataObject': 123,
    'TaskTimeLimitInSeconds': 123,
    'TaskAvailabilityLifetimeInSeconds': 123,
    'MaxConcurrentTaskCount': 123,
    'AnnotationConsolidationConfig': {
        'AnnotationConsolidationLambdaArn': 'arn:aws:lambda:us-east-1:432418664414:function:ACS-ImageMultiClassMultiLabel'
    },
    'Tags':[
        {'Key': 'string', 'Value': 'string'}
    ]
}

Provide a Template for Multi-label Image Classification

If you create a labeling job using the API, you must supply a worker task template in UiTemplateS3Uri. Copy and modify the following template. Only modify the short-instructions, full-instructions, and header.

Upload this template to S3, and provide the S3 URI for this file in UiTemplateS3Uri.

<crowd-form>
<crowd-image-classifier-multi-select
    name="crowd-image-classifier-multi-select"
    src="{{ task.input.taskObject | grant_read_access }}"
    header="Please identify all classes in image"
    categories="{{ task.input.labels | to_json | escape }}"
>
<full-instructions header="Multi Label Image classification instructions">
  <ol><li><strong>Read</strong> the task carefully and inspect the image.</li>
  <li><strong>Read</strong> the options and review the examples provided to understand more about the labels.</li>
  <li><strong>Choose</strong> the appropriate labels that best suit the image.</li></ol>
</full-instructions>
<short-instructions>
  <h3><span style="color: rgb(0, 138, 0);">Good example</span></h3>
  <p>Enter description to explain the correct label to the workers</p>
</short-instructions>
</crowd-image-classifier-multi-select>
</crowd-form>
Multi-label Image Classification Output Data

Once you have created a multi-label image classification labeling job, your output data will be located in the Amazon S3 bucket specified in the S3OutputPath parameter when using the API or in the Output dataset location field of the Job overview section of the console.

To learn more about the output manifest file generated by Ground Truth and the file structure the Ground Truth uses to store your output data, see Output Data (p. 614).

To see an example of output manifest files for multi-label image classification labeling job, see Multi-label Classification Job Output (p. 619).

Image Label Verification

Building a highly accurate training dataset for your machine learning (ML) algorithm is an iterative process. Typically, you review and continuously adjust your labels until you are satisfied that they accurately represent the ground truth, or what is directly observable in the real world.

You can use an Amazon SageMaker Ground Truth image label verification task to direct workers to review a dataset's labels and improve label accuracy. Workers can indicate if the existing labels are correct or rate label quality. They can also add comments to explain their reasoning. Amazon SageMaker Ground Truth supports label verification for Bounding Box (p. 376) and Image Semantic Segmentation (p. 382) labels.

You create an image label verification labeling job using the Ground Truth section of the Amazon SageMaker console or the CreateLabelingJob operation.

Ground Truth provides a worker console similar to the following for labeling tasks. When you create the labeling job with the console, you can modify the images and content that are shown. To learn how to create a labeling job using the Ground Truth console, see Create a Labeling Job (Console) (p. 544).
Use Ground Truth to Label Text

Use Ground Truth to text. Select one of the following built in task types to learn more about that task type. Each page includes instructions to help you create a labeling job using that task type.

Tip
To learn more about supported file types and input data quotas, see Input Data (p. 572).

Topics
- Named Entity Recognition (p. 396)
- Text Classification (Single Label) (p. 400)
- Text Classification (Multi-label) (p. 403)

Named Entity Recognition

To extract information from unstructured text and classify it into predefined categories, use an Amazon SageMaker Ground Truth named entity recognition (NER) labeling task. Traditionally, NER involves sifting through text data to locate noun phrases, called named entities, and categorizing each with a label, such as "person," "organization," or "brand." You can broaden this task to label longer spans of text and categorize those sequences with predefined labels that you specify.

When tasked with a named entity recognition labeling job, workers apply your labels to specific words or phrases within a larger text block. They choose a label, then apply it by using the cursor to highlight the part of the text to which the label applies. The Ground Truth named entity recognition tool supports
overlapping annotations, in-context label selection, and multi-label selection for a single highlight. Also, workers can use their keyboards to quickly select labels.

You can create a named entity recognition labeling job using the Ground Truth section of the Amazon SageMaker console or the CreateLabelingJob operation.

**Important**
If you manually create an input manifest file, use "source" to identify the text that you want labeled. For more information, see Input Data (p. 572).

**Create a Named Entity Recognition Labeling Job (Console)**

You can follow the instructions Create a Labeling Job (Console) (p. 544) to learn how to create a named entity recognition labeling job in the SageMaker console. In Step 10, choose Text from the Task category drop down menu, and choose Named entity recognition as the task type.

Ground Truth provides a worker UI similar to the following for labeling tasks. When you create the labeling job with the console, you specify instructions to help workers complete the job and labels that workers can choose from.

**Create a Named Entity Recognition Labeling Job (API)**

To create a named entity recognition labeling job, using the SageMaker API operation CreateLabelingJob. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of CreateLabelingJob.

Follow the instructions on Create a Labeling Job (API) (p. 547) and do the following while you configure your request:

- Pre-annotation Lambda functions for this task type end with PRE-NamedEntityRecognition. To find the pre-annotation Lambda ARN for your Region, see PreHumanTaskLambdaArn.
• Annotation-consolidation Lambda functions for this task type end with ACS-NamedEntityRecognition. To find the annotation-consolidation Lambda ARN for your Region, see AnnotationConsolidationLambdaArn.

• You must provide the following ARN for HumanTaskUiArn:

```
```

Replace `aws-region` with the AWS Region you use to create the labeling job. For example, use us-west-1 if you create a labeling job in US West (N. California).

• Provide worker instructions in the label category configuration file using the instructions parameter. You can use a string, or HTML markup language in the shortInstruction and fullInstruction fields. For more details, see Provide Worker Instructions in a Label Category Configuration File (p. 399).

```
"instructions": {"shortInstruction":"<h1>Add header</h1><p>Add Instructions</p>"},
"fullInstruction": "<p>Add additional instructions.</p>"}
```

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region. All parameters in red should be replaced with your specifications and resources.

```python
response = client.create_labeling_job(
    LabelingJobName='example-ner-labeling-job',
    LabelAttributeName='label',
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json'
            }
        },
        'DataAttributes': {
            'ContentClassifiers': [
                'FreeOfPersonallyIdentifiableInformation','FreeOfAdultContent'
            ],
        }
    },
    OutputConfig={
        'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
        'KmsKeyId': 'string'
    },
    RoleArn='arn:aws:iamp:*:role/**',
    LabelCategoryConfigS3Uri='s3://bucket/path/label-categories.json',
    StoppingConditions={
        'MaxHumanLabeledObjectCount': 123,
        'MaxPercentageOfInputDatasetLabeled': 123
    },
    HumanTaskConfig={
        'WorkteamArn': 'arn:aws:sagemaker:region:*:workteam/private-crowd/**',
        'UiConfig': {
            'TaskKeywords': ['Named entity Recognition'],
            'TaskTitle': 'Named entity Recognition task',
            'TaskDescription': 'Apply the labels provided to specific words or phrases within the larger text block.'
        }
    }
)```
Provide Worker Instructions in a Label Category Configuration File

You must provide worker instructions in the label category configuration file you identify with the LabelCategoryConfigS3Uri parameter in CreateLabelingJob. You can use these instructions to provide details about the task you want workers to perform and help them use the tool efficiently.

You provide short and long instructions using shortInstruction and fullInstruction in the instructions parameter, respectively. To learn more about these instruction types, see Creating Instruction Pages (p. 542).

The following is an example of a label category configuration file with instructions that can be used for a named entity recognition labeling job.

```json
{
  "document-version": "2018-11-28",
  "labels": [
    {
      "label": "label1",
      "shortDisplayName": "L1"
    },
    {
      "label": "label2",
      "shortDisplayName": "L2"
    },
    {
      "label": "label3",
      "shortDisplayName": "L3"
    },
    {
      "label": "label4",
      "shortDisplayName": "L4"
    },
    {
      "label": "label5",
      "shortDisplayName": "L5"
    }
  ],
  "instructions": {
    "shortInstruction": "Enter description of the labels that workers have to choose from<br> Add examples to help workers understand the label",
    "fullInstruction": "Read the text carefully.<br> Highlight words, phrases, or sections of the text. Choose the label that best matches what you have highlighted."}
}``
Named Entity Recognition Output Data

Once you have created a named entity recognition labeling job, your output data will be located in the Amazon S3 bucket specified in the S3OutputPath parameter when using the API or in the Output dataset location field of the Job overview section of the console.

To learn more about the output manifest file generated by Ground Truth and the file structure the Ground Truth uses to store your output data, see Output Data (p. 614).

Text Classification (Single Label)

To categorize articles and text into predefined categories, use text classification. For example, you can use text classification to identify the sentiment conveyed in a review or the emotion underlying a section of text. Use Amazon SageMaker Ground Truth text classification to have workers sort text into categories that you define.

You create a text classification labeling job using the Ground Truth section of the Amazon SageMaker console or the CreateLabelingJob operation.

Important

If you manually create an input manifest file, use "source" to identify the text that you want labeled. For more information, see Input Data (p. 572).

Create a Text Classification Labeling Job (Console)

You can follow the instructions Create a Labeling Job (Console) (p. 544) to learn how to create a text classification labeling job in the SageMaker console. In Step 10, choose Text from the Task category drop down menu, and choose Text Classification (Single Label) as the task type.

Ground Truth provides a worker UI similar to the following for labeling tasks. When you create the labeling job with the console, you specify instructions to help workers complete the job and labels that workers can choose from.
Create a Text Classification Labeling Job (API)

To create a text classification labeling job, use the SageMaker API operation `CreateLabelingJob`. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of `CreateLabelingJob`.

Follow the instructions on Create a Labeling Job (API) (p. 547) and do the following while you configure your request:

- Pre-annotation Lambda functions for this task type end with `PRE-TextMultiClass`. To find the pre-annotation Lambda ARN for your Region, see `PreHumanTaskLambdaArn`.
- Annotation-consolidation Lambda functions for this task type end with `ACS-TextMultiClass`. To find the annotation-consolidation Lambda ARN for your Region, see `AnnotationConsolidationLambdaArn`.

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region. All parameters in red should be replaced with your specifications and resources.

```python
response = client.create_labeling_job(
    LabelingJobName='example-text-classification-labeling-job',
    LabelAttributeName='label',
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json'
            }
        },
        'DataAttributes': {
            'ContentClassifiers': [
                'FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent',
            ]
        }
    },
    OutputConfig={
        'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
        'KmsKeyId': 'string'
    })
```
Provide a Template for Text Classification Labeling Jobs

If you create a labeling job using the API, you must supply a worker task template in `UiTemplateS3Uri`. Copy and modify the following template. Only modify the `short-instructions`, `full-instructions`, and `header`.

Upload this template to S3, and provide the S3 URI for this file in `UiTemplateS3Uri`.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-classifier
    name="crowd-classifier"
    categories="{{ task.input.labels | to_json | escape }}"
    header="classify text"
  >
    <classification-target style="white-space: pre-wrap">
      {{ task.input.taskObject }}
    </classification-target>
    <full-instructions header="Classifier instructions">
      <ol>
        <li><strong>Read</strong> the text carefully.</li>
        <li><strong>Read</strong> the examples to understand more about the options.</li>
        <li><strong>Choose</strong> the appropriate labels that best suit the text.</li>
      </ol>
    </full-instructions>
    <short-instructions>
      <p>Enter description of the labels that workers have to choose from</p>
      <p><br></p>
      <p>Add examples to help workers understand the label</p>
    </short-instructions>
</crowd-form>
```
Text Classification Output Data

Once you have created a text classification labeling job, your output data will be located in the Amazon S3 bucket specified in the S3OutputPath parameter when using the API or in the Output dataset location field of the Job overview section of the console.

To learn more about the output manifest file generated by Ground Truth and the file structure the Ground Truth uses to store your output data, see Output Data (p. 614).

To see an example of an output manifest files from a text classification labeling job, see Classification Job Output (p. 618).

Text Classification (Multi-label)

To categorize articles and text into multiple predefined categories, use the multi-label text classification task type. For example, you can use this task type to identify more than one emotion conveyed in text.

When working on a multi-label text classification task, workers should choose all applicable labels, but must choose at least one. When creating a job using this task type, you can provide up to 50 label categories.

Amazon SageMaker Ground Truth doesn't provide a "none" category for when none of the labels applies. To provide this option to workers, include a label similar to "none" or "other" when you create a multi-label text classification job.

To restrict workers to choosing a single label for each document or text selection, use the Text Classification (Single Label) (p. 400) task type.

Important
If you manually create an input manifest file, use "source" to identify the text that you want labeled. For more information, see Input Data (p. 572).

Create a Multi-Label Text Classification Labeling Job (Console)

You can follow the instructions Create a Labeling Job (Console) (p. 544) to learn how to create a multi-label text classification labeling job in the Amazon SageMaker console. In Step 10, choose Text from the Task category drop down menu, and choose Text Classification (Multi-label) as the task type.

Ground Truth provides a worker UI similar to the following for labeling tasks. When you create the labeling job with the console, you specify instructions to help workers complete the job and labels that workers can choose from.
Create a Multi-Label Text Classification Labeling Job (API)

To create a multi-label text classification labeling job, use the SageMaker API operation `CreateLabelingJob`. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of `CreateLabelingJob`.

Follow the instructions on Create a Labeling Job (API) (p. 547) and do the following while you configure your request:

- Pre-annotation Lambda functions for this task type end with `PRE-TextMultiClassMultiLabel`. To find the pre-annotation Lambda ARN for your Region, see `PreHumanTaskLambdaArn`.
- Annotation-consolidation Lambda functions for this task type end with `ACS-TextMultiClassMultiLabel`. To find the annotation-consolidation Lambda ARN for your Region, see `AnnotationConsolidationLambdaArn`.

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region. All parameters in red should be replaced with your specifications and resources.

```python
response = client.create_labeling_job(
    LabelingJobName='example-multi-label-text-classification-labeling-job',
    LabelAttributeName='label',
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json'
            }
        },
        'DataAttributes': {
            'ContentClassifiers': [
                'FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent',
            ]
        }
    },
    OutputConfig={
        'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
        'KmsKeyId': 'string'
    },
)
```
Create a Template for Multi-label Text Classification

If you create a labeling job using the API, you must supply a worker task template in `UiTemplateS3Uri`. Copy and modify the following template. Only modify the `short-instructions`, `full-instructions`, and `header`.

Upload this template to S3, and provide the S3 URI for this file in `UiTemplateS3Uri`.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
<crowd-classifier-multi-select
    name="crowd-classifier-multi-select"
    categories="{{ task.input.labels | to_json | escape }}"
    header="Please identify all classes in the below text"
>
    <classification-target style="white-space: pre-wrap">
        {{ task.input.taskObject }}
    </classification-target>

    <full-instructions header="Classifier instructions">
        <ol>
            <li><strong>Read</strong> the text carefully.</li>
            <li><strong>Read</strong> the examples to understand more about the options.</li>
            <li><strong>Choose</strong> the appropriate labels that best suit the text.</li>
        </ol>
    </full-instructions>

    <short-instructions>
        <p>Enter description of the labels that workers have to choose from</p>
        <p><br></p>
        <p>Add examples to help workers understand the label</p>
    </short-instructions>
</crowd-classifier-multi-select>
</crowd-form>
```
To learn how to create a custom template, see Creating Custom Labeling Workflows (p. 509).

### Multi-label Text Classification Output Data

Once you have created a multi-label text classification labeling job, your output data will be located in the Amazon S3 bucket specified in the S3OutputPath parameter when using the API or in the Output dataset location field of the Job overview section of the console.

To learn more about the output manifest file generated by Ground Truth and the file structure the Ground Truth uses to store your output data, see Output Data (p. 614).

To see an example of output manifest files for multi-label text classification labeling job, see Multi-label Classification Job Output (p. 619).

### Label Videos and Video Frames

You can use Ground Truth to classify videos and annotate video frames (still images extracted from videos) using one of the three built-in video task types. These task types streamline the process of creating video and video frame labeling jobs using the Amazon SageMaker console, API, and language-specific SDKs.

- **Video clip classification** – Enable workers to classify videos into categories you specify. For example, you can use this task type to have workers categorize videos into topics like sports, comedy, music, and education. To learn more, see Video Classification (p. 406).
- **Video frame labeling jobs** – Enable workers to annotate video frames extracted from a video using bounding boxes, polylines, polygons or keypoint annotation tools. Ground Truth offers two built-in task types to label video frames:
  - **Video frame object detection**: Enable workers to identify and locate objects in video frames.
  - **Video frame object tracking**: Enable workers to track the movement of objects across video frames.
  - **Video frame adjustment jobs**: Have workers adjust labels, label category attributes, and frame attributes from a previous video frame object detection or object tracking labeling job.
  - **Video frame verification jobs**: Have workers verify labels, label category attributes, and frame attributes from a previous video frame object detection or object tracking labeling job.

If you have video files, you can use the Ground Truth automatic frame extraction tool to extract video frames from your videos. To learn more, see Video Frame Input Data (p. 608).

**Tip**

To learn more about supported file types and input data quotas, see Input Data (p. 572).

### Video Classification

Use an Amazon SageMaker Ground Truth video classification labeling task when you need workers to classify videos using predefined labels that you specify. Workers are shown videos and are asked to choose one label for each video.

You create a video classification labeling job using the Ground Truth section of the Amazon SageMaker console or the CreateLabelingJob operation.
Your video files must be encoded in a format that is supported by the browser used by the work team that labels your data. It is recommended that you verify that all video file formats in your input manifest file display correctly using the worker UI preview. You can communicate supported browsers to your workers using worker instructions. To see supported file formats, see Supported Data Formats (p. 575).

**Important**
For this task type, if you create your own manifest file, use "source-ref" to identify the location of each video file in Amazon S3 that you want labeled. For more information, see Input Data (p. 572).

**Create a Video Classification Labeling Job (Console)**

You can follow the instructions in Create a Labeling Job (Console) (p. 544) to learn how to create a video classification labeling job in the SageMaker console. In step 10, choose Video from the Task category dropdown list, and choose Video Classification as the task type.

Ground Truth provides a worker UI similar to the following for labeling tasks. When you create a labeling job in the console, you specify instructions to help workers complete the job and labels from which workers can choose.
Instructions

View full instructions

View tool guide

Select a single label that best describes this video clip. Select none of the above if none of the other labels apply.

Select Submit when you are done.
Create a Video Classification Labeling Job (API)

This section covers details you need to know when you create a labeling job using the SageMaker API operation CreateLabelingJob. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of CreateLabelingJob.

Follow the instructions on Create a Labeling Job (API) (p. 547) and do the following while you configure your request:

- Use a pre-annotation Lambda function that ends with PRE-VideoClassification. To find the pre-annotation Lambda ARN for your Region, see PreHumanTaskLambdaArn.
- Use an annotation-consolidation Lambda function that ends with ACS-VideoClassification. To find the annotation-consolidation Lambda ARN for your Region, see AnnotationConsolidationLambdaArn.

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region.

```python
response = client.create_labeling_job(
    LabelingJobName='example-video-classification-labeling-job',
    LabelAttributeName='label',
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json'
            }
        },
        'DataAttributes': {
            'ContentClassifiers': [
                'FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent'
            ]
        }
    },
    OutputConfig={
        'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
        'KmsKeyId': 'string'
    },
    RoleArn='arn:aws:iam::*:role/*',
    LabelCategoryConfigS3Uri='s3://bucket/path/label-categories.json',
    StoppingConditions={
        'MaxHumanLabeledObjectCount': 123,
        'MaxPercentageOfInputDatasetLabeled': 123
    },
    HumanTaskConfig={
        'WorkteamArn': 'arn:aws:sagemaker:region:*:workteam/private-crowd/*',
        'UiConfig': {
            'UiTemplateS3Uri': 's3://bucket/path/worker-task-template.html'
        },
        'PreHumanTaskLambdaArn': 'arn:aws:lambda:us-east-1:432418664414:function:PRE-VideoClassification',
        'TaskKeywords': [
            'Video Classification'
        ],
        'TaskTitle': 'Video classification task',
        'TaskDescription': 'Select a label to classify this video',
        'NumberOfHumanWorkersPerDataObject': 123,
        'TaskTimeLimitInSeconds': 123,
        'TaskAvailabilityLifetimeInSeconds': 123,
        'MaxConcurrentTaskCount': 123,
        'AnnotationConsolidationConfig': {
        }
    }
)
```
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'AnnotationConsolidationLambdaArn': 'arn:aws:lambda:useast-1:432418664414:function:ACS-VideoClassification'
},
Tags=[
{
'Key': 'string',
'Value': 'string'
},
]
)

Provide a Template for Video Classiﬁcation
If you create a labeling job using the API, you must supply a worker task template in UiTemplateS3Uri.
Copy and modify the following template by modifying the short-instructions, fullinstructions, and header. Upload this template to Amazon S3, and provide the Amazon S3 URI to
this ﬁle in UiTemplateS3Uri.
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
<crowd-classifier
name="crowd-classifier"
categories="{{ task.input.labels | to_json | escape }}"
header="Please classify video"
>
<classification-target>
<video width="100%" controls/>
<source src="{{ task.input.taskObject | grant_read_access }}"
type="video/mp4"/>
<source src="{{ task.input.taskObject | grant_read_access }}"
type="video/webm"/>
<source src="{{ task.input.taskObject | grant_read_access }}"
type="video/ogg"/>
Your browser does not support the video tag.
</video>
</classification-target>
<full-instructions header="Video classification instructions">
<ol><li><strong>Read</strong> the task carefully and inspect the
video.</li>
<li><strong>Read</strong> the options and review the examples
provided to understand more about the labels.</li>
<li><strong>Choose</strong> the appropriate label that best suits
the video.</li></ol>
</full-instructions>
<short-instructions>
<h3><span style="color: rgb(0, 138, 0);">Good example</span></h3>
<p>Enter description to explain the correct label to the workers</
p>
<p><img src="https://d7evko5405gb7.cloudfront.net/
fe4fed9b-660c-4477-9294-2c66a15d6bbe/src/images/quick-instructions-example-placeholder.png"
style="max-width:100%"></p>
<h3><span style="color: rgb(230, 0, 0);">Bad example</span></h3>
<p>Enter description of an incorrect label</p>
<p><img src="https://d7evko5405gb7.cloudfront.net/
fe4fed9b-660c-4477-9294-2c66a15d6bbe/src/images/quick-instructions-example-placeholder.png"
style="max-width:100%"></p>
</short-instructions>
</crowd-classifier>
</crowd-form>

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Video Classification Output Data

Once you have created a video classification labeling job, your output data is located in the Amazon S3 bucket specified in the $S3OutputPath parameter when using the API or in the Output dataset location field of the Job overview section of the console.

To learn more about the output manifest file generated by Ground Truth and the file structure the Ground Truth uses to store your output data, see Output Data (p. 614).

To see an example of output manifest files for video classification labeling jobs, see Classification Job Output (p. 618).

Label Video Frames

You can use Ground Truth built-in video frame task types to have workers annotate video frames using bounding boxes, polylines, polygons or keypoints. A video frame is a sequence of images that have been extracted from a video.

If you do not have video frames, you can provide video files (MP4 files) and use the Ground Truth automated frame extraction tool to extract video frames. To learn more, see Provide Video Files (p. 610).

You can use the following built-in video task types to create video frame labeling jobs using the Amazon SageMaker console, API, and language-specific SDKs.

- **Video frame object detection** – Use this task type when you want workers to identify and locate objects in sequences of video frames. You provide a list of categories, and workers can select one category at a time and annotate objects which the category applies to in all frames. For example, you can use this task to ask workers to identify and localize various objects in a scene, such as cars, bikes, and pedestrians.

- **Video frame object tracking** – Use this task type when you want workers to track the movement of instances of objects across sequences of video frames. When a worker adds an annotation to a single frame, that annotation is associated with a unique instance ID. The worker adds annotations associated with the same ID in all other frames to identify the same object or person. For example, a worker can track the movement of a vehicle across a sequences of video frames by drawing bounding boxes associated with the same ID around the vehicle in each frame that it appears.

Use the following topics to learn more about these built-in task types and how to create a labeling job using each task type. See Task Types (p. 420) to learn more about the annotations tools (bounding boxes, polylines, polygons and keypoints) available for these task types.

Before you create a labeling job, we recommend that you review Video Frame Labeling Job Overview (p. 419).

Topics

- Video Frame Object Detection (p. 411)
- Video Frame Object Tracking (p. 415)
- Video Frame Labeling Job Overview (p. 419)

Video Frame Object Detection

You can use the video frame object detection task type to have workers identify and locate objects in a sequence of video frames (images extracted from a video) using bounding boxes, polylines, polygons
or keypoint annotation tools. The tool you choose defines the video frame task type you create. For example, you can use a bounding box video frame object detection task type workers to identify and localize various objects in a series of video frames, such as cars, bikes, and pedestrians.

You can create a video frame object detection labeling job using the Amazon SageMaker Ground Truth console, the SageMaker API, and language-specific AWS SDKs. To learn more, see Create a Video Frame Object Detection Labeling Job (p. 412) and select your preferred method. See Task Types (p. 420) to learn more about the annotations tools you can choose from when you create a labeling job.

Ground Truth provides a worker UI and tools to complete your labeling job tasks: Preview the Worker UI (p. 412).

You can create a job to adjust annotations created in a video object detection labeling job using the video object detection adjustment task type. To learn more, see Create Video Frame Object Detection Adjustment or Verification Labeling Job (p. 415).

Preview the Worker UI

Ground Truth provides workers with a web user interface (UI) to complete your video frame object detection annotation tasks. You can preview and interact with the worker UI when you create a labeling job in the console. If you are a new user, we recommend that you create a labeling job through the console using a small input dataset to preview the worker UI and ensure your video frames, labels, and label attributes appear as expected.

The UI provides workers with the following assistive labeling tools to complete your object detection tasks:

- For all tasks, workers can use the Copy to next and Copy to all features to copy an annotation to the next frame or to all subsequent frames respectively.
- For tasks that include the bounding box tools, workers can use a Predict next feature to draw a bounding box in a single frame, and then have Ground Truth predict the location of boxes with the same label in all other frames. Workers can then make adjustments to correct predicted box locations.

Create a Video Frame Object Detection Labeling Job

You can create a video frame object detection labeling job using the SageMaker console or the CreateLabelingJob API operation.

This section assumes that you have reviewed the Video Frame Labeling Job Overview (p. 419) and have chosen the type of input data and the input dataset connection you are using.

Create a Labeling Job (Console)

You can follow the instructions in Create a Labeling Job (Console) (p. 544) to learn how to create a video frame object tracking job in the SageMaker console. In step 10, choose Video - Object detection from the Task category dropdown list. Select the task type you want by selecting one of the cards in Task selection.
**Task type**  Info

**Task category**
Select the type of data being labeled to view available task templates for it or select 'Custom'.

**Video - Object detection**

**Task selection**
Select the task that a human worker will perform to label objects in your dataset.

- **Bounding box**
  Get workers to draw bounding boxes around specified objects in your video.  Info

- **Polyline**
  Get workers to draw polyline around specified objects in your video.  Info
Create a Labeling Job (API)

You create an object detection labeling job using the SageMaker API operation `CreateLabelingJob`. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of `CreateLabelingJob`.

Create a Labeling Job (API) (p. 547) provides an overview of the CreateLabelingJob operation. Follow these instructions and do the following while you configure your request:

- You must enter an ARN for `HumanTaskUiArn`. Use
  `arn:aws:sagemaker:<region>:394669845002:human-task-ui/VideoObjectDetection`. Replace `<region>` with the AWS Region in which you are creating the labeling job.

  Do not include an entry for the `UiTemplateS3Uri` parameter.

- Your `LabelAttributeName` must end in `-ref`. For example, `video-od-labels-ref`.

- Your input manifest file must be a video frame sequence manifest file. You can create this manifest file using the SageMaker console, or create it manually and upload it to Amazon S3. For more information, see Input Data Setup (p. 610).

- You can only use private or vendor work teams to create video frame object detection labeling jobs.

- You specify your labels, label category and frame attributes, the task type, and worker instructions in a label category configuration file. Specify the task type (bounding boxes, polylines, polygons or keypoint) using `annotationType` in your label category configuration file. For more information, see Create a Labeling Category Configuration File with Label Category and Frame Attributes (p. 557) to learn how to create this file.

- You need to provide pre-defined ARNs for the pre-annotation and post-annotation (ACS) Lambda functions. These ARNs are specific to the AWS Region you use to create your labeling job.

  - To find the pre-annotation Lambda ARN, refer to `PreHumanTaskLambdaArn`. Use the Region in which you are creating your labeling job to find the correct ARN that ends with `PRE-VideoObjectDetection`.

  - To find the post-annotation Lambda ARN, refer to `AnnotationConsolidationLambdaArn`. Use the Region in which you are creating your labeling job to find the correct ARN that ends with `ACS-VideoObjectDetection`.

- The number of workers specified in `NumberOfHumanWorkersPerDataObject` must be 1.

- Automated data labeling is not supported for video frame labeling jobs. Do not specify values for parameters in `LabelingJobAlgorithmsConfig`.

- Video frame object tracking labeling jobs can take multiple hours to complete. You can specify a longer time limit for these labeling jobs in `TaskTimeLimitInSeconds` (up to 7 days, or 604,800 seconds).

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region.

```python
response = client.create_labeling_job(
    LabelingJobName='example-video-od-labeling-job,
    LabelAttributeName='label',
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': 's3://DOC-EXAMPLE-BUCKET/path/video-frame-sequence-input-manifest.json'
            }
        }
    },
    'DataAttributes': {
        'ContentClassifiers': [
```
Create Video Frame Object Detection Adjustment or Verification Labeling Job

You can create an adjustment and verification labeling job using the Ground Truth console or CreateLabelingJob API. To learn more about adjustment and verification labeling jobs, and to learn how create one, see Verify and Adjust Labels (p. 502).

Output Data Format

When you create a video frame object detection labeling job, tasks are sent to workers. When these workers complete their tasks, labels are written to the Amazon S3 output location you specified when you created the labeling job. To learn about the video frame object detection output data format, see Video Frame Object Detection Output (p. 626). If you are a new user of Ground Truth, see Output Data (p. 614) to learn more about the Ground Truth output data format.

Video Frame Object Tracking

You can use the video frame object tracking task type to have workers track the movement of objects in a sequence of video frames (images extracted from a video) using bounding boxes, polylines, polygons...
Label Videos and Video Frames

or keypoint *annotation tools*. The tool you choose defines the video frame task type you create. For example, you can use a bounding box video frame object tracking task type to ask workers to track the movement of objects, such as cars, bikes, and pedestrians by drawing boxes around them.

You provide a list of categories, and each annotation that a worker adds to a video frame is identified as an *instance* of that category using an instance ID. For example, if you provide the label category car, the first car that a worker annotates will have the instance ID car:1. The second car the worker annotates will have the instance ID car:2. To track an object's movement, the worker adds annotations associated with the same instance ID around to object in all frames.

You can create a video frame object tracking labeling job using the Amazon SageMaker Ground Truth console, the SageMaker API, and language-specific AWS SDKs. To learn more, see Create a Video Frame Object Detection Labeling Job (p. 412) and select your preferred method. See Task Types (p. 420) to learn more about the annotations tools you can choose from when you create a labeling job.

Ground Truth provides a worker UI and tools to complete your labeling job tasks: Preview the Worker UI (p. 412).

You can create a job to adjust annotations created in a video object detection labeling job using the video object detection adjustment task type. To learn more, see Create Video Frame Object Detection Adjustment or Verification Labeling Job (p. 415).

**Preview the Worker UI**

Ground Truth provides workers with a web user interface (UI) to complete your video frame object tracking annotation tasks. You can preview and interact with the worker UI when you create a labeling job in the console. If you are a new user, we recommend that you create a labeling job through the console using a small input dataset to preview the worker UI and ensure your video frames, labels, and label attributes appear as expected.

The UI provides workers with the following assistive labeling tools to complete your object tracking tasks:

- For all tasks, workers can use the **Copy to next** and **Copy to all** features to copy an annotation with the same unique ID to the next frame or to all subsequent frames respectively.
- For tasks that include the bounding box tools, workers can use a **Predict next** feature to draw a bounding box in a single frame, and then have Ground Truth predict the location of boxes with the same unique ID in all other frames. Workers can then make adjustments to correct predicted box locations.

**Create a Video Frame Object Tracking Labeling Job**

You can create a video frame object tracking labeling job using the SageMaker console or the CreateLabelingJob API operation.

This section assumes that you have reviewed the Video Frame Labeling Job Overview (p. 419) and have chosen the type of input data and the input dataset connection you are using.

**Create a Labeling Job (Console)**

You can follow the instructions in Create a Labeling Job (Console) (p. 544) to learn how to create a video frame object tracking job in the SageMaker console. In step 10, choose **Video - Object tracking** from the **Task category** dropdown list. Select the task type you want by selecting one of the cards in **Task selection**.
Task type

Task category
Select the type of data being labeled to view available task templates for it or select 'Custom' for a self-built task.

Video - Object tracking

Task selection
Select the task that a human worker will perform to label objects in your dataset.

Bounding box
Get workers to track specific instances of objects in your video across multiple frames in your bounding boxes.

Polyline
Get workers to track specific instances of objects in your video across multiple frames in your polylines.
Create a Labeling Job (API)

You create an object tracking labeling job using the SageMaker API operation CreateLabelingJob. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of CreateLabelingJob.

Create a Labeling Job (API) (p. 547) provides an overview of the CreateLabelingJob operation. Follow these instructions and do the following while you configure your request:

- You must enter an ARN for HumanTaskUiArn. Use
  Replace <region> with the AWS Region in which you are creating the labeling job.

  Do not include an entry for the UiTemplateS3Uri parameter.
- Your LabelAttributeName must end in -ref. For example, ot-labels-ref.
- Your input manifest file must be a video frame sequence manifest file. You can create this manifest file using the SageMaker console, or create it manually and upload it to Amazon S3. For more information, see Input Data Setup (p. 610). If you create a streaming labeling job, the input manifest file is optional.
- You can only use private or vendor work teams to create video frame object detection labeling jobs.
- You specify your labels, label category and frame attributes, the task type, and worker instructions in a label category configuration file. Specify the task type (bounding boxes, polylines, polygons or keypoint) using annotationType in your label category configuration file. For more information, see Create a Labeling Category Configuration File with Label Category and Frame Attributes (p. 557) to learn how to create this file.
- You need to provide pre-defined ARNs for the pre-annotation and post-annotation (ACS) Lambda functions. These ARNs are specific to the AWS Region you use to create your labeling job.
  - To find the pre-annotation Lambda ARN, refer to PreHumanTaskLambdaArn. Use the Region in which you are creating your labeling job to find the correct ARN that ends with PRE-VideoObjectTracking.
  - To find the post-annotation Lambda ARN, refer to AnnotationConsolidationLambdaArn. Use the Region in which you are creating your labeling job to find the correct ARN that ends with ACS-VideoObjectTracking.
- The number of workers specified in NumberOfHumanWorkersPerDataObject must be 1.
- Automated data labeling is not supported for video frame labeling jobs. Do not specify values for parameters in LabelingJobAlgorithmsConfig.
- Video frame object tracking labeling jobs can take multiple hours to complete. You can specify a longer time limit for these labeling jobs in TaskTimeLimitInSeconds (up to 7 days, or 604,800 seconds).

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job in the US East (N. Virginia) Region.

```python
def create_labeling_job():
    response = client.create_labeling_job(
        LabelingJobName='example-video-ot-labeling-job,
        LabelAttributeName='label',
        InputConfig={
            'DataSource': {
                'S3DataSource': {
                    'ManifestS3Uri': 's3://DOC-EXAMPLE-BUCKET/path/video-frame-sequence-input-manifest.json'
                }
            }
        },
        DataAttributes={
            'ContentClassifiers': ['FreeOfPersonallyIdentifiableInformation','FreeOfAdultContent']
        }
    )
```
Create a Video Frame Object Tracking Adjustment or Verification Labeling Job

You can create an adjustment and verification labeling job using the Ground Truth console or CreateLabelingJob API. To learn more about adjustment and verification labeling jobs, and to learn how create one, see Verify and Adjust Labels (p. 502).

Output Data Format

When you create a video frame object tracking labeling job, tasks are sent to workers. When these workers complete their tasks, labels are written to the Amazon S3 output location you specified when you created the labeling job. To learn about the video frame object tracking output data format, see Video Frame Object Tracking Output (p. 628). If you are a new user of Ground Truth, see Output Data (p. 614) to learn more about the Ground Truth output data format.

Video Frame Labeling Job Overview

Use this page to learn about the object detection and object tracking video frame labeling jobs. The information on this page applies to both of these built-in task types.

The video frame labeling job is unique because of the following:
You can either provide data objects that are ready to be annotated (video frames), or you can provide video files and have Ground Truth automatically extract video frames.

Workers have the ability to save work as they go.

You cannot use the Amazon Mechanical Turk workforce to complete your labeling tasks.

Ground Truth provides a worker UI, as well as assistive and basic labeling tools, to help workers complete your tasks. You do not need to provide a worker task template.

Use the following topics to learn more.

**Topics**

- Input Data (p. 420)
- Job Completion Times (p. 420)
- Task Types (p. 420)
- Workforces (p. 421)
- Worker User Interface (UI) (p. 421)
- Video Frame Job Permission Requirements (p. 423)

**Input Data**

The video frame labeling job uses sequences of video frames. A single sequence is a series of images that have been extracted from a single video. You can either provide your own sequences of video frames, or have Ground Truth automatically extract video frame sequences from your video files. To learn more, see Provide Video Files (p. 610).

Ground Truth uses sequence files to identify all images in a single sequence. All of the sequences that you want to include in a single labeling job are identified in an input manifest file. Each sequence is used to create a single worker task. You can automatically create sequence files and an input manifest file using Ground Truth automatic data setup. To learn more, see Automated Video Frame Input Data Setup (p. 611).

To learn how to manually create sequence files and an input manifest file, see Create a Video Frame Input Manifest File (p. 613).

**Job Completion Times**

Video and video frame labeling jobs can take workers hours to complete. You can set the total amount of time that workers can work on each task when you create a labeling job. The maximum time you can set for workers to work on tasks is 7 days. The default value is 3 days.

We strongly recommend that you create tasks that workers can complete within 12 hours. Workers must keep the worker UI open while working on a task. They can save work as they go and Ground Truth saves their work every 15 minutes.

When using the SageMaker CreateLabelingJob API operation, set the total time a task is available to workers in the TaskTimeLimitInSeconds parameter of HumanTaskConfig.

When you create a labeling job in the console, you can specify this time limit when you select your workforce type and your work team.

**Task Types**

When you create a video object tracking or video object detection labeling job, you specify the type of annotation that you want workers to create while working on your labeling task. The annotation type determines the type of output data Ground Truth returns and defines the task type for your labeling job.
If you are creating a labeling job using the API operation `CreateLabelingJob`, you specify the task type using the label category configuration file parameter `annotationType`. To learn more, see Create a Labeling Category Configuration File with Label Category and Frame Attributes (p. 557).

The following task types are available for both video object tracking or video object detection labeling jobs:

- **Bounding box** – Workers are provided with tools to create bounding box annotations. A bounding box is a box that a worker draws around an objects to identify the pixel-location and label of that object in the frame.

- **Polyline** – Workers are provided with tools to create polyline annotations. A polyline is defined by the series of ordered x, y coordinates. Each point added to the polyline is connected to the previous point by a line. The polyline does not have to be closed (the start point and end point do not have to be the same) and there are no restrictions on the angles formed between lines.

- **Polygon** – Workers are provided with tools to create polygon annotations. A polygon is a closed shape defined by a series of ordered x, y coordinates. Each point added to the polygon is connected to the previous point by a line and there are no restrictions on the angles formed between lines. Two lines (sides) of the polygon cannot cross. The start and end point of a polygon must be the same.

- **Keypoint** – Workers are provided with tools to create keypoint annotations. A keypoint is a single point associated with an x, y coordinate in the video frame.

**Workforces**

When you create a video frame labeling job, you need to specify a work team to complete your annotation tasks. You can choose a work team from a private workforce of your own workers, or from a vendor workforce that you select in the AWS Marketplace. You cannot use the Amazon Mechanical Turk workforce for video frame labeling jobs.

To learn more about vendor workforces, see Managing Vendor Workforces (p. 698).

To learn how to create and manage a private workforce, see Use a Private Workforce (p. 699).

**Worker User Interface (UI)**

Ground Truth provides a worker user interface (UI), tools, and assistive labeling features to help workers complete your video labeling tasks. You can preview the worker UI when you create a labeling job in the console.

When you create a labeling job using the API operation `CreateLabelingJob`, you must provide an ARN provided by Ground Truth in the parameter `HumanTaskUiArn` to specify the worker UI for your task type. You can use `HumanTaskUiArn` with the SageMaker `RenderUiTemplate` API operation to preview the worker UI.

You provide worker instructions, labels, and optionally, attributes that workers can use to provide more information about labels and video frames. These attributes are referred to as label category attributes and frame attributes respectively. They are all displayed in the worker UI.

**Label Category and Frame Attributes**

When you create a video object tracking or video object detection labeling job, you can add one or more `label category attributes` and `frame attributes`:

- **Label category attribute** – A list of options (strings), a free form text box, or a numeric field associated with one or more labels. It is used by workers to provide metadata about a label.

- **Frame attribute** – A list of options (strings), a free form text box, or a numeric field that appears on each video frame a worker is sent to annotate. It is used by workers to provide metadata about video frames.
Additionally, you can use label and frame attributes to have workers verify labels in a video frame label verification job.

Use the following sections to learn more about these attributes. To learn how to add label category and frame attributes to a labeling job, use the Create Labeling Job sections on the task type page (p. 411) of your choice.

**Label Category Attributes**

Add label category attributes to labels to give workers the ability to provide more information about the annotations they create. A label category attribute is added to an individual label, or to all labels. When a label category attribute is applied to all labels it is referred to as a *global label category attribute*.

For example, if you add the label category *car*, you might also want to capture additional data about your labeled cars, such as if they are occluded or the size of the car. You can capture this metadata using label category attributes. In this example, if you added the attribute *occluded* to the car label category, you can assign *partial*, *completely*, *no* to the *occluded* attribute and enable workers to select one of these options.

When you create a label verification job, you add labels category attributes to each label you want workers to verify.

**Frame level Attributes**

Add frame attributes to give workers the ability to provide more information about individual video frames. Each frame attribute you add appears on all frames.

For example, you can add a number-frame attribute to have workers identify the number of objects they see in a particular frame.

In another example, you may want to provide a free-form text box to give workers the ability to provide an answer to a question.

When you create a label verification job, you can add one or more frame attributes to ask workers to provide feedback on all labels in a video frame.

**Worker Instructions**

You can provide worker instructions to help your workers complete your video frame labeling tasks. You might want to cover the following topics when writing your instructions:

- Best practices and things to avoid when annotating objects.
- The label category attributes provided (for object detection and object tracking tasks) and how to use them.
- How to save time while labeling by using keyboard shortcuts.

You can add your worker instructions using the SageMaker console while creating a labeling job. If you create a labeling job using the API operation CreateLabelingJob, you specify worker instructions in your label category configuration file.

In addition to your instructions, Ground Truth provides a link to help workers navigate and use the worker portal. View these instructions by selecting the task type on Worker Instructions (p. 423).

**Declining Tasks**

Workers are able to decline tasks.

Workers decline a task if the instructions are not clear, input data is not displaying correctly, or if they encounter some other issue with the task. If the number of workers per dataset object (NumberOfHumanWorkersPerDataObject) decline the task, the data object is marked as expired and will not be sent to additional workers.
Video Frame Job Permission Requirements

When you create a video frame labeling job, in addition to the permission requirements found in Assign IAM Permissions to Use Ground Truth (p. 650), you must add a CORS policy to your S3 bucket that contains your input manifest file.

Add a CORS Permission Policy to S3 Bucket

When you create a video frame labeling job, you specify buckets in S3 where your input data and manifest file are located and where your output data will be stored. These buckets may be the same. You must attach the following Cross-origin resource sharing (CORS) policy to your input and output buckets. If you use the Amazon S3 console to add the policy to your bucket, you must use the JSON format.

**JSON**

```json
{
  "AllowedHeaders": [
    "*
  ],
  "AllowedMethods": [
    "GET",
    "HEAD",
    "PUT"
  ],
  "AllowedOrigins": [
    "*
  ],
  "ExposeHeaders": [
    "Access-Control-Allow-Origin"
  ],
  "MaxAgeSeconds": 3000
}
```

**XML**

```xml
<?xml version="1.0" encoding="UTF-8"?>
<CORSConfiguration xmlns="http://s3.amazonaws.com/doc/2006-03-01/">
  <CORSRule>
    <AllowedOrigin>*</AllowedOrigin>
    <AllowedMethod>GET</AllowedMethod>
    <AllowedMethod>HEAD</AllowedMethod>
    <AllowedMethod>PUT</AllowedMethod>
    <MaxAgeSeconds>3000</MaxAgeSeconds>
    <ExposeHeader>Access-Control-Allow-Origin</ExposeHeader>
  </CORSRule>
</CORSConfiguration>
```

To learn how to add a CORS policy to an S3 bucket, see How do I add cross-domain resource sharing with CORS? in the Amazon Simple Storage Service User Guide.

Worker Instructions

This topic provides an overview of the Ground Truth worker portal and the tools available to complete your video frame labeling task. First, select the type of task you are working on from Topics.

**Important**

It is recommended that you complete your task using a Google Chrome or Firefox web browser.
For adjustment jobs, select the original labeling job task type that produced the labels you are adjusting. Review and adjust the labels in your task as needed.

Topics
- Work on Video Frame Object Tracking Tasks (p. 424)
- Work on Video Frame Object Detection Tasks (p. 431)

Work on Video Frame Object Tracking Tasks

Video frame object tracking tasks require you to track the movement of objects across video frames. A video frame is a still image from a video scene.

You can use the worker UI to navigate between video frames and use the tools provided to identify unique objects and track their movement from one from to the next. Use this page to learn how to navigate your worker UI, use the tools provided, and complete your task.

It is recommended that you complete your task using a Google Chrome or Firefox web browser.

Important
- If you see annotations have already been added to one or more video frames when you open your task, adjust those annotations and add additional annotations as needed.

Topics
- Your Task (p. 424)
- Navigate the UI (p. 426)
- Bulk Edit Label and Frame Attributes (p. 426)
- Tool Guide (p. 427)
- Icons Guide (p. 429)
- Shortcuts (p. 430)
- Release, Stop and Resume, and Decline Tasks (p. 431)
- Saving Your Work and Submitting (p. 431)

Your Task

When you work on a video frame object tracking task, you need to select a category from the Label category menu on the right side of your worker portal to start annotating. After you've chosen a category, use the tools provided to annotate the objects that the category applies to. This annotation will be associated with a unique label ID that should only be used for that object. Use this same label ID to create additional annotations for the same object in all of the video frames that it appears in. Refer to Tool Guide (p. 427) to learn more about the tools provided.

After you've added a label, you may see a downward pointing arrow next to the label in the Labels menu. Select this arrow and then select one option for each label attribute you see to provide more information about that label.

You may see frame attributes under the Labels menu. These attributes will appear on each frame in your task. Use these attribute prompts to enter additional information about each frame.
After you've added a label, you can quickly add and edit a label category attribute value by using the downward pointing arrow next to the label in the Labels menu. If you select the pencil icon next to the label in the Labels menu, the Edit instance menu will appear. You can edit the label ID, label category, and label category attributes using this menu.

To edit an annotation, select the label of the annotation that you want to edit in the Labels menu or select the annotation in the frame. When you edit or delete an annotation, the action will only modify the annotation in a single frame.

If you are working on a task that includes a bounding box tool, use the predict next icon to predict the location of all bounding boxes that you have drawn in a frame in the next frame. If you select a single box and then select the predict next icon, only that box will be predicted in the next frame. If you have not added any boxes to the current frame, you will receive an error. You must add at least one box to the frame before using this feature.
After you've used the predict next icon, review the location of each box in the next frame and make adjustments to the box location and size if necessary.

For all other tools, you can use the **Copy to next** and **Copy to all** tools to copy your annotations to the next or all frames respectively.

**Navigate the UI**

You can navigate between video frames using the navigation bar in the bottom-left corner of your UI.

Use the play button to automatically move through the entire sequence of frames.

Use the next frame and previous frame buttons to move forward or back one frame at a time. You can also input a frame number to navigate to that frame.

You can zoom in to and out of all video frames. Once you have zoomed into a video frame, you can move around in that frame using the move icon. When you set a new view in a single video frame by zooming and moving within that frame, all video frames are set to the same view. You can reset all video frames to their original view using the fit screen icon. For additional view options, see [Icons Guide](#) (p. 429).

When you are in the worker UI, you see the following menus:

- **Instructions** – Review these instructions before starting your task. Additionally, select More instructions and review these instructions.
- **Shortcuts** – Use this menu to view keyboard shortcuts that you can use to navigate video frames and use the tools provided.
- **Help** – Use this option to refer back to this documentation.

**Bulk Edit Label and Frame Attributes**

You can bulk edit label attributes and frame attributes (attributes).

When you bulk edit an attribute, you specify one or more ranges of frames that you want to apply the edit to. The attribute you select is edited in all frames in that range, including the start and end frames you specify. When you bulk edit label attributes, the range you specify must contain the label that the label attribute is attached to. If you specify frames that do not contain this label, you will receive an error.

To bulk edit an attribute you must specify the desired value for the attribute first. For example, if you want to change an attribute from *Yes* to *No*, you must select *No*, and then perform the bulk edit.

You can also specify a new value for an attribute that has not been filled in and then use the bulk edit feature to fill in that value in multiple frames. To do this, select the desired value for the attribute and complete the following procedure.

**To bulk edit a label or attribute:**

1. Use your mouse to right click the attribute you want to bulk edit.
2. Specify the range of frames you want to apply the bulk edit to using a dash (–) in the text box. For example, if you want to apply the edit to frames one through ten, enter `1-10`. If you want to apply the edit to frames two to five, eight to ten and twenty enter `2-5,8-10,20`.
3. Select **Confirm**.

If you get an error message, verify that you entered a valid range and that the label associated with the label attribute you are editing (if applicable) exists in all frames specified.

You can quickly add a label to all previous or subsequent frames using the **Duplicate to previous frames** and **Duplicate to next frames** options in the **Label** menu at the top of your screen.
**Tool Guide**

Your task will include one or more tools. The tool provided dictates the type of annotations you will create to identify and track objects. Use the following table to learn more about each tool provided.

<table>
<thead>
<tr>
<th>Tool</th>
<th>Icon</th>
<th>Action</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bounding box</td>
<td><img src="image" alt="Bounding box Icon" /></td>
<td>Add a bounding box annotation.</td>
<td>Choose this icon to add a bounding box. Each bounding box you add is associated with the category you choose from the Label category drop down menu. Select the bounding box or its associated label to adjust it.</td>
</tr>
<tr>
<td>Bounding box</td>
<td><img src="image" alt="Bounding box Icon" /></td>
<td>Predict bounding boxes in the next frame.</td>
<td>Select a bounding box, and then choose this icon to predict the location of that box in the next frame. You can select the icon multiple times in a row to automatically detect the location of box in multiple frames. For example, select this icon 5 times to predict the location of a bounding box in the next 5 frames.</td>
</tr>
<tr>
<td>Keypoint</td>
<td><img src="image" alt="Keypoint Icon" /></td>
<td>Add a keypoint annotation.</td>
<td>Choose this icon to add a keypoint. Click on an object the image to place the keypoint at that location. Each keypoint you add is associated with the category you choose from the Label category drop down menu. Select a keypoint or its associated label to adjust it.</td>
</tr>
<tr>
<td>Polyline</td>
<td><img src="image" alt="Polyline Icon" /></td>
<td>Add a polyline annotation.</td>
<td>Choose this icon to add a polyline. To add a polyline, continuously click around the object of interest to add new points. To stop drawing a polyline, select the last point that you placed a second time.</td>
</tr>
<tr>
<td>Tool</td>
<td>Icon</td>
<td>Action</td>
<td>Description</td>
</tr>
<tr>
<td>----------</td>
<td>------</td>
<td>-------------------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Polygon</td>
<td><img src="image" alt="Polygon Icon" /></td>
<td>Add a polygon annotation.</td>
<td>Choose this icon to add a polygon. To add a polygon, continuously click around the object of interest to add new points. To stop drawing the polygon, select the start point (this point will be green). A polygon is a closed shape defined by a series of points that you place. Each point added to the polygon is connected to the previous point by a line and there are no restrictions on the angles formed between lines. The start and end point must be the same. Each polygon you add is associated with the category you choose from the Label category drop down menu. Select the polygon or its associated label to adjust it.</td>
</tr>
<tr>
<td>Tool</td>
<td>Icon</td>
<td>Action</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>------</td>
<td>---------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Copy to Next</td>
<td>![icon]</td>
<td>Copy annotations to the next frame.</td>
<td>If one or more annotations are selected in the current frame, those annotations are copied to the next frame. If no annotations are selected, all annotations in the current frame will be copied to the next frame.</td>
</tr>
<tr>
<td>Copy to All</td>
<td>![icon]</td>
<td>Copy annotations to all subsequent frames.</td>
<td>If one or more annotations are selected in the current frame, those annotations are copied to all subsequent frames. If no annotations are selected, all annotations in the current frame will be copied to all subsequent frames.</td>
</tr>
</tbody>
</table>

**Icons Guide**

Use this table to learn about the icons you see in your UI. You can automatically select some of these icons using the keyboard shortcuts found in the **Shortcuts** menu.

<table>
<thead>
<tr>
<th>Icon</th>
<th>Action</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>![icon]</td>
<td>brightness</td>
<td>Choose this icon to adjust the brightness of all video frames.</td>
</tr>
<tr>
<td>![icon]</td>
<td>contrast</td>
<td>Choose this icon to adjust the contrast of all video frames.</td>
</tr>
<tr>
<td>![icon]</td>
<td>zoom in</td>
<td>Choose this icon to zoom into all of the video frames.</td>
</tr>
</tbody>
</table>
Label Videos and Video Frames

<table>
<thead>
<tr>
<th>Icon</th>
<th>Action</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Zoom Out Icon" /></td>
<td><strong>zoom out</strong></td>
<td>Choose this icon to zoom out of all of the video frames.</td>
</tr>
<tr>
<td><img src="image" alt="Move Screen Icon" /></td>
<td><strong>move screen</strong></td>
<td>After you’ve zoomed into a video frame, choose this icon to move around in that video frame. You can move around the video frame using your mouse by clicking and dragging the frame in the direction you want it to move. This will change the view in all view frames.</td>
</tr>
<tr>
<td><img src="image" alt="Fit Screen Icon" /></td>
<td><strong>fit screen</strong></td>
<td>Reset all video frames to their original position.</td>
</tr>
<tr>
<td><img src="image" alt="Undo Icon" /></td>
<td><strong>undo</strong></td>
<td>Undo an action. You can use this icon to remove a bounding box that you just added, or to undo an adjustment you made to a bounding box.</td>
</tr>
<tr>
<td><img src="image" alt="Redo Icon" /></td>
<td><strong>redo</strong></td>
<td>Redo an action that was undone using the undo icon.</td>
</tr>
<tr>
<td><img src="image" alt="Delete Label Icon" /></td>
<td><strong>delete label</strong></td>
<td>Delete a label. This will delete the bounding box associated with the label in a single frame.</td>
</tr>
<tr>
<td><img src="image" alt="Show or Hide Label Icon" /></td>
<td><strong>show or hide label</strong></td>
<td>Select this icon to show a label that has been hidden. If this icon has a slash through it, select it to hide the label.</td>
</tr>
<tr>
<td><img src="image" alt="Edit Label Icon" /></td>
<td><strong>edit label</strong></td>
<td>Select this icon to open the <strong>Edit instance</strong> menu. Use this menu to edit a label category, ID, and to add or edit label attributes.</td>
</tr>
</tbody>
</table>

**Shortcuts**

The keyboard shortcuts listed in the **Shortcuts** menu can help you quickly select icons, undo and redo annotations, and use tools to add and edit annotations. For example, once you add a bounding box, you can use **P** to quickly predict the location of that box in subsequent frames.

Before you start your task, it is recommended that you review the **Shortcuts** menu and become acquainted with these commands.
Release, Stop and Resume, and Decline Tasks

When you open the labeling task, three buttons on the top right allow you to decline the task (Decline task), release it (Release task), and stop and resume it at a later time (Stop and resume later). The following list describes what happens when you select one of these options:

- **Decline task**: You should only decline a task if something is wrong with the task, such as unclear video frame images or an issue with the UI. If you decline a task, you will not be able to return to the task.

- **Release Task**: Use this option to release a task and allow others to work on it. When you release a task, you lose all work done on that task and other workers on your team can pick it up. If enough workers pick up the task, you may not be able to return to it. When you select this button and then select Confirm, you are returned to the worker portal. If the task is still available, its status will be Available. If other workers pick it up, it will disappear from your portal.

- **Stop and resume later**: You can use the Stop and resume later button to stop working and return to the task at a later time. You should use the Save button to save your work before you select Stop and resume later. When you select this button and then select Confirm, you are returned to the worker portal, and the task status is Stopped. You can select the same task to resume work on it.

Be aware that the person that creates your labeling tasks specifies a time limit in which all tasks must be completed by. If you do not return to and complete this task within that time limit, it will expire and your work will not be submitted. Contact your administrator for more information.

Saving Your Work and Submitting

You should periodically save your work using the Save button. Ground Truth will automatically save your work every 15 minutes.

When you open a task, you must complete your work on it before pressing Submit.

Work on Video Frame Object Detection Tasks

Video frame object detection tasks required you to classify and identify the location of objects in video frames using annotations. A video frame is a still image from a video scene.

You can use the worker UI to navigate between video frames and create annotations to identify objects of interest. Use the sections on this page to learn how to navigate your worker UI, use the tools provided, and complete your task.

It is recommended that you complete your task using a Google Chrome web browser.

**Important**

If you see annotations have already been added to one or more video frames when you open your task, adjust those annotations and add additional annotations as needed.

Topics

- Your Task (p. 432)
- Navigate the UI (p. 433)
- Bulk Edit Label and Frame Attributes (p. 433)
- Tool Guide (p. 434)
- UI Icon Guide (p. 437)
- Shortcuts (p. 438)
- Release, Stop and Resume, and Decline Tasks (p. 438)
- Saving Your Work and Submitting (p. 439)
Your Task

When you work on a video frame object detection task, you need to select a category from the Label category menu on the right side of your worker portal to start annotating. After you've chosen a category, draw annotations around objects that this category applies to. To learn more about the tools you see in your worker UI, refer to the Tool Guide (p. 434).

After you've added a label, you may see a downward pointing arrow next to the label in the Labels menu. Select this arrow and then select one option for each label attribute you see to provide more information about that label.

You may see frame attributes under the Labels menu. These attributes will appear on each frame in your task. Use these attribute prompts to enter additional information about each frame.
To edit an annotation, select the label of the annotation that you want to edit in the **Labels** menu or select the annotation in the frame. When you edit or delete an annotation, the action will only modify the annotation in a single frame.

If you are working on a task that includes a bounding box tool, use the predict next icon to predict the location of all bounding boxes that you have drawn in a frame in the next frame. If you select a single box and then select the predict next icon, only that box will be predicted in the next frame. If you have not added any boxes to the current frame, you will receive an error. You must add at least one box to the frame before using this feature.

**Note**
The predict next feature will not overwrite manually created annotations. It will only add annotations. If you use predict next and as a result have more than one bounding box around a single object, delete all but one box. Each object should only be identified with a single box.

After you've used the predict next icon, review the location of each box in the next frame and make adjustments to the box location and size if necessary.

For all other tools, you can use the **Copy to next** and **Copy to all** tools to copy your annotations to the next or all frames respectively.

**Navigate the UI**

You can navigate between video frames using the navigation bar in the bottom-left corner of your UI.

Use the play button to automatically play through multiple frames.

Use the next frame and previous frame buttons to move forward or back one frame at a time. You can also input a frame number to navigate to that frame.

You can zoom in to and out of all video frames. Once you have zoomed into a video frame, you can move around in that frame using the move icon. When you navigate to a new view in a single video frame by zooming and moving within that frame, all video frames are set to the same view. You can reset all video frames to their original view using the fit screen icon. To learn more, see *UI Icon Guide* (p. 437).

When you are in the worker UI, you see the following menus:

- **Instructions** – Review these instructions before starting your task. Additionally, select **More instructions** and review these instructions.
- **Shortcuts** – Use this menu to view keyboard shortcuts that you can use to navigate video frames and use the annotation tools provided.
- **Help** – Use this option to refer back to this documentation.

If you

**Bulk Edit Label and Frame Attributes**

You can bulk edit label attributes and frame attributes (attributes).

When you bulk edit an attribute, you specify one or more ranges of frames that you want to apply the edit to. The attribute you select is edited in all frames in that range, including the start and end frames you specify. When you bulk edit label attributes, the range you specify must contain the label that the label attribute is attached to. If you specify frames that do not contain this label, you will receive an error.

To bulk edit an attribute you must specify the desired value for the attribute first. For example, if you want to change an attribute from Yes to No, you must select No, and then perform the bulk edit.

You can also specify a new value for an attribute that has not been filled in and then use the bulk edit feature to fill in that value in multiple frames. To do this, select the desired value for the attribute and complete the following procedure.
To bulk edit a label or attribute:

1. Use your mouse to right click the attribute you want to bulk edit.
2. Specify the range of frames you want to apply the bulk edit to using a dash (-) in the text box. For example, if you want to apply the edit to frames one through ten, enter 1-10. If you want to apply the edit to frames two to five, eight to ten and twenty enter 2-5, 8-10, 20.
3. Select Confirm.

If you get an error message, verify that you entered a valid range and that the label associated with the label attribute you are editing (if applicable) exists in all frames specified.

You can quickly add a label to all previous or subsequent frames using the Duplicate to previous frames and Duplicate to next frames options in the Label menu at the top of your screen.

Tool Guide

Your task will include one or more tools. The tool provided dictates the type of annotations you will create to identify and label objects. Use the following table to learn more about the tool or tools you may see in your worker UI.

<table>
<thead>
<tr>
<th>Tool</th>
<th>Icon</th>
<th>Action</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bounding box</td>
<td><img src="https://example.com/bounding-box.png" alt="Icon" /></td>
<td>Add a bounding box annotation.</td>
<td>Choose this icon to add a bounding box. Each bounding box you add is associated with the category you choose from the Label category drop down menu. Select the bounding box or its associated label to adjust it.</td>
</tr>
<tr>
<td>Predict next</td>
<td><img src="https://example.com/predict-next.png" alt="Icon" /></td>
<td>Predict bounding boxes in the next frame.</td>
<td>Select a bounding box, and then choose this icon to predict the location of that box in the next frame. You can select the icon multiple times in a row to automatically detect the location of box in multiple frames. For example, select this icon 5 times to predict the location of a bounding box in the next 5 frames.</td>
</tr>
<tr>
<td>Keypoint</td>
<td><img src="https://example.com/keypoint.png" alt="Icon" /></td>
<td>Add a keypoint annotation.</td>
<td>Choose this icon to add a keypoint. Click on an object the image to place the keypoint at that location. Each keypoint you add is associated with the</td>
</tr>
</tbody>
</table>

434
<table>
<thead>
<tr>
<th>Tool</th>
<th>Icon</th>
<th>Action</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Polyline</td>
<td><img src="image" alt="Polyline Icon" /></td>
<td>Add a polyline annotation.</td>
<td>category you choose from the Label category drop down menu. Select a keypoint or its associated label to adjust it.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Choose this icon to add a polyline. To add a polyline, continuously click around the object of interest to add new points. To stop drawing a polyline, select the last point that you placed a second time (this point will be green), or press Enter on your keyboard. Each point added to the polyline is connected to the previous point by a line. The polyline does not have to be closed (the start point and end point do not have to be the same) and there are no restrictions on the angles formed between lines. Each polyline you add is associated with the category you choose from the Label category drop down menu. Select the polyline or its associated label to adjust it.</td>
</tr>
<tr>
<td>Tool</td>
<td>Icon</td>
<td>Action</td>
<td>Description</td>
</tr>
<tr>
<td>-------------</td>
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<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Polygon</td>
<td><img src="image" alt="Polygon Icon" /></td>
<td>Add a polygon annotation.</td>
<td>Choose this icon to add a polygon. To add a polygon, continuously click around the object of interest to add new points. To stop drawing the polygon, select the start point (this point will be green). A polygon is a closed shape defined by a series of points that you place. Each point added to the polygon is connected to the previous point by a line and there are no restrictions on the angles formed between lines. Two lines (sides) of the polygon cannot cross. A line will become red if it violates this condition. The start and end point must be the same. Each polygon you add is associated with the category you choose from the Label category drop down menu. Select the polygon or its associated label to adjust it.</td>
</tr>
<tr>
<td>Copy to Next</td>
<td><img src="image" alt="Copy to Next Icon" /></td>
<td>Copy annotations to the next frame.</td>
<td>If one or more annotations are selected in the current frame, those annotations are copied to the next frame. If no annotations are selected, all annotations in the current frame will be copied to the next frame.</td>
</tr>
<tr>
<td>Tool</td>
<td>Icon</td>
<td>Action</td>
<td>Description</td>
</tr>
<tr>
<td>----------</td>
<td>------</td>
<td>---------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Copy to All</td>
<td><img src="image" alt="Copy to All Icon" /></td>
<td>Copy annotations to all subsequent frames.</td>
<td>If one or more annotations are selected in the current frame, those annotations are copied to all subsequent frames. If no annotations are selected, all annotations in the current frame will be copied to all subsequent frames.</td>
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</tbody>
</table>

**UI Icon Guide**

Use this table to learn about the icons you see in your worker task portal. You can automatically select these icons using the keyboard shortcuts found in the *Shortcuts* menu.

<table>
<thead>
<tr>
<th>Icon</th>
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</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Brightness Icon" /></td>
<td>Choose this icon to adjust the brightness of all video frames.</td>
</tr>
<tr>
<td><img src="image" alt="Contrast Icon" /></td>
<td>Choose this icon to adjust the contrast of all video frames.</td>
</tr>
<tr>
<td><img src="image" alt="Zoom In Icon" /></td>
<td>Choose this icon to zoom into all of the video frames.</td>
</tr>
<tr>
<td><img src="image" alt="Zoom Out Icon" /></td>
<td>Choose this icon to zoom out of all of the video frames.</td>
</tr>
<tr>
<td><img src="image" alt="Move Screen Icon" /></td>
<td>After you've zoomed into a video frame, choose this icon to move around in that video frame. You can move around in the video frame using your mouse by clicking and dragging the frame in the direction you want it to move. This will change the view in all view frames.</td>
</tr>
<tr>
<td><img src="image" alt="Fit Screen Icon" /></td>
<td>Reset all video frames to their original position.</td>
</tr>
</tbody>
</table>
Icon | Description
--- | ---
undo | Undo an action. You can use this icon to remove a bounding box that you just added, or to undo an adjustment you made to a bounding box.
redo | Redo an action that was undone using the undo icon.
delete label | Delete a label. This will delete the bounding box associated with the label in a single frame.
show or hide label | Select this icon to show a label that has been hidden. If this icon has a slash through it, select it to hide the label.

**Shortcuts**

The keyboard shortcuts listed in the **Shortcuts** menu can help you quickly select icons, undo and redo annotations, and use tools to add and edit annotations. For example, once you add a bounding box, you can use P to quickly predict the location of that box in subsequent frames.

Before you start your task, it is recommended that you review the **Shortcuts** menu and become acquainted with these commands.

**Release, Stop and Resume, and Decline Tasks**

When you open the labeling task, three buttons on the top right allow you to decline the task (**Decline task**), release it (**Release task**), and stop and resume it at a later time (**Stop and resume later**). The following list describes what happens when you select one of these options:

- **Decline task**: You should only decline a task if something is wrong with the task, such as unclear video frame images or an issue with the UI. If you decline a task, you will not be able to return to the task.
- **Release Task**: Use this option to release a task and allow others to work on it. When you release a task, you lose all work done on that task and other workers on your team can pick it up. If enough workers pick up the task, you may not be able to return to it. When you select this button and then select **Confirm**, you are returned to the worker portal. If the task is still available, its status will be **Available**. If other workers pick it up, it will disappear from your portal.
- **Stop and resume later**: You can use the **Stop and resume later** button to stop working and return to the task at a later time. You should use the **Save** button to save your work before you select **Stop and resume later**. When you select this button and then select **Confirm**, you are returned to the worker portal, and the task status is **Stopped**. You can select the same task to resume work on it.

Be aware that the person that creates your labeling tasks specifies a time limit in which all tasks must be completed by. If you do not return to and complete this task within that time limit, it will expire and your work will not be submitted. Contact your administrator for more information.
Saving Your Work and Submitting

You should periodically save your work. Ground Truth automatically saves your work every 15 minutes.

When you open a task, you must complete your work before pressing Submit.

Use Ground Truth to Label 3D Point Clouds

Create a 3D point cloud labeling job to have workers label objects in 3D point clouds generated from 3D sensors like Light Detection and Ranging (LiDAR) sensors and depth cameras, or generated from 3D reconstruction by stitching images captured by an agent like a drone.

3D Point Clouds

Point clouds are made up of three-dimensional (3D) visual data that consists of points. Each point is described using three coordinates, typically x, y, and z. To add color or variations in point intensity to the point cloud, points may be described with additional attributes, such as i for intensity or values for the red (r), green (g), and blue (b) 8-bit color channels. When you create a Ground Truth 3D point cloud labeling job, you can provide point cloud and, optionally, sensor fusion data.

The following image shows a single, 3D point cloud scene rendered by Ground Truth and displayed in the semantic segmentation worker UI.
LiDAR

A Light Detection and Ranging (LiDAR) sensor is a common type of sensor used to collect measurements that are used to generate point cloud data. LiDAR is a remote sensing method that uses light in the form of a pulsed laser to measure the distances of objects from the sensor. You can provide 3D point cloud data generated from a LiDAR sensor for a Ground Truth 3D point cloud labeling job using the raw data formats described in Accepted Raw 3D Data Formats (p. 584).

Sensor Fusion

Ground Truth 3D point cloud labeling jobs include a sensor fusion feature that supports video camera sensor fusion for all task types. Some sensors come with multiple LiDAR devices and video cameras that capture images and associate them with a LiDAR frame. To help annotators visually complete your tasks with high confidence, you can use the Ground Truth sensor fusion feature to project annotations (labels) from a 3D point cloud to 2D camera images and vice versa using 3D scanner (such as LiDAR) extrinsic matrix and camera extrinsic and intrinsic matrices. To learn more, see Sensor Fusion (p. 601).

Label 3D Point Clouds

Ground Truth provides a user interface (UI) and tools that workers use to label or annotate 3D point clouds. When you use the object detection or semantic segmentation task types, workers can annotate a single point cloud frame. When you use object tracking, workers annotate a sequence of frames. You can use object tracking to track object movement across all frames in a sequence.

The following demonstrates how a worker would use the Ground Truth worker portal and tools to annotate a 3D point cloud for an object detection task. For similar visual examples of other task types, see 3D Point Cloud Task types (p. 443).
Double click on the point cloud to zoom in.

Double click on the label ID to zoom in the object on point cloud.

**3D Cuboid Controls**
When you are in Edit Cuboid mode

- **C**: Create
- **V**: Edit
- **Cmd + Drag**: Change dimension
- **Option + Drag**: Move cuboid
- **Option + O**: Fit label to points
- **Option + G**: Set to ground
- **Shift + Drag**: Rotate cuboid
- **[**: Previous label
- **]**: Next label
- **Cmd + ,**: Toggle show/hide label
Assistive Labeling Tools for Point Cloud Annotation

Ground Truth offers assistive labeling tools to help workers complete your point cloud annotation tasks faster and with more accuracy. For details about assistive labeling tools that are included in the worker UI for each task type, select a task type (p. 443) and refer to the View the Worker Task Interface section of that page.

Next Steps

You can create six types of tasks when you use Ground Truth 3D point cloud labeling jobs. Use the topics in 3D Point Cloud Task types (p. 443) to learn more about these task types and to learn how to create a labeling job using the task type of your choice.

The 3D point cloud labeling job is different from other Ground Truth labeling modalities. Before creating a labeling job, we recommend that you read 3D Point Cloud Labeling Jobs Overview (p. 468). Additionally, review input data quotas in 3D Point Cloud and Video Frame Labeling Job Quotas (p. 582).

For an end-to-end demo using the SageMaker API and AWS Python SDK (boto 3) to create a 3D point cloud labeling job, see create-3D-pointcloud-labeling-job.ipynb in the SageMaker Examples notebook tab.

Important
If you use a notebook instance created before June 5th, 2020 to run this notebook, you must stop and restart that notebook instance for the notebook to work.

Topics
• 3D Point Cloud Task types (p. 443)
• 3D Point Cloud Labeling Jobs Overview (p. 468)
• Worker Instructions (p. 471)

3D Point Cloud Task types

You can use Ground Truth 3D point cloud labeling modality for a variety of use cases. The following list briefly describes each 3D point cloud task type. For additional details and instructions on how to create a labeling job using a specific task type, select the task type name to see its task type page.

• 3D point cloud object detection – Use this task type when you want workers to locate and classify objects in a 3D point cloud by adding and fitting 3D cuboids around objects.
• 3D point cloud object tracking – Use this task type when you want workers to add and fit 3D cuboids around objects to track their movement across a sequence of 3D point cloud frames. For example, you can use this task type to ask workers to track the movement of vehicles across multiple point cloud frames.
• 3D point cloud semantic segmentation – Use this task type when you want workers to create a point-level semantic segmentation mask by painting objects in a 3D point cloud using different colors where each color is assigned to one of the classes you specify.
• 3D point cloud adjustment task types – Each of the task types above has an associated adjustment task type that you can use to audit and adjust annotations generated from a 3D point cloud labeling job. Refer to the task type page of the associated type to learn how to create an adjustment labeling job for that task.

3D Point Cloud Object Detection

Use this task type when you want workers to classify objects in a 3D point cloud by drawing 3D cuboids around objects. For example, you can use this task type to ask workers to identify different types of objects in a point cloud, such as cars, bikes, and pedestrians.
For this task type, the *data object* that workers label is a single point cloud frame. Ground Truth renders a 3D point cloud using point cloud data you provide. You can also provide camera data to give workers more visual information about scenes in the frame, and to help workers draw 3D cuboids around objects.

Ground Truth provides workers with tools to annotate objects with 9 degrees of freedom \((x,y,z,rx,ry,rz,l,w,h)\) in three dimensions in both 3D scene and projected side views (top, side, and back). If you provide sensor fusion information (like camera data), when a worker adds a cuboid to identify an object in the 3D point cloud, the cuboid shows up and can be modified in the 2D images. After a cuboid has been added, all edits made to that cuboid in the 2D or 3D scene are projected into the other view.

You can create a job to adjust annotations created in a 3D point cloud object detection labeling job using the 3D point cloud object detection adjustment task type.

If you are a new user of the Ground Truth 3D point cloud labeling modality, we recommend you review 3D Point Cloud Labeling Jobs Overview (p. 468). This labeling modality is different from other Ground Truth task types, and this page provides an overview of important details you should be aware of when creating a 3D point cloud labeling job.

**Topics**

- View the Worker Task Interface (p. 444)
- Create a 3D Point Cloud Object Detection Labeling Job (p. 448)
- Create a 3D Point Cloud Object Detection Adjustment or Verification Labeling Job (p. 449)
- Output Data Format (p. 450)

**View the Worker Task Interface**

Ground Truth provides workers with a web portal and tools to complete your 3D point cloud object detection annotation tasks. When you create the labeling job, you provide the Amazon Resource Name (ARN) for a pre-built Ground Truth worker UI in the `HumanTaskUiArn` parameter. When you create a labeling job using this task type in the console, this worker UI is automatically used. You can preview and interact with the worker UI when you create a labeling job in the console. If you are a new user, it is recommended that you create a labeling job using the console to ensure your label attributes, point cloud frames, and if applicable, images, appear as expected.

The following is a GIF of the 3D point cloud object detection worker task interface. If you provide camera data for sensor fusion in the world coordinate system, images are matched up with scenes in the point cloud frame. These images appear in the worker portal as shown in the following GIF.
Hello, chopt@amazon.com

**Shortcuts**

- **Double click on the point cloud to zoom in**
- **Double click on the label ID to zoom in the object on point cloud.**

**3D Cuboid Controls**

When you are in Edit Cuboid mode

- **C**  Create
- **V**  Edit
- **Cmd + Drag**  Change dimension
- **Option + Drag**  Move cuboid
- **Option + O**  Fit label to points
- **Option + G**  Set to ground
- **Shift + Drag**  Rotate cuboid
- **[**  Previous label
- **]**  Next label
- **Cmd + ,**  Toggle show/hide label
Worker can navigate in the 3D scene using their keyboard and mouse. They can:

- Double click on specific objects in the point cloud to zoom into them.
- Use a mouse-scroller or trackpad to zoom in and out of the point cloud.
- Use both keyboard arrow keys and Q, E, A, and D keys to move Up, Down, Left, Right. Use keyboard keys W and S to zoom in and out.

Once a worker places a cuboid in the 3D scene, a side-view will appear with the three projected side views: top, side, and back. These side-views show points in and around the placed cuboid and help workers refine cuboid boundaries in that area. Workers can zoom in and out of each of those side-views using their mouse.

The following video demonstrates movements around the 3D point cloud and in the side-view.
Additional view options and features are available in the View menu in the worker UI. See the worker instruction page for a comprehensive overview of the Worker UI.

**Assistive Labeling Tools**

Ground Truth helps workers annotate 3D point clouds faster and more accurately using machine learning and computer vision powered assistive labeling tools for 3D point cloud object tracking tasks. The following assistive labeling tools are available for this task type:

- **Snapping** – Workers can add a cuboid around an object and use a keyboard shortcut or menu option to have Ground Truth's autofit tool snap the cuboid tightly around the object.
- **Set to ground** – After a worker adds a cuboid to the 3D scene, the worker can automatically snap the cuboid to the ground. For example, the worker can use this feature to snap a cuboid to the road or sidewalk in the scene.
- **Multi-view labeling** – After a worker adds a 3D cuboid to the 3D scene, a side panel displays front, side, and top perspectives to help the worker adjust the cuboid tightly around the object. In all of these views, the cuboid includes an arrow that indicates the orientation, or heading of the object. When the worker adjusts the cuboid, the adjustment will appear in real time on all of the views (that is, 3D, top, side, and front).
- **Sensor fusion** – If you provide data for sensor fusion, workers can adjust annotations in the 3D scenes and in 2D images, and the annotations will be projected into the other view in real time. Additionally, workers will have the option to view the direction the camera is facing and the camera frustum.
- **View options** – Enables workers to easily hide or view cuboids, label text, a ground mesh, and additional point attributes like color or intensity. Workers can also choose between perspective and orthogonal projections.

**Create a 3D Point Cloud Object Detection Labeling Job**

You can create a 3D point cloud labeling job using the SageMaker console or API operation, `CreateLabelingJob`. To create a labeling job for this task type you need the following:

- A single-frame input manifest file. To learn how to create this type of manifest file, see Create a Point Cloud Frame Input Manifest File (p. 586). If you are a new user of Ground Truth 3D point cloud labeling modalities, you may also want to review Accepted Raw 3D Data Formats (p. 584).
- A work team from a private or vendor workforce. You cannot use Amazon Mechanical Turk for video frame labeling jobs. To learn how to create workforces and work teams, see Create and Manage Workforces (p. 694).

Additionally, make sure that you have reviewed and satisfied the Assign IAM Permissions to Use Ground Truth (p. 650).

Use one of the following sections to learn how to create a labeling job using the console or an API.

**Create a Labeling Job (Console)**

You can follow the instructions Create a Labeling Job (Console) (p. 544) in order to learn how to create a 3D point cloud object detection labeling job in the SageMaker console. While you are creating your labeling job, be aware of the following:

- Your input manifest file must be a single-frame manifest file. For more information, see Create a Point Cloud Frame Input Manifest File (p. 586).
- Optionally, you can provide label category and frame attributes. Workers can assign one or more of these attributes to annotations to provide more information about that object. For example, you might want to use the attribute occluded to have workers identify when an object is partially obstructed.
• Automated data labeling and annotation consolidation are not supported for 3D point cloud labeling tasks.

• 3D point cloud object detection labeling jobs can take multiple hours to complete. You can specify a longer time limit for these labeling jobs when you select your work team (up to 7 days, or 604800 seconds).

Create a Labeling Job (API)

This section covers details you need to know when you create a labeling job using the SageMaker API operation CreateLabelingJob. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of CreateLabelingJob.

Create a Labeling Job (API) (p. 547), provides an overview of the CreateLabelingJob operation. Follow these instructions and do the following while you configure your request:

• You must enter an ARN for HumanTaskUiArn. Use arn:aws:sagemaker:<region>:394669845002:human-task-ui/PointCloudObjectDetection. Replace <region> with the AWS Region you are creating the labeling job in.

  There should not be an entry for the UiTemplateS3Uri parameter.

• Your input manifest file must be a single-frame manifest file. For more information, see Create a Point Cloud Frame Input Manifest File (p. 586).

• You specify your labels, label category and frame attributes, and worker instructions in a label category configuration file. To learn how to create this file, see Create a Labeling Category Configuration File with Label Category and Frame Attributes (p. 557).

• You need to provide pre-defined ARNs for the pre-annotation and post-annotation (ACS) Lambda functions. These ARNs are specific to the AWS Region you use to create your labeling job.

  To find the pre-annotation Lambda ARN, refer to PreHumanTaskLambdaArn. Use the Region you are creating your labeling job in to find the correct ARN. For example, if you are creating your labeling job in us-east-1, the ARN will be arn:aws:lambda:us-east-1:432418664414:function:PRE-3DPointCloudObjectDetection.

  To find the post-annotation Lambda ARN, refer to AnnotationConsolidationLambdaArn. Use the Region you are creating your labeling job in to find the correct ARN. For example, if you are creating your labeling job in us-east-1, the ARN will be arn:aws:lambda:us-east-1:432418664414:function:ACS-3DPointCloudObjectDetection.

• The number of workers specified in NumberOfHumanWorkersPerDataObject must be 1.

• Automated data labeling is not supported for 3D point cloud labeling jobs. You should not specify values for parameters in LabelingJobAlgorithmsConfig.

• 3D point cloud object detection labeling jobs can take multiple hours to complete. You can specify a longer time limit for these labeling jobs in TaskTimeLimitInSeconds (up to 7 days, or 604,800 seconds).

Create a 3D Point Cloud Object Detection Adjustment or Verification Labeling Job

You can create an adjustment or verification labeling job using the Ground Truth console or CreateLabelingJob API. To learn more about adjustment and verification labeling jobs, and to learn how create one, see Verify and Adjust Labels (p. 502).

When you create an adjustment labeling job, your input data to the labeling job can include labels, and yaw, pitch, and roll measurements from a previous labeling job or external source. In the adjustment job, pitch, and roll will be visualized in the worker UI, but cannot be modified. Yaw is adjustable.
Ground Truth uses Tait-Bryan angles with the following intrinsic rotations to visualize yaw, pitch and roll in the worker UI. First, rotation is applied to the vehicle according to the z-axis (yaw). Next, the rotated vehicle is rotated according to the intrinsic y’-axis (pitch). Finally, the vehicle is rotated according to the intrinsic x’’-axis (roll).

**Output Data Format**

When you create a 3D point cloud object detection labeling job, tasks are sent to workers. When these workers complete their tasks, labels are written to the Amazon S3 bucket you specified when you created the labeling job. The output data format determines what you see in your Amazon S3 bucket when your labeling job status (`LabelingJobStatus`) is `Completed`.

If you are a new user of Ground Truth, see [Output Data](p. 614) to learn more about the Ground Truth output data format. To learn about the 3D point cloud object detection output data format, see [3D Point Cloud Object Detection Output](p. 632).

### 3D Point Cloud Object Tracking

Use this task type when you want workers to add and fit 3D cuboids around objects to track their movement across 3D point cloud frames. For example, you can use this task type to ask workers to track the movement of vehicles across multiple point cloud frames.

For this task type, the data object that workers label is a sequence of point cloud frames. A **sequence** is defined as a temporal series of point cloud frames. Ground Truth renders a series of 3D point cloud visualizations using a sequence you provide and workers can switch between these 3D point cloud frames in the worker task interface.

Ground Truth provides workers with tools to annotate objects with 9 degrees of freedom: \((x,y,z,rx,ry,rz,l,w,h)\) in three dimensions in both 3D scene and projected side views (top, side, and back). When a worker draws a cuboid around an object, that cuboid is given a unique ID, for example `Car:1` for one car in the sequence and `Car:2` for another. Workers use that ID to label the same object in multiple frames.

You can also provide camera data to give workers more visual information about scenes in the frame, and to help workers draw 3D cuboids around objects. When a worker adds a 3D cuboid to identify an object in either the 2D image or the 3D point cloud, and the cuboid shows up in the other view.

You can adjust annotations created in a 3D point cloud object detection labeling job using the 3D point cloud object tracking adjustment task type.

If you are a new user of the Ground Truth 3D point cloud labeling modality, we recommend you review [3D Point Cloud Labeling Jobs Overview](p. 468). This labeling modality is different from other Ground Truth task types, and this page provides an overview of important details you should be aware of when creating a 3D point cloud labeling job.

**Topics**

- [View the Worker Task Interface](p. 450)
- [Create a 3D Point Cloud Object Tracking Labeling Job](p. 458)
- [Create a 3D Point Cloud Object Tracking Adjustment or Verification Labeling Job](p. 459)
- [Output Data Format](p. 459)

**View the Worker Task Interface**

Ground Truth provides workers with a web portal and tools to complete your 3D point cloud object tracking annotation tasks. When you create the labeling job, you provide the Amazon Resource Name
(ARN) for a pre-built Ground Truth UI in the HumanTaskUiArn parameter. When you create a labeling job using this task type in the console, this UI is automatically used. You can preview and interact with the worker UI when you create a labeling job in the console. If you are a new user, it is recommended that you create a labeling job using the console to ensure your label attributes, point cloud frames, and if applicable, images, appear as expected.

The following is a GIF of the 3D point cloud object tracking worker task interface and demonstrates how the worker can navigate the point cloud frames in the sequence. The annotating tools are a part of the worker task interface. They are not available for the preview interface.
Once workers add a single cuboid, that cuboid is replicated in all frames of the sequence with the same ID. Once workers adjust the cuboid in another frame, Ground Truth will interpolate the movement of that object and adjust all cuboids between the manually adjusted frames. The following GIF demonstrates this interpolation feature. In the navigation bar on the bottom-left, red-areas indicate manually adjusted frames.
<table>
<thead>
<tr>
<th>Instructions</th>
<th>Shortcuts</th>
<th>Label</th>
<th>View</th>
<th>3D Point Cloud</th>
<th>Help</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Point cloud View</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
If you provide camera data for sensor fusion, images are matched up with scenes in point cloud frames. These images appear in the worker portal as shown in the following GIF.

Worker can navigate in the 3D scene using their keyboard and mouse. They can:

• Double click on specific objects in the point cloud to zoom into them.
• Use a mouse-scroller or trackpad to zoom in and out of the point cloud.
• Use both keyboard arrow keys and Q, E, A, and D keys to move Up, Down, Left, Right. Use keyboard keys W and S to zoom in and out.

Once a worker places a cuboids in the 3D scene, a side-view will appear with the three projected side views: top, side, and back. These side-views show points in and around the placed cuboid and help workers refine cuboid boundaries in that area. Workers can zoom in and out of each of those side-views using their mouse.

The following video demonstrates movements around the 3D point cloud and in the side-view.
Additional view options and features are available. See the worker instruction page for a comprehensive overview of the Worker UI.

Worker Tools

Workers can navigate through the 3D point cloud by zooming in and out, and moving in all directions around the cloud using the mouse and keyboard shortcuts. If workers click on a point in the point cloud, the UI will automatically zoom into that area. Workers can use various tools to draw 3D cuboid around objects. For more information, see Assistive Labeling Tools.

After workers have placed a 3D cuboid in the point cloud, they can adjust these cuboids to fit tightly around cars using a variety of views: directly in the 3D cuboid, in a side-view featuring three zoomed-in perspectives of the point cloud around the box, and if you include images for sensor fusion, directly in the 2D image.

View options that enable workers to easily hide or view label text, a ground mesh, and additional point attributes. Workers can also choose between perspective and orthogonal projections.

Assistive Labeling Tools

Ground Truth helps workers annotate 3D point clouds faster and more accurately using UX, machine learning and computer vision powered assistive labeling tools for 3D point cloud object tracking tasks. The following assistive labeling tools are available for this task type:

- **Label autofill** – When a worker adds a cuboid to a frame, a cuboid with the same dimensions and orientation is automatically added to all frames in the sequence.
- **Label interpolation** – After a worker has labeled a single object in two frames, Ground Truth uses those annotations to interpolate the movement of that object between those two frames.
- **Bulk label and attribute management** – Workers can add, delete, and rename annotations, label category attributes, and frame attributes in bulk.
  - Workers can manually delete annotations for a given object before or after a frame. For example, a worker can delete all labels for an object after frame 10 if that object is no longer located in the scene after that frame.
  - If a worker accidentally bulk deletes all annotations for an object, they can add them back. For example, if a worker deletes all annotations for an object before frame 100, they can bulk add them to those frames.
  - Workers can rename a label in one frame and all 3D cuboids assigned that label are updated with the new name across all frames.
  - Workers can use bulk editing to add or edit label category attributes and frame attributes in multiple frames.
- **Snapping** – Workers can add a cuboid around an object and use a keyboard shortcut or menu option to have Ground Truth's autofit tool snap the cuboid tightly around the object's boundaries.
- **Fit to ground** – After a worker adds a cuboid to the 3D scene, the worker can automatically snap the cuboid to the ground. For example, the worker can use this feature to snap a cuboid to the road or sidewalk in the scene.
- **Multi-view labeling** – After a worker adds a 3D cuboid to the 3D scene, a side-panel displays front and two side perspectives to help the worker adjust the cuboid tightly around the object. Workers can annotation the 3D point cloud, the side panel and the adjustments appear in the other views in real time.
- **Sensor fusion** – If you provide data for sensor fusion, workers can adjust annotations in the 3D scenes and in 2D images, and the annotations will be projected into the other view in real time.
- **Auto-merge cuboids** – Workers can automatically merge two cuboids across all frames if they determine that cuboids with different labels actually represent a single object.
- **View options** – Enables workers to easily hide or view label text, a ground mesh, and additional point attributes like color or intensity. Workers can also choose between perspective and orthogonal projections.
Create a 3D Point Cloud Object Tracking Labeling Job

You can create a 3D point cloud labeling job using the SageMaker console or API operation, `CreateLabelingJob`. To create a labeling job for this task type you need the following:

- A sequence input manifest file. To learn how to create this type of manifest file, see Create a Point Cloud Sequence Input Manifest (p. 592). If you are a new user of Ground Truth 3D point cloud labeling modalities, we recommend that you review Accepted Raw 3D Data Formats (p. 584).
- A work team from a private or vendor workforce. You cannot use Amazon Mechanical Turk for 3D point cloud labeling jobs. To learn how to create workforces and work teams, see Create and Manage Workforces (p. 694).

Additionally, make sure that you have reviewed and satisfied the Assign IAM Permissions to Use Ground Truth (p. 650).

To learn how to create a labeling job using the console or an API, see the following sections.

Create a Labeling Job (API)

This section covers details you need to know when you create a labeling job using the SageMaker API operation `CreateLabelingJob`. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of `CreateLabelingJob`.

`Create a Labeling Job (API)` (p. 547) provides an overview of the `CreateLabelingJob` operation. Follow these instructions and do the following while you configure your request:

- You must enter an ARN for `HumanTaskUiArn`. Use 
  `arn:aws:sagemaker:<region>:394669845002:human-task-ui/PointCloudObjectTracking`. Replace `<region>` with the AWS Region you are creating the labeling job in.

  There should not be an entry for the `UiTemplateS3Uri` parameter.
- Your `LabelAttributeName` must end in `-ref`. For example, `ot-labels-ref`.
- Your input manifest file must be a point cloud frame sequence manifest file. For more information, see Create a Point Cloud Sequence Input Manifest (p. 592).
- You specify your labels, label category and frame attributes, and worker instructions in a label category configuration file. For more information, see Create a Labeling Category Configuration File with Label Category and Frame Attributes (p. 557) to learn how to create this file.
- You need to provide pre-defined ARNs for the pre-annotation and post-annotation (ACS) Lambda functions. These ARNs are specific to the AWS Region you use to create your labeling job.
  - To find the pre-annotation Lambda ARN, refer to `PreHumanTaskLambdaArn`. Use the Region you are creating your labeling job in to find the correct ARN that ends with `PRE-3DPointCloudObjectTracking`.
  - To find the post-annotation Lambda ARN, refer to `AnnotationConsolidationLambdaArn`. Use the Region you are creating your labeling job in to find the correct ARN that ends with `ACS-3DPointCloudObjectTracking`.
- The number of workers specified in `NumberOfHumanWorkersPerDataObject` should be 1.
- Automated data labeling is not supported for 3D point cloud labeling jobs. You should not specify values for parameters in `LabelingJobAlgorithmsConfig`.
- 3D point cloud object tracking labeling jobs can take multiple hours to complete. You can specify a longer time limit for these labeling jobs in `TaskTimeLimitInSeconds` (up to 7 days, or 604,800 seconds).
Create a Labeling Job (Console)

You can follow the instructions Create a Labeling Job (Console) (p. 544) in order to learn how to create a 3D point cloud object tracking labeling job in the SageMaker console. While you are creating your labeling job, be aware of the following:

- Your input manifest file must be a sequence manifest file. For more information, see Create a Point Cloud Sequence Input Manifest (p. 592).
- Optionally, you can provide label category attributes. Workers can assign one or more of these attributes to annotations to provide more information about that object. For example, you might want to use the attribute occluded to have workers identify when an object is partially obstructed.
- Automated data labeling and annotation consolidation are not supported for 3D point cloud labeling tasks.
- 3D point cloud object tracking labeling jobs can take multiple hours to complete. You can specify a longer time limit for these labeling jobs when you select your work team (up to 7 days, or 604800 seconds).

Create a 3D Point Cloud Object Tracking Adjustment or Verification Labeling Job

You can create an adjustment and verification labeling job using the Ground Truth console or CreateLabelingJob API. To learn more about adjustment and verification labeling jobs, and to learn how create one, see Verify and Adjust Labels (p. 502).

When you create an adjustment labeling job, your input data to the labeling job can include labels, and yaw, pitch, and roll measurements from a previous labeling job or external source. In the adjustment job, pitch, and roll will be visualized in the worker UI, but cannot be modified. Yaw is adjustable.

Ground Truth uses Tait-Bryan angles with the following intrinsic rotations to visualize yaw, pitch and roll in the worker UI. First, rotation is applied to the vehicle according to the z-axis (yaw). Next, the rotated vehicle is rotated according to the intrinsic y'-axis (pitch). Finally, the vehicle is rotated according to the intrinsic x''-axis (roll).

Output Data Format

When you create a 3D point cloud object tracking labeling job, tasks are sent to workers. When these workers complete their tasks, their annotations are written to the Amazon S3 bucket you specified when you created the labeling job. The output data format determines what you see in your Amazon S3 bucket when your labeling job status (LabelingJobStatus) is Completed.

If you are a new user of Ground Truth, see Output Data (p. 614) to learn more about the Ground Truth output data format. To learn about the 3D point cloud object tracking output data format, see 3D Point Cloud Object Tracking Output (p. 634).

3D Point Cloud Semantic Segmentation

Semantic segmentation involves classifying individual points of a 3D point cloud into pre-specified categories. Use this task type when you want workers to create a point-level semantic segmentation mask for 3D point clouds. For example, if you specify the classes car, pedestrian, and bike, workers select one class at a time, and color all of the points that this class applies to the same color in the point cloud.

For this task type, the data object that workers label is a single point cloud frame. Ground Truth generates a 3D point cloud visualization using point cloud data you provide. You can also provide camera data to give workers more visual information about scenes in the frame, and to help workers paint objects. When a worker paints an object in either the 2D image or the 3D point cloud, the paint shows up in the other view.
You can adjust annotations created in a 3D point cloud object detection labeling job using the 3D point cloud semantic segmentation adjustment task type.

If you are a new user of the Ground Truth 3D point cloud labeling modality, we recommend you review 3D Point Cloud Labeling Jobs Overview (p. 468). This labeling modality is different from other Ground Truth task types, and this topic provides an overview of important details you should be aware of when creating a 3D point cloud labeling job.

**Topics**

- View the Worker Task Interface (p. 460)
- Create a 3D Point Cloud Semantic Segmentation Labeling Job (p. 466)
- Create a 3D Point Cloud Semantic Segmentation Adjustment or Verification Labeling Job (p. 467)
- Output Data Format (p. 467)

**View the Worker Task Interface**

Ground Truth provides workers with a web portal and tools to complete your 3D point cloud semantic segmentation annotation tasks. When you create the labeling job, you provide the Amazon Resource Name (ARN) for a pre-built Ground Truth UI in the HumanTaskUiArn parameter. When you create a labeling job using this task type in the console, this UI is automatically used. You can preview and interact with the worker UI when you create a labeling job in the console. If you are a new user, it is recommended that you create a labeling job using the console to ensure your label attributes, point cloud frames, and if applicable, images, appear as expected.

The following is a GIF of the 3D point cloud semantic segmentation worker task interface. If you provide camera data for sensor fusion, images are matched with scenes in the point cloud frame. Workers can paint objects in either the 3D point cloud or the 2D image, and the paint appears in the corresponding location in the other medium. These images appear in the worker portal as shown in the following GIF.
Worker can navigate in the 3D scene using their keyboard and mouse. They can:

- Double click on specific objects in the point cloud to zoom into them.
- Use a mouse-scroller or trackpad to zoom in and out of the point cloud.
- Use both keyboard arrow keys and Q, E, A, and D keys to move Up, Down, Left, Right. Use keyboard keys W and S to zoom in and out.

The following video demonstrates movements around the 3D point cloud. Workers can hide and re-expand all side views and menus. In this GIF, the side-views and menus have been collapsed.
The following GIF demonstrates how a worker can label multiple objects quickly, refine painted objects using the Unpaint option and then view only points that have been painted.
Additionally, make sure that you have reviewed and satisfied the Assign IAM Permissions to Use Ground Truth (p. 650).

Use one of the following sections to learn how to create a labeling job using the console or an API.

Create a Labeling Job (Console)

You can follow the instructions Create a Labeling Job (Console) (p. 544) in order to learn how to create a 3D point cloud semantic segmentation labeling job in the SageMaker console. While you are creating your labeling job, be aware of the following:

- Your input manifest file must be a single-frame manifest file. For more information, see Create a Point Cloud Frame Input Manifest File (p. 586).
- Automated data labeling and annotation consolidation are not supported for 3D point cloud labeling tasks.
- 3D point cloud semantic segmentation labeling jobs can take multiple hours to complete. You can specify a longer time limit for these labeling jobs when you select your work team (up to 7 days, or 604800 seconds).
Create a Labeling Job (API)

This section covers details you need to know when you create a labeling job using the SageMaker API operation CreateLabelingJob. This API defines this operation for all AWS SDKs. To see a list of language-specific SDKs supported for this operation, review the See Also section of CreateLabelingJob.

The page, Create a Labeling Job (API) (p. 547), provides an overview of the CreateLabelingJob operation. Follow these instructions and do the following while you configure your request:

- You must enter an ARN for HumanTaskUiArn. Use arn:aws:sagemaker:<region>:394669845002:human-task-ui/PointCloudSemanticSegmentation. Replace <region> with the AWS Region you are creating the labeling job in.

  There should not be an entry for the UiTemplateS3Uri parameter.

- Your LabelAttributeName must end in -ref. For example, ss-labels-ref.

- Your input manifest file must be a single-frame manifest file. For more information, see Create a Point Cloud Frame Input Manifest File (p. 586).

- You specify your labels and worker instructions in a label category configuration file. See Create a Labeling Category Configuration File with Label Category and Frame Attributes (p. 557) to learn how to create this file.

- You need to provide a pre-defined ARNs for the pre-annotation and post-annotation (ACS) Lambda functions. These ARNs are specific to the AWS Region you use to create your labeling job.

  To find the pre-annotation Lambda ARN, refer to PreHumanTaskLambdaArn. Use the Region you are creating your labeling job in to find the correct ARN. For example, if you are creating your labeling job in us-east-1, the ARN will be arn:aws:lambda:us-east-1:432418664414:function:PRE-3DPointCloudSemanticSegmentation.

  To find the post-annotation Lambda ARN, refer to AnnotationConsolidationLambdaArn. Use the Region you are creating your labeling job in to find the correct ARN. For example, if you are creating your labeling job in us-east-1, the ARN will be arn:aws:lambda:us-east-1:432418664414:function:ACS-3DPointCloudSemanticSegmentation.

- The number of workers specified in NumberOfHumanWorkersPerDataObject should be 1.

- Automated data labeling is not supported for 3D point cloud labeling jobs. You should not specify values for parameters in LabelingJobAlgorithmsConfig.

- 3D point cloud semantic segmentation labeling jobs can take multiple hours to complete. You can specify a longer time limit for these labeling jobs in TaskTimeLimitInSeconds (up to 7 days, or 604800 seconds).

Create a 3D Point Cloud Semantic Segmentation Adjustment or Verification Labeling Job

You can create an adjustment and verification labeling job using the Ground Truth console or CreateLabelingJob API. To learn more about adjustment and verification labeling jobs, and to learn how to create one, see Verify and Adjust Labels (p. 502).

Output Data Format

When you create a 3D point cloud semantic segmentation labeling job, tasks are sent to workers. When these workers complete their tasks, their annotations are written to the Amazon S3 bucket you specified when you created the labeling job. The output data format determines what you see in your Amazon S3 bucket when your labeling job status (LabelingJobStatus) is Completed.

If you are a new user of Ground Truth, see Output Data (p. 614) to learn more about the Ground Truth output data format. To learn about the 3D point cloud object detection output data format, see 3D Point Cloud Semantic Segmentation Output (p. 630).
3D Point Cloud Labeling Jobs Overview

This topic provides an overview of the unique features of a Ground Truth 3D point cloud labeling job. You can use the 3D point cloud labeling jobs to have workers label objects in a 3D point cloud generated from a 3D sensors like LiDAR and depth cameras or generated from 3D reconstruction by stitching images captured by an agent like a drone.

Job Pre-processing Time

When you create a 3D point cloud labeling job, you need to provide an input manifest file (p. 584). The input manifest file can be:

- A frame input manifest file that has a single point cloud frame on each line.
- A sequence input manifest file that has a single sequence on each line. A sequence is defined as a temporal series of point cloud frames.

For both types of manifest files, job pre-processing time (that is, the time before Ground Truth starts sending tasks to your workers) depends on the total number and size of point cloud frames you provide in your input manifest file. For frame input manifest files, this is the number of lines in your manifest file. For sequence manifest files, this is the number of frames in each sequence multiplied by the total number of sequences, or lines, in your manifest file.

Additionally, the number of points per point cloud and the number of fused sensor data objects (like images) factor into job pre-processing times. On average, Ground Truth can pre-process 200 point cloud frames in approximately 5 minutes. If you create a 3D point cloud labeling job with a large number of point cloud frames, you might experience longer job pre-processing times. For example, if you create a sequence input manifest file with 4 point cloud sequences, and each sequence contains 200 point clouds, Ground Truth pre-processes 800 point clouds and so your job pre-processing time might be around 20 minutes. During this time, your labeling job status is InProgress.

While your 3D point cloud labeling job is pre-processing, you receive CloudWatch messages notifying you of the status of your job. To identify these messages, search for 3D_POINT_CLOUD_PROCESSING_STATUS in your labeling job logs.

For frame input manifest files, your CloudWatch logs will have a message similar to the following:

```
{
    "labeling-job-name": "example-point-cloud-labeling-job",
    "event-name": "3D_POINT_CLOUD_PROCESSING_STATUS",
    "event-log-message": "datasetObjectId from: 0 to 10, status: IN_PROGRESS"
}
```

The event log message, datasetObjectId from: 0 to 10, status: IN_PROGRESS identifies the number of frames from your input manifest that have been processed. You receive a new message every time a frame has been processed. For example, after a single frame has processed, you receive another message that says datasetObjectId from: 1 to 10, status: IN_PROGRESS.

For sequence input manifest files, your CloudWatch logs will have a message similar to the following:

```
{
    "labeling-job-name": "example-point-cloud-labeling-job",
    "event-name": "3D_POINT_CLOUD_PROCESSING_STATUS",
    "event-log-message": "datasetObjectId: 0, status: IN_PROGRESS"
}
```

The event log message, datasetObjectId from: 0, status: IN_PROGRESS identifies the number of sequences from your input manifest that have been processed. You receive a new message every
time a sequence has been processed. For example, after a single sequence has processed, you receive a message that says datasetObjectId from: 1, status: IN_PROGRESS as the next sequence begins processing.

**Job Completion Times**

3D point cloud labeling jobs can take workers hours to complete. You can set the total amount of time that workers can work on each task when you create a labeling job. The maximum time you can set for workers to work on tasks is 7 days. The default value is 3 days.

It is strongly recommended that you create tasks that workers can complete within 12 hours. Workers must keep the worker UI open while working on a task. They can save work as they go and Ground Truth will save their work every 15 minutes.

When using the SageMaker CreateLabelingJob API operation, set the total time a task is available to workers in the TaskTimeLimitInSeconds parameter of HumanTaskConfig.

When you create a labeling job in the console, you can specify this time limit when you select your workforce type and your work team.

**Workforces**

When you create a 3D point cloud labeling job, you need to specify a work team that will complete your point cloud annotation tasks. You can choose a work team from a private workforce of your own workers, or from a vendor workforce that you select in the AWS Marketplace. You cannot use the Amazon Mechanical Turk workforce for 3D point cloud labeling jobs.

To learn more about vendor workforce, see Managing Vendor Workforces (p. 698).

To learn how to create and manage a private workforce, see Use a Private Workforce (p. 699).

**Worker User Interface (UI)**

Ground Truth provides a worker user interface (UI), tools, and assistive labeling features to help workers complete your 3D point cloud labeling tasks.

You can preview the worker UI when you create a labeling job in the console.

When you create a labeling job using the API operation CreateLabelingJob, you must provide an ARN provided by Ground Truth in the parameter HumanTaskUiArn to specify the worker UI for your task type. You can use HumanTaskUiArn with the SageMaker RenderUiTemplate API operation to preview the worker UI.

You provide worker instructions, labels, and optionally, label category attributes that are displayed in the worker UI.

**Label Category Attributes**

When you create a 3D point cloud object tracking or object detection labeling job, you can add one or more label category attributes. You can add frame attributes to all 3D point cloud task types:

- **Label category attribute** – A list of options (strings), a free form text box, or a numeric field associated with one or more labels. It is used by workers to provide metadata about a label.
- **Frame attribute** – A list of options (strings), a free form text box, or a numeric field that appears on each point cloud frame a worker is sent to annotate. It is used by workers to provide metadata about frames.

Additionally, you can use label and frame attributes to have workers verify labels in a 3D point cloud label verification job.
Use the following sections to learn more about these attributes. To learn how to add label category and frame attributes to a labeling job, use the Create Labeling Job section on the task type page of your choice.

**Label Category Attributes**

Add label category attributes to labels to give workers the ability to provide more information about the annotations they create. A label category attribute is added to an individual label, or to all labels. When a label category attribute is applied to all labels it is referred to as a *global label category attribute*.

For example, if you add the label category `car`, you might also want to capture additional data about your labeled cars, such as if they are occluded or the size of the car. You can capture this metadata using label category attributes. In this example, if you added the attribute `occluded` to the car label category, you can assign `partial`, `completely`, `no` to the `occluded` attribute and enable workers to select one of these options.

When you create a label verification job, you add labels category attributes to each label you want workers to verify.

**Frame Attributes**

Add frame attributes to give workers the ability to provide more information about individual point cloud frames. You can specify up to 10 frame attributes, and these attributes will appear on all frames.

For example, you can add a frame attribute that allows workers to enter a number. You may want to use this attribute to have workers identify the number of objects they see in a particular frame.

In another example, you may want to provide a free-form text box to give workers the ability to provide a free form answer to a question.

When you create a label verification job, you can add one or more frame attributes to ask workers to provide feedback on all labels in a point cloud frame.

**Worker Instructions**

You can provide worker instructions to help your workers complete your point cloud labeling tasks. You might want to use these instructions to do the following:

- Best practices and things to avoid when annotating objects.
- Explanation of the label category attributes provided (for object detection and object tracking tasks), and how to use them.
- Advice on how to save time while labeling by using keyboard shortcuts.

You can add your worker instructions using the SageMaker console while creating a labeling job. If you create a labeling job using the API operation `CreateLabelingJob`, you specify worker instructions in your label category configuration file.

In addition to your instructions, Ground Truth provides a link to help workers navigate and use the worker portal. View these instructions by selecting the task type on Worker Instructions (p. 471).

**Declining Tasks**

Workers are able to decline tasks.

Workers decline a task if the instructions are not clear, input data is not displaying correctly, or if they encounter some other issue with the task. If the number of workers per dataset object (`NumberOfHumanWorkersPerDataObject`) decline the task, the data object is marked as expired and will not be sent to additional workers.
3D Point Cloud Labeling Job Permission Requirements

When you create a 3D point cloud labeling job, in addition to the permission requirements found in Assign IAM Permissions to Use Ground Truth (p. 650), you must add a CORS policy to your S3 bucket that contains your input manifest file.

Add a CORS Permission Policy to S3 Bucket

When you create a 3D point cloud labeling job, you specify buckets in S3 where your input data and manifest file are located and where your output data will be stored. These buckets may be the same. You must attach the following Cross-origin resource sharing (CORS) policy to your input and output buckets. If you use the Amazon S3 console to add the policy to your bucket, you must use the JSON format.

**JSON**

```json
[
  {
    "AllowedHeaders": ["*"],
    "AllowedMethods": ["GET", "HEAD", "PUT"],
    "AllowedOrigins": ["*"],
    "ExposeHeaders": ["Access-Control-Allow-Origin"],
    "MaxAgeSeconds": 3000
  }
]
```

**XML**

```xml
<?xml version="1.0" encoding="UTF-8"?>
<CORSConfiguration xmlns="http://s3.amazonaws.com/doc/2006-03-01/">
  <CORSRule>
    <AllowedOrigin>*</AllowedOrigin>
    <AllowedMethod>GET</AllowedMethod>
    <AllowedMethod>HEAD</AllowedMethod>
    <AllowedMethod>PUT</AllowedMethod>
    <MaxAgeSeconds>3000</MaxAgeSeconds>
    <ExposeHeader>Access-Control-Allow-Origin</ExposeHeader>
    <AllowedHeader>*</AllowedHeader>
  </CORSRule>
</CORSConfiguration>
```

To learn how to add a CORS policy to an S3 bucket, see How do I add cross-domain resource sharing with CORS? in the Amazon Simple Storage Service User Guide.

Worker Instructions

This topic provides an overview of the Ground Truth worker portal and the tools available to complete your 3D Point Cloud labeling task. First, select the type of task you are working on from Topics.

For adjustment jobs, select the original labeling job task type that produced the labels you are adjusting. Review and adjust the labels in your task as needed.
Important
It is recommended that you complete your task using a Google Chrome or Firefox web browser.

Topics
• 3D Point Cloud Semantic Segmentation (p. 472)
• 3D Point Cloud Object Detection (p. 481)
• 3D Point Cloud Object Tracking (p. 491)

3D Point Cloud Semantic Segmentation
Use this page to become familiarize with the user interface and tools available to complete your 3D point cloud semantic segmentation task.

Topics
• Your Task (p. 472)
• Navigate the UI (p. 477)
• Icon Guide (p. 479)
• Shortcuts (p. 480)
• Release, Stop and Resume, and Decline Tasks (p. 480)
• Saving Your Work and Submitting (p. 481)

Your Task
When you work on a 3D point cloud semantic segmentation task, you need to select a category from the Annotations menu on the right side of your worker portal using the drop down menu Label Categories. After you've selected a category, use the paint brush and polygon tools to paint each object in the 3D point cloud that this category applies to. For example, if you select the category Car, you would use these tools to paint all of the cars in the point cloud. The following video demonstrates how to use the paint brush tool to paint an object.

If you see one or more images in your worker portal, you can paint in the images or paint in the 3D point cloud and the paint will show up in the other medium.

You may see frame attributes under the Labels menu. Use these attribute prompts to enter additional information about the point cloud.
Important
If you see that objects have already been painted when you open the task, adjust those annotations.

The following video includes an image that can be annotated. You may not see an image in your task.
After you've painted one or more objects using a label category, you can select that category from the Label Category menu on the right to only view points painted for that category.
Navigate the UI

You can navigate in the 3D scene using your keyboard and mouse. You can:

- Double click on specific objects in the point cloud to zoom into them.
- Use a mouse-scroller or trackpad to zoom in and out of the point cloud.
- Use both keyboard arrow keys and Q, E, A, and D keys to move Up, Down, Left, Right. Use keyboard keys W and S to zoom in and out.

The following video demonstrates movements around the 3D point cloud and in the side-view. You can hide and re-expand all side views using the full screen icon. In this GIF, the side-views and menus have been collapsed.
When you are in the worker UI, you see the following menus:

- **Instructions** – Review these instructions before starting your task.
- **Shortcuts** – Use this menu to view keyboard shortcuts that you can use to navigate the point cloud and use the annotation tools provided.
- **View** – Use this menu to toggle different view options on and off. For example, you can use this menu to add a ground mesh to the point cloud, and to choose the projection of the point cloud.
- **3D Point Cloud** – Use this menu to add additional attributes to the points in the point cloud, such as color, and pixel intensity. Note that some or all of these options may not be available.
- **Paint** – Use this menu to modify the functionality of the paint brush.

When you open a task, the move scene icon is on, and you can move around the point cloud using your mouse and the navigation buttons in the point cloud area of the screen. To return to the original view you see when you first opened the task, choose the reset scene icon.

After you select the paint icon, you can add paint to the point cloud and images (if included). You must select the move scene icon again to move to another area in the 3D point cloud or image.

To collapse all panels on the right and make the 3D point cloud full screen, select the full screen icon.

For the camera images and side-panels, you have the following view options:

- **C** – View the camera angle on point cloud view.
- **F** – View the frustum, or field of view, of the camera used to capture that image on point cloud view.
- **P** – View the point cloud overlaid on the image.

**Icon Guide**

Use this table to learn about the icons available in your worker task portal.

<table>
<thead>
<tr>
<th>Icon</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="brush" /></td>
<td>brush</td>
<td>Choose this icon to turn on the brush tool. To use with this tool, choose and move over the objects that you want to paint with your mouse. After you choose it, everything you paint be associated with the category you chose.</td>
</tr>
<tr>
<td><img src="image" alt="polygon" /></td>
<td>polygon</td>
<td>Choose this icon to use the polygon paint tool. Use this tool to draw polygons around objects that you want to paint. After you choose it, everything you draw a polygon around will be associated with the category you have chosen.</td>
</tr>
<tr>
<td><img src="image" alt="reset scene" /></td>
<td>reset scene</td>
<td>Choose this icon to reset the view of the point cloud, side panels, and if applicable, all images to their original position when the task was first opened.</td>
</tr>
<tr>
<td><img src="image" alt="move scene" /></td>
<td>move scene</td>
<td>Choose this icon to move the scene. By default, this icon will be selected when you first start a task.</td>
</tr>
</tbody>
</table>
Icon | Name | Description
--- | --- | ---
| | full screen | Choose this icon to make the 3D point cloud visualization full screen, and to collapse all side panels.
| | ruler | Use this icon to measure distances, in meters, in the point cloud. You may want to use this tool if your instructions ask you to annotate all objects in a given distance from the center of the cuboid or the object used to capture data.

When you select this icon, you can place the starting point (first marker) anywhere in the point cloud by selecting it with your mouse. The tool will automatically use interpolation to place a marker on the closest point within threshold distance to the location you select, otherwise the marker will be placed on ground. If you place a starting point by mistake, you can use the Escape key to revert marker placement.

After you place the first marker, you see a dotted line and a dynamic label that indicates the distance you have moved away from the first marker. Click somewhere else on the point cloud to place a second marker. When you place the second marker, the dotted line becomes solid, and the distance is set.

After you set a distance, you can edit it by selecting either marker. You can delete a ruler by selecting anywhere on the ruler and using the Delete key on your keyboard.

**Shortcuts**

The shortcuts listed in the **Shortcuts** menu can help you navigate the 3D point cloud and use the paint tool.

Before you start your task, it is recommended that you review the **Shortcuts** menu and become acquainted with these commands.

**Release, Stop and Resume, and Decline Tasks**

When you open the labeling task, three buttons on the top right allow you to decline the task (**Decline task**), release it (**Release task**), and stop and resume it at a later time (**Stop and resume later**). The following list describes what happens when you select one of these options:

- **Decline task**: You should only decline a task if something is wrong with the task, such as an issue with the 3D point cloud, images or the UI. If you decline a task, you will not be able to return to the task.
- **Release Task**: If you release a task, you loose all work done on that task. When the task is released, other workers on your team can pick it up. If enough workers pick up the task, you may not be able to return to it. When you select this button and then select **Confirm**, you are returned to the worker portal. If the task is still available, its status will be **Available**. If other workers pick it up, it will disappear from your portal.
- **Stop and resume later**: You can use the **Stop and resume later** button to stop working and return to the task at a later time. You should use the **Save** button to save your work before you select **Stop and
**resumelater.** When you select this button and then select **Confirm**, you are returned to the worker portal, and the task status is **Stopped**. You can select the same task to resume work on it.

Be aware that the person that creates your labeling tasks specifies a time limit in which all tasks must be completed by. If you do not return to and complete this task within that time limit, it will expire and your work will not be submitted. Contact your administrator for more information.

**Saving Your Work and Submitting**

You should periodically save your work. Ground Truth will automatically save your work every 15 minutes. When you open a task, you must complete your work on it before pressing **Submit**.

**3D Point Cloud Object Detection**

Use this page to become familiar with the user interface and tools available to complete your 3D point cloud object detection task.

**Topics**

- Your Task (p. 481)
- Navigate the UI (p. 483)
- Icon Guide (p. 489)
- Shortcuts (p. 490)
- Release, Stop and Resume, and Decline Tasks (p. 490)
- Saving Your Work and Submitting (p. 491)

**Your Task**

When you work on a 3D point cloud object detection task, you need to select a category from the **Annotations** menu on the right side of your worker portal using the **Label Categories** menu. After you've chosen a category, use the add cuboid and fit cuboid tools to fit a cuboid around objects in the 3D point cloud that this category applies to. After you place a cuboid, you can modify its dimensions, location, and orientation directly in the point cloud, and the three panels shown on the right.

If you see one or more images in your worker portal, you can also modify cuboids in the images or in the 3D point cloud and the edits will show up in the other medium.

If you see cuboids have already been added to the 3D point cloud when you open your task, adjust those cuboids and add additional cuboids as needed.

To edit a cuboid, including moving, re-orienting, and changing cuboid dimensions, you must use shortcut keys. You can see a full list of shortcut keys in the **Shortcuts** menu in your UI. The following are important key-combinations that you should become familiar with before starting your labeling task.

<table>
<thead>
<tr>
<th>Mac Command</th>
<th>Windows Command</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cmd + Drag</td>
<td>Ctrl + Drag</td>
<td>Modify the dimensions of the cuboid.</td>
</tr>
<tr>
<td>Option + Drag</td>
<td>Alt + Drag</td>
<td>Move the cuboid.</td>
</tr>
<tr>
<td>Shift + Drag</td>
<td>Shift + Drag</td>
<td>Rotate the cuboid.</td>
</tr>
<tr>
<td>Option + O</td>
<td>Alt + O</td>
<td>Fit the cuboid tightly around the points it has been drawn around.</td>
</tr>
</tbody>
</table>

Before using the option, make sure to save your work.
<table>
<thead>
<tr>
<th>Mac Command</th>
<th>Windows Command</th>
<th>Action</th>
</tr>
</thead>
<tbody>
<tr>
<td>Option + G</td>
<td>Alt + G</td>
<td>Set the cuboid to the ground.</td>
</tr>
</tbody>
</table>

Individual labels may have one or more label attributes. If a label has a label attribute associated with it, it will appear when you select the downward pointing arrow next to the label from the `Label Id` menu. Fill in required values for all label attributes.

You may see frame attributes under the `Labels` menu. Use these attribute prompts to enter additional information about each frame.
Navigate the UI

You can navigate in the 3D scene using your keyboard and mouse. You can:

- Double click on specific objects in the point cloud to zoom into them.
- You can use the [ and ] keys on your keyboard to zoom into and move from one label to the next. If no label is selected, when you select [ or ], the UI will zoom into the first label in the Label Id list.
- Use a mouse-scroller or trackpad to zoom in and out of the point cloud.
- Use both keyboard arrow keys and Q, E, A, and D keys to move Up, Down, Left, Right. Use keyboard keys W and S to zoom in and out.

Once you place a cuboids in the 3D scene, a side-view will appear with three projected views: top, side, and back. These side-views show points in and around the placed cuboid and help workers refine cuboid boundaries in that area. Workers can zoom in and out of each of those side-views using their mouse.

The following video demonstrates movements around the 3D point cloud and in the side-view.
When you are in the worker UI, you see the following menus:

- **Instructions** – Review these instructions before starting your task.
- **Shortcuts** – Use this menu to view keyboard shortcuts that you can use to navigate the point cloud and use the annotation tools provided.
- **Label** – Use this menu to modify a cuboid. First, select a cuboid, and then choose an option from this menu. This menu includes assistive labeling tools like setting a cuboid to the ground and automatically fitting the cuboid to the object’s boundaries.
- **View** – Use this menu to toggle different view options on and off. For example, you can use this menu to add a ground mesh to the point cloud, and to choose the projection of the point cloud.
- **3D Point Cloud** – Use this menu to add additional attributes to the points in the point cloud, such as color, and pixel intensity. Note that these options may not be available.

When you open a task, the move scene icon is on, and you can move around the point cloud using your mouse and the navigation buttons in the point cloud area of the screen. To return to the original view you see when you first opened the task, choose the reset scene icon. Resetting the view will not modify your annotations.

After you select the add cuboid icon, you can add cuboids to the 3D point cloud visualization. Once you've added a cuboid, you can adjust it in the three views (top, side, and front) and in the images (if included).
Hello, chopt@amazon.com

**Shortcuts**

Double click on the point cloud to zoom in

Double click on the label ID to zoom in the object on point cloud.

**3D Cuboid Controls**
When you are in Edit Cuboid mode

- **C** Create
- **V** Edit
- **Cmd** + **Drag** Change dimension
- **Option** + **Drag** Move cuboid
- **Option** + **O** Fit label to points
- **Option** + **G** Set to ground
- **Shift** + **Drag** Rotate cuboid
- **[** Previous label
- **]** Next label
- **Cmd** + , Toggle show/hide label
You must choose the move scene icon again to move to another area in the 3D point cloud or image.

To collapse all panels on the right and make the 3D point cloud full-screen, choose the full screen icon.

If camera images are included, you may have the following view options:

- **C** – View the camera angle on point cloud view.
- **F** – View the frustum, or field of view, of the camera used to capture that image on point cloud view.
- **P** – View the point cloud overlaid on the image.
- **B** – View cuboids in the image.

The following video demonstrates how to use these view options. The **F** option is used to view the field of view of the camera (the gray area), the **C** options shows the direction the camera is facing and angle of the camera (blue lines), and the **B** option is used to view the cuboid.
# Icon Guide

Use this table to learn about the icons you see in your worker task portal.

<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>add cuboid</td>
<td>Choose this icon to add a cuboid. Each cuboid you add is associated with the category you chose.</td>
</tr>
<tr>
<td>edit cuboid</td>
<td>Choose this icon to edit a cuboid. After you have added a cuboid, you can edit its dimensions, location, and orientation. After a cuboid is added, it automatically switches to edit cuboid mode.</td>
</tr>
<tr>
<td>ruler</td>
<td>Use this icon to measure distances, in meters, in the point cloud. You may want to use this tool if your instructions ask you to annotate all objects in a given distance from the center of the cuboid or the object used to capture data. When you select this icon, you can place the starting point (first marker) anywhere in the point cloud by selecting it with your mouse. The tool will automatically use interpolation to place a marker on the closest point within threshold distance to the location you select, otherwise the marker will be placed on ground. If you place a starting point by mistake, you can use the Escape key to revert marker placement. After you place the first marker, you see a dotted line and a dynamic label that indicates the distance you have moved away from the first marker. Click somewhere else on the point cloud to place a second marker. When you place the second marker, the dotted line becomes solid, and the distance is set. After you set a distance, you can edit it by selecting either marker. You can delete a ruler by selecting anywhere on the ruler and using the Delete key on your keyboard.</td>
</tr>
<tr>
<td>reset scene</td>
<td>Choose this icon to reset the view of the point cloud, side panels, and if applicable, all images to their original position when the task was first opened.</td>
</tr>
<tr>
<td>move scene</td>
<td>Choose this icon to move the scene. By default, this icon is chosen when you first start a task.</td>
</tr>
<tr>
<td>Icon</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td><img src="image" alt="Full Screen Icon" /></td>
<td>Choose this icon to make the 3D point cloud visualization full screen, and to collapse all side panels.</td>
</tr>
<tr>
<td><img src="image" alt="Show Labels Icon" /></td>
<td>Show labels in the 3D point cloud visualization, and if applicable, in images.</td>
</tr>
<tr>
<td><img src="image" alt="Hide Labels Icon" /></td>
<td>Hide labels in the 3D point cloud visualization, and if applicable, in images.</td>
</tr>
<tr>
<td><img src="image" alt="Delete Labels Icon" /></td>
<td>Delete a label.</td>
</tr>
</tbody>
</table>

**Shortcuts**

The shortcuts listed in the **Shortcuts** menu can help you navigate the 3D point cloud and use tools to add and edit cuboids.

Before you start your task, it is recommended that you review the **Shortcuts** menu and become acquainted with these commands. You need to use some of the 3D cuboid controls to edit your cuboid.

**Release, Stop and Resume, and Decline Tasks**

When you open the labeling task, three buttons on the top right allow you to decline the task (**Decline task**), release it (**Release task**), and stop and resume it at a later time (**Stop and resume later**). The following list describes what happens when you select one of these options:

- **Decline task**: You should only decline a task if something is wrong with the task, such as an issue with the 3D point cloud, images or the UI. If you decline a task, you will not be able to return to the task.

- **Release Task**: If you release a task, you loose all work done on that task. When the task is released, other workers on your team can pick it up. If enough workers pick up the task, you may not be able to return to it. When you select this button and then select **Confirm**, you are returned to the worker portal. If the task is still available, its status will be **Available**. If other workers pick it up, it will disappear from your portal.

- **Stop and resume later**: You can use the **Stop and resume later** button to stop working and return to the task at a later time. You should use the **Save** button to save your work before you select **Stop and resume later**. When you select this button and then select **Confirm**, you are returned to the worker portal, and the task status is **Stopped**. You can select the same task to resume work on it.

Be aware that the person that creates your labeling tasks specifies a time limit in which all tasks much be completed by. If you do not return to and complete this task within that time limit, it will expire and your work will not be submitted. Contact your administrator for more information.
Saving Your Work and Submitting

You should periodically save your work. Ground Truth will automatically save your work every 15 minutes.

When you open a task, you must complete your work on it before pressing **Submit**.

3D Point Cloud Object Tracking

Use this page to become familiar with the user interface and tools available to complete your 3D point cloud object detection task.

**Topics**

- Your Task (p. 491)
- Navigate the UI (p. 495)
- Bulk Edit Label Category and Frame Attributes (p. 499)
- Icon Guide (p. 500)
- Shortcuts (p. 501)
- Release, Stop and Resume, and Decline Tasks (p. 501)
- Saving Your Work and Submitting (p. 502)

Your Task

When you work on a 3D point cloud object tracking task, you need to select a category from the **Annotations** menu on the right side of your worker portal using the **Label Categories** menu. After you've selected a category, use the add cuboid and fit cuboid tools to fit a cuboid around objects in the 3D point cloud that this category applies to. After you place a cuboid, you can modify its location, dimensions, and orientation directly in the point cloud, and the three panels shown on the right. If you see one or more images in your worker portal, you can also modify cuboids in the images or in the 3D point cloud and the edits will show up in the other medium.

**Important**

If you see cuboids have already been added to the 3D point cloud frames when you open your task, adjust those cuboids and add additional cuboids as needed.

To edit a cuboid, including moving, re-orienting, and changing cuboid dimensions, you must use shortcut keys. You can see a full list of shortcut keys in the **Shortcuts** menu in your UI. The following are important key-combinations that you should become familiar with before starting your labeling task.

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</thead>
<tbody>
<tr>
<td>Cmd + Drag</td>
<td>Ctrl + Drag</td>
<td>Modify the dimensions of the cuboid.</td>
</tr>
<tr>
<td>Option + Drag</td>
<td>Alt + Drag</td>
<td>Move the cuboid.</td>
</tr>
<tr>
<td>Shift + Drag</td>
<td>Shift + Drag</td>
<td>Rotate the cuboid.</td>
</tr>
<tr>
<td>Option + O</td>
<td>Alt + O</td>
<td>Fit the cuboid tightly around the points it has been drawn around.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Before using the option, make sure the cuboid fully-surrounds the object of interest.</td>
</tr>
<tr>
<td>Option + G</td>
<td>Alt + G</td>
<td>Set the cuboid to the ground.</td>
</tr>
</tbody>
</table>
When you open your task, two frames will be loaded. If your task includes more than two frames, you need to use the navigation bar in the lower-left corner, or the load frames icon to load additional frames. You should annotate and adjust labels in all frames before submitting.

After you fit a cuboid tightly around the boundaries of an object, navigate to another frame using the navigation bar in the lower-left corner of the UI. If that same object has moved to a new location, add another cuboid and fit it tightly around the boundaries of the object. Each time you manually add a cuboid, you see the frame sequence bar in the lower-left corner of the screen turn red where that frame is located temporally in the sequence.

Your UI automatically infers the location of that object in all other frames after you've placed a cuboid. This is called interpolation. You can see the movement of that object, and the inferred and manually created cuboids using the arrows. Adjust inferred cuboids as needed. The following video demonstrates how to navigate between frames. The following video shows how, if you add a cuboid in one frame, and then adjust it in another, your UI will automatically infer the location of the cuboid in all of the frames in-between.
Tip
You can turn off the automatic cuboid interpolation across frames using the 3D Point Cloud menu item. Select 3D Point Cloud from the top-menu, and then select Interpolate Cuboids Across Frames. This will uncheck this option and stop cuboid interpolation. You can reselect this item to turn cuboid interpolation back on.

Turning cuboid interpolation off will not impact cuboids that have already been interpolated across frames.

Individual labels may have one or more label attributes. If a label has a label attribute associated with it, it will appear when you select the downward pointing arrow next to the label from the Label Id menu. Fill in required values for all label attributes.

You may see frame attributes under the Label Id menu. These attributes will appear on each frame in your task. Use these attribute prompts to enter additional information about each frame.

![Frame 1 attributes](image)
Navigate the UI

You can navigate in the 3D scene using your keyboard and mouse. You can:

- Double click on specific objects in the point cloud to zoom into them.
- You can use the [ and ] keys on your keyboard to zoom into and move from one label to the next. If no label is selected, when you select [ or ], the UI will zoom into the first label in the Label Id list.
- Use a mouse-scroller or trackpad to zoom in and out of the point cloud.
- Use both keyboard arrow keys and Q, E, A, and D keys to move Up, Down, Left, Right. Use keyboard keys W and S to zoom in and out.

Once you place a cuboids in the 3D scene, a side-view will appear with three projected views: top, side, and back. These side-views show points in and around the placed cuboid and help workers refine cuboid boundaries in that area. Workers can zoom in and out of each of those side-views using their mouse.

The following video demonstrates movements around the 3D point cloud and in the side-view.
When you are in the worker UI, you see the following menus:

- **Instructions** – Review these instructions before starting your task.
- **Shortcuts** – Use this menu to view keyboard shortcuts that you can use to navigate the point cloud and use the annotation tools provided.
- **Label** – Use this menu to modify a cuboid. First, select a cuboid, and then choose an option from this menu. This menu includes assistive labeling tools like setting a cuboid to the ground and automatically fitting the cuboid to the object's boundaries.
- **View** – Use this menu to toggle different view options on and off. For example, you can use this menu to add a ground mesh to the point cloud, and to choose the projection of the point cloud.
- **3D Point Cloud** – Use this menu to add additional attributes to the points in the point cloud, such as color, and pixel intensity. Note that these options may not be available.

When you open a task, the move scene icon is on, and you can move around the point cloud using your mouse and the navigation buttons in the point cloud area of the screen. To return to the original view you see when you first opened the task, choose the reset scene icon.

After you select the add cuboid icon, you can add cuboids to the point cloud and images (if included). You must select the move scene icon again to move to another area in the 3D point cloud or image.

To collapse all panels on the right and make the 3D point cloud full-screen, choose the full screen icon.

If camera images are included, you may have the following view options:

- **C** – View the camera angle on point cloud view.
- **F** – View the frustum, or field of view, of the camera used to capture that image on point cloud view.
- **P** – View the point cloud overlaid on the image.
- **B** – View cuboids in the image.

The following video demonstrates how to use these view options. The **F** option is used to view the field of view of the camera (the gray area), the **C** options shows the direction the camera is facing and angle of the camera (blue lines), and the **B** option is used to view the cuboid.
Delete Cuboids

You can select a cuboid or label ID and:

- Delete an individual cuboid in the current frame you are viewing.
- Delete all cuboids with that label ID before or after the frame you are viewing.
- Delete all cuboids with that label ID in all frames.

A common use-case for cuboid deletion is if the object leaves the scene.

You can use one or more of these options to delete both manually placed and interpolated cuboids with the same label ID.

- To delete all cuboids before or after the frame you are currently on, select the cuboid, select the Label menu item at the top of the UI and then select one of Delete in previous frames or Delete in next frames. Use the Shortcuts menu to see the shortcut keys you can use for these options.
- To delete a label in all frames, select Delete in all frames from the Labels menu, or use the shortcut Shift + Delete on your keyboard.
- To delete an individual cuboid from a single frame, select the cuboid and either select the trashcan icon next to that label ID in the Label ID sidebar on the right or use the Delete key on your keyboard to delete that cuboid.

If you have manually placed more than one cuboid with the same label in different frames, when you delete one of the manually placed cuboids, all interpolated cuboids adjust. This adjustment happens because the UI uses manually placed cuboids as anchor points when calculating the location of interpolated cuboid. When you remove one of these anchor points, the UI must recalculate the position of interpolated cuboids.

If you delete a cuboid from a frame, but later decide that you want to get it back, you can use the Duplicate to previous frames or Duplicate to next frames options in the Label menu to copy the cuboid into all the previous or all of the following frames, respectively.

Bulk Edit Label Category and Frame Attributes

You can bulk edit label attributes and frame attributes.

When you bulk edit an attribute, you specify one or more ranges of frames that you want to apply the edit to. The attribute you select is edited in all frames in that range, including the start and end frames you specify. When you bulk edit label attributes, the range you specify must contain the label that the label attribute is attached to. If you specify frames that do not contain this label, you will receive an error.

To bulk edit an attribute you must specify the desired value for the attribute first. For example, if you want to change an attribute from Yes to No, you must select No, and then perform the bulk edit.

You can also specify a new value for an attribute that has not been filled in and then use the bulk edit feature to fill in that value in multiple frames. To do this, select the desired value for the attribute and complete the following procedure.

To bulk edit a label or attribute:

1. Use your mouse to right click the attribute you want to bulk edit.
2. Specify the range of frames you want to apply the bulk edit to using a dash (-) in the text box. For example, if you want to apply the edit to frames one through ten, enter 1-10. If you want to apply the edit to frames two to five, eight to ten and twenty enter 2-5, 8-10, 20.
3. Select Confirm.
If you get an error message, verify that you entered a valid range and that the label associated with the label attribute you are editing (if applicable) exists in all frames specified.

You can quickly add a label to all previous or subsequent frames using the **Duplicate to previous frames** and **Duplicate to next frames** options in the **Label** menu at the top of your screen.

### Icon Guide

Use this table to learn about the icons you see in your worker task portal.

<table>
<thead>
<tr>
<th>Icon</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>add cuboid</td>
<td>Choose this icon to add a cuboid. Each cuboid you add is associated with the category you chose.</td>
</tr>
<tr>
<td>edit cuboid</td>
<td>Choose this icon to edit a cuboid. After you add a cuboid, you can edit its dimensions, location, and orientation. After a cuboid is added, it automatically switches to edit cuboid mode.</td>
</tr>
<tr>
<td>ruler</td>
<td>Use this icon to measure distances, in meters, in the point cloud. You may want to use this tool if your instructions ask you to annotate all objects in a given distance from the center of the cuboid or the object used to capture data. When you select this icon, you can place the starting point (first marker) anywhere in the point cloud by selecting it with your mouse. The tool will automatically use interpolation to place a marker on the closest point within threshold distance to the location you select, otherwise the marker will be placed on ground. If you place a starting point by mistake, you can use the Escape key to revert marker placement. After you place the first marker, you see a dotted line and a dynamic label that indicates the distance you have moved away from the first marker. Click somewhere else on the point cloud to place a second marker. When you place the second marker, the dotted line becomes solid, and the distance is set. After you set a distance, you can edit it by selecting either marker. You can delete a ruler by selecting anywhere on the ruler and using the Delete key on your keyboard.</td>
</tr>
<tr>
<td>reset scene</td>
<td>Choose this icon to reset the view of the point cloud, side panels, and if applicable, all images to their original position when the task was first opened.</td>
</tr>
<tr>
<td>move scene</td>
<td>Choose this icon to move the scene. By default, this icon is chosen when you first start a task.</td>
</tr>
<tr>
<td>Icon</td>
<td>Description</td>
</tr>
<tr>
<td>------</td>
<td>-------------</td>
</tr>
<tr>
<td>![full screen icon]</td>
<td>Choose this icon to make the 3D point cloud visualization full screen and to collapse all side panels.</td>
</tr>
<tr>
<td>![load frames icon]</td>
<td>Choose this icon to load additional frames.</td>
</tr>
<tr>
<td>![hide labels icon]</td>
<td>Hide labels in the 3D point cloud visualization, and if applicable, in images.</td>
</tr>
<tr>
<td>![show labels icon]</td>
<td>Show labels in the 3D point cloud visualization, and if applicable, in images.</td>
</tr>
<tr>
<td>![delete labels icon]</td>
<td>Delete a label. This option can only be used to delete labels you have manually created or adjusted.</td>
</tr>
</tbody>
</table>

**Shortcuts**

The shortcuts listed in the **Shortcuts** menu can help you navigate the 3D point cloud and use tools to add and edit cuboids.

Before you start your task, it is recommended that you review the **Shortcuts** menu and become acquainted with these commands. You need to use some of the 3D cuboid controls to edit your cuboid.

**Release, Stop and Resume, and Decline Tasks**

When you open the labeling task, three buttons on the top right allow you to decline the task (**Decline task**), release it (**Release task**), and stop and resume it at a later time (**Stop and resume later**). The following list describes what happens when you select one of these options:

- **Decline task**: You should only decline a task if something is wrong with the task, such as an issue with the 3D point clouds, images or the UI. If you decline a task, you will not be able to return to the task.
- **Release Task**: Use this option to release a task and allow others to work on it. When you release a task, you loose all work done on that task and other workers on your team can pick it up. If enough workers pick up the task, you may not be able to return to it. When you select this button and then select **Confirm**, you are returned to the worker portal. If the task is still available, its status will be **Available**. If other workers pick it up, it will disappear from your portal.
- **Stop and resume later**: You can use the **Stop and resume later** button to stop working and return to the task at a later time. You should use the **Save** button to save your work before you select **Stop and resume later**. When you select this button and then select **Confirm**, you are returned to the worker portal, and the task status is **Stopped**. You can select the same task to resume work on it.
Verify and Adjust Labels

Be aware that the person that creates your labeling tasks specifies a time limit in which all tasks must be completed by. If you do not return to and complete this task within that time limit, it will expire and your work will not be submitted. Contact your administrator for more information.

Saving Your Work and Submitting

You should periodically save your work. Ground Truth will automatically save your work every 15 minutes. When you open a task, you must complete your work on it before pressing Submit.

Verify and Adjust Labels

When the labels on a dataset need to be validated, Amazon SageMaker Ground Truth provides functionality to have workers verify that labels are correct or to adjust previous labels.

These types of jobs fall into two distinct categories:

- **Label verification** — Workers indicate if the existing labels are correct, or rate their quality, and can add comments to explain their reasoning. Workers will not be able to modify or adjust labels.

  If you create a 3D point cloud or video frame label adjustment or verification job, you can choose to make label category attributes (not supported for 3D point cloud semantic segmentation) and frame attributes editable by workers.

- **Label adjustment** — Workers adjust prior annotations and, if applicable, label category and frame attributes to correct them.

The following Ground Truth built-in task types support adjustment and verification labeling jobs:

- Bounding box
- Semantic segmentation
- 3D point cloud object detection, 3D point cloud object tracking, and 3D point cloud semantic segmentation
- All video frame object detection and video frame object tracking task types — bounding box, polyline, polygon and keypoint

**Tip**

For 3D point cloud and video frame labeling verification jobs, it is recommended that you add new label category attributes or frame attributes to the labeling job. Workers can use these attribute to verify individual labels or the entire frame. To learn more about label category and frame attributes, see Worker User Interface (UI) (p. 469) for 3D point cloud and Worker User Interface (UI) (p. 421) for video frame.

You can start a label verification and adjustment jobs using the SageMaker console or the API.

**Topics**

- Requirements to Create Verification and Adjustment Labeling Jobs (p. 503)
- Create a Label Verification Job (Console) (p. 503)
- Create a Label Adjustment Job (Console) (p. 505)
- Start a Label Verification or Adjustment Job (API) (p. 506)
- Label Verification and Adjustment Data in the Output Manifest (p. 508)
- Cautions and Considerations (p. 509)
Verify and Adjust Labels

Requirements to Create Verification and Adjustment Labeling Jobs

To create a label verification or adjustment job, the following criteria must be satisfied.

- For non streaming labeling jobs: The input manifest file you use must contain the label attribute name (`LabelAttributeName`) of the labels that you want adjusted. When you chain a successfully completed labeling job, the output manifest file is used as the input manifest file for the new, chained job. To learn more about the format of the output manifest file Ground Truth produces for each task type, see Output Data (p. 614).

- For streaming labeling jobs: The Amazon SNS message you sent to the Amazon SNS input topic of the adjustment or verification labeling job must contain the label attribute name of the labels you want adjusted or verified. To see an example of how you can create an adjustment or verification labeling job with streaming labeling jobs, see this Jupyter Notebook example in GitHub.

- The task type of the verification or adjustment labeling job must be the same as the task type of the original job unless you are using the Image Label Verification (p. 395) task type to verify bounding box or semantic segmentation image labels. See the next bullet point for more details about the video frame task type requirements.

- For video frame annotation verification and adjustment jobs, you must use the same annotation task type used to create the annotations from the previous labeling job. For example, if you create a video frame object detection job to have workers draw bounding boxes around objects, and then you create a video object detection adjustment job, you must specify `bounding boxes` as the annotation task type. To learn more video frame annotation task types, see Task Types (p. 420).

- The task type you select for the adjustment or verification labeling job must support an audit workflow. The following Ground Truth built-in task types support adjustment and verification labeling jobs: bounding box, semantic segmentation, 3D point cloud object detection, 3D point cloud object tracking, and 3D point cloud semantic segmentation, and all video frame object detection and video frame object tracking task types — bounding box, polyline, polygon and keypoint.

Create a Label Verification Job (Console)

Bounding box and semantic segmentation labeling jobs are created by choosing the Label verification task type in the console. To create a verification job for 3D point cloud and video frame task types, you must choose the same task type as the original labeling job and choose to display existing labels. Use one of the following sections to create a label verification job for your task type.

Topics

- Create an Image Label Verification Job (Console) (p. 503)
- Create a Point Cloud or Video Frame Label Verification Job (Console) (p. 504)

Create an Image Label Verification Job (Console)

Use the following procedure to create a bounding box or semantic segmentation verification job using the console. This procedure assumes that you have already created a bounding box or semantic segmentation labeling job and its status is Complete. This the labeling job that produces the labels you want verified.

To create an image label verification job:

2. Start a new labeling job by chaining (p. 646) a prior job or start from scratch, specifying an input manifest that contains labeled data objects.
3. In the **Task type** pane, select **Label verification**.

4. Choose **Next**.

5. In the **Workers** section, choose the type of workforce you would like to use. For more details about your workforce options see [Create and Manage Workforces](p. 694).

6. (Optional) After you’ve selected your workforce, specify the **Task timeout** and **Task expiration time**.

7. In the **Existing-labels display options** pane, the system shows the available label attribute names in your manifest. Choose the label attribute name that identifies the labels that you want workers to verify. Ground Truth tries to detect and populate these values by analyzing the manifest, but you might need to set the correct value.

8. Use the instructions areas of the tool designer to provide context about what the previous labelers were asked to do and what the current verifiers need to check.

   You can add new labels that workers choose from to verify labels. For example, you can ask workers to verify the image quality, and provide the labels **Clear** and **Blurry**. Workers will also have the option to add a comment to explain their selection.

9. Choose **See preview** to check that the tool is displaying the prior labels correctly and presents the label verification task clearly.

10. Select **Create**. This will create and start your labeling job.

### Create a Point Cloud or Video Frame Label Verification Job (Console)

Use the following procedure to create a 3D point cloud or video frame verification job using the console. This procedure assumes that you have already created a labeling job using the task type that produces the types of labels you want to be verified and its status is Complete.

**To create an image label verification job:**


2. Start a new labeling job by chaining (p. 646) a prior job or start from scratch, specifying an input manifest that contains labeled data objects.

3. In the **Task type** pane, select the same task type as the labeling job that you chained. For example, if the original labeling job was a video frame object detection keypoint labeling job, select that task type.

4. Choose **Next**.

5. In the **Workers** section, choose the type of workforce you would like to use. For more details about your workforce options see [Create and Manage Workforces](p. 694).

6. (Optional) After you’ve selected your workforce, specify the **Task timeout** and **Task expiration time**.

7. Toggle on the switch next to **Display existing labels**.

8. Select **Verification**.

9. For **Label attribute name**, choose the name from your manifest that corresponds to the labels that you want to display for verification. You will only see label attribute names for labels that match the task type you selected on the previous screen. Ground Truth tries to detect and populate these values by analyzing the manifest, but you might need to set the correct value.

10. Use the instructions areas of the tool designer to provide context about what the previous labelers were asked to do and what the current verifiers need to check.

   You cannot modify or add new labels. You can remove, modify and add new label category attributes or frame attributes. It is recommended that you add new label category attributes or frame attributes to the labeling job. Workers can use these attribute to verify individual labels or the entire frame.
By default, preexisting label category attributes and frame attributes will not be editable by workers. If you want to make a label category or frame attribute editable, select the Allow workers to edit this attribute check box for that attribute.

To learn more about label category and frame attributes, see Worker User Interface (UI) (p. 469) for 3D point cloud and Worker User Interface (UI) (p. 421) for video frame.

11. Choose See preview to check that the tool is displaying the prior labels correctly and presents the label verification task clearly.

12. Select Create. This will create and start your labeling job.

Create a Label Adjustment Job (Console)

Use one of the following sections to create a label verification job for your task type.

Topics
- Create an Image Label Adjustment Job (Console) (p. 505)
- Create a Point Cloud or Video Frame Label Adjustment Job (Console) (p. 506)

Create an Image Label Adjustment Job (Console)

Use the following procedure to create a bounding box or semantic segmentation adjustment labeling job using the console. This procedure assumes that you have already created a bounding box or semantic segmentation labeling job and its status is Complete. This the labeling job that produces the labels you want adjusted.

To create an image label adjustment job (console)

2. Start a new labeling job by chaining (p. 646) a prior job or start from scratch, specifying an input manifest that contains labeled data objects.
3. Choose the same task type as the original labeling job.
4. Choose Next.
5. In the Workers section, choose the type of workforce you would like to use. For more details about your workforce options see Create and Manage Workforces (p. 694).
6. (Optional) After you've selected your workforce, specify the Task timeout and Task expiration time.
7. Expand Existing-labels display options by selecting the arrow next to the title.
8. Check the box next to I want to display existing labels from the dataset for this job.
9. For Label attribute name, choose the name from your manifest that corresponds to the labels that you want to display for adjustment. You will only see label attribute names for labels that match the task type you selected on the previous screen. Ground Truth tries to detect and populate these values by analyzing the manifest, but you might need to set the correct value.
10. Use the instructions areas of the tool designer to provide context about what the previous labelers were tasked with doing and what the current verifiers need to check and adjust.
11. Choose See preview to check that the tool shows the prior labels correctly and presents the task clearly.
12. Select Create. This will create and start your labeling job.
Create a Point Cloud or Video Frame Label Adjustment Job (Console)

Use the following procedure to create a 3D point cloud or video frame adjustment job using the console. This procedure assumes that you have already created a labeling job using the task type that produces the types of labels you want to be verified and its status is Complete.

**To create a 3D point cloud or video frame label adjustment job (console)**

1. Open the SageMaker console: https://console.aws.amazon.com/sagemaker/ and choose **Labeling jobs**.
2. Start a new labeling job by chaining (p. 646) a prior job or start from scratch, specifying an input manifest that contains labeled data objects.
3. Choose the same task type as the original labeling job.
4. Toggle on the switch next to **Display existing labels**.
5. Select **Adjustment**.
6. For **Label attribute name**, choose the name from your manifest that corresponds to the labels that you want to display for adjustment. You will only see label attribute names for labels that match the task type you selected on the previous screen. Ground Truth tries to detect and populate these values by analyzing the manifest, but you might need to set the correct value.
7. Use the instructions areas of the tool designer to provide context about what the previous labelers were asked to do and what the current adjusters need to check.
   
   You cannot remove or modify existing labels but you can add new labels. You can remove, modify and add new label category attributes or frame attributes.

   Be default, preexisting label category attributes and frame attributes will be editable by workers. If you want to make a label category or frame attribute uneditable, deselect the **Allow workers to edit this attribute** check box for that attribute.

   To learn more about label category and frame attributes, see Worker User Interface (UI) (p. 469) for 3D point cloud and Worker User Interface (UI) (p. 421) for video frame.
8. Choose **See preview** to check that the tool shows the prior labels correctly and presents the task clearly.
9. Select **Create**. This will create and start your labeling job.

Start a Label Verification or Adjustment Job (API)

Start a label verification or adjustment job by chaining a successfully completed job or starting a new job from scratch using the `CreateLabelingJob` operation. The procedure is almost the same as setting up a new labeling job with `CreateLabelingJob`, with a few modifications. Use the following sections to learn what modifications are required to chain a labeling job to create an adjustment or verification labeling job.

When you create an adjustment or verification labeling job using the Ground Truth API, you must use a different LabelAttributeName than the original labeling job. The original labeling job is the job used to create the labels you want adjusted or verified.

**Important**

The label category configuration file you identify for an adjustment or verification job in `LabelCategoryConfigS3Uri` of `CreateLabelingJob` must contain the same labels used in the original labeling job. You can add new labels. For 3D point cloud and video frame jobs, you can add new label category and frame attributes to the label category configuration file.
Bounding Box and Semantic Segmentation

To create a bounding box or semantic segmentation label verification or adjustment job, use the following guidelines to specify API attributes for the CreateLabelingJob operation.

- Use the `LabelAttributeName` parameter to specify the output label name that you want to use for verified or adjusted labels. You must use a different `LabelAttributeName` than the one used for the original labeling job.
- If you are chaining the job, the labels from the previous labeling job to be adjusted or verified will be specified in the custom UI template. To learn how to create a custom template, see Create Custom Worker Task Templates (p. 3448).

Identify the location of the UI template in the `UiTemplateS3Uri` parameter. SageMaker provides widgets that you can use in your custom template to display old labels. Use the initial-value attribute in one of the following crowd elements to extract the labels that need verification or adjustment and include them in your task template:

- `crowd-semantic-segmentation` (p. 779)—Use this crowd element in your custom UI task template to specify semantic segmentation labels that need to be verified or adjusted.
- `crowd-bounding-box` (p. 726)—Use this crowd element in your custom UI task template to specify bounding box labels that need to be verified or adjusted.

The `LabelCategoryConfigS3Uri` parameter must contain the same label categories as the previous labeling job.

- Use the bounding box or semantic segmentation adjustment or verification lambda ARNs for `PreHumanTaskLambdaArn` and `AnnotationConsolidationLambdaArn`:
  - For bounding box, the adjustment labeling job lambda function ARNs end with `AdjustmentBoundingBox` and the verification lambda function ARNs end with `VerificationBoundingBox`.
  - For semantic segmentation, the adjustment labeling job lambda function ARNs end with `AdjustmentSemanticSegmentation` and the verification lambda function ARNs end with `VerificationSemanticSegmentation`.

3D Point Cloud and Video Frame

- Use the `LabelAttributeName` parameter to specify the output label name that you want to use for verified or adjusted labels. You must use a different `LabelAttributeName` than the one used for the original labeling job.
- You must use the human task UI Amazon Resource Name (ARN) (`HumanTaskUiArn`) used for the original labeling job. To see supported ARNs, see `HumanTaskUiArn`.
- In the label category configuration file, you must specify the label attribute name (`LabelAttributeName`) of the previous labeling job that you use to create the adjustment or verification labeling job in the `auditLabelAttributeName` parameter.
- You specify whether your labeling job is a verification or adjustment labeling job using the `editsAllowed` parameter in your label category configuration file identified by the `LabelCategoryConfigS3Uri` parameter.
  - For verification labeling jobs, you must use the `editsAllowed` parameter to specify that all labels cannot be modified. `editsAllowed` must be set to "none" in each entry in `labels`. Optionally, you can specify whether or not label categories attributes and frame attributes can be adjusted by workers.
  - Optionally, for adjustment labeling jobs, you can use the `editsAllowed` parameter to specify labels, label category attributes, and frame attributes that can or cannot be modified by workers. If you do not use this parameter, all labels, label category attributes, and frame attributes will be adjustable.
To learn more about the editsAllowed parameter and configuring your label category configuration file, see Label Category Configuration File Schema (p. 557).

- Use the 3D point cloud or video frame adjustment lambda ARNs for PreHumanTaskLambdaArn and AnnotationConsolidationLambdaArn for both adjustment and verification labeling jobs:
  - For 3D point clouds, the adjustment and verification labeling job lambda function ARNs end with Adjustment3DPointCloudSemanticSegmentation, Adjustment3DPointCloudObjectTracking, and Adjustment3DPointCloudObjectDetection for 3D point cloud semantic segmentation, object detection, and object tracking respectively.
  - For video frames, the adjustment and verification labeling job lambda function ARNs end with AdjustmentVideoObjectDetection and AdjustmentVideoObjectTracking for video frame object detection and object tracking respectively.

Ground Truth stores the output data from a label verification or adjustment job in the S3 bucket that you specified in the S3OutputPath parameter of the CreateLabelingJob operation. For more information about the output data from a label verification or adjustment labeling job, see Label Verification and Adjustment Data in the Output Manifest (p. 508).

**Label Verification and Adjustment Data in the Output Manifest**

Amazon SageMaker Ground Truth writes label verification data to the output manifest within the metadata for the label. It adds two properties to the metadata:

- A type property, with a value of "groundtruth/label-verification."
- A worker-feedback property, with an array of comment values. This property is added when the worker enters comments. If there are no comments, the field doesn't appear.

The following example output manifest shows how label verification data appears:

```json
{
  "source-ref": "S3 bucket location",
  "verify-bounding-box": "1",
  "verify-bounding-box-metadata": {
    "class-name": "bad",
    "confidence": 0.93,
    "type": "groundtruth/label-verification",
    "job-name": "verify-bounding-boxes",
    "human-annotated": "yes",
    "creation-date": "2018-10-18T22:18:13.527256",
    "worker-feedback": [
      {"comment": "The bounding box on the bird is too wide on the right side."},
      {"comment": "The bird on the upper right is not labeled."}
    ]
  }
}
```

The worker output of adjustment tasks resembles the worker output of the original task, except that it contains the adjusted values and an adjustment-status property with the value of adjusted or unadjusted to indicate whether an adjustment was made.

For more examples of the output of different tasks, see Output Data (p. 614).
Cautions and Considerations

To get expected behavior when creating a label verification or adjustment job, carefully verify your input data.

- If you are using image data, verify that your manifest file contains hexadecimal RGB color information.
- To save money on processing costs, filter your data to ensure you are not including unwanted objects in your labeling job input manifest.
- Add required Amazon S3 permissions to ensure your input data is processed correctly.

When you create an adjustment or verification labeling job using the Ground Truth API, you must use a different LabelAttributeName than the original labeling job.

Color Information Requirements for Semantic Segmentation Jobs

To properly reproduce color information in verification or adjustment tasks, the tool requires hexadecimal RGB color information in the manifest (for example, #FFFFFF for white). When you set up a Semantic Segmentation verification or adjustment job, the tool examines the manifest to determine if this information is present. If it can't find it, Amazon SageMaker Ground Truth displays an error message and the ends job setup.

In prior iterations of the Semantic Segmentation tool, category color information wasn't output in hexadecimal RGB format to the output manifest. That feature was introduced to the output manifest at the same time the verification and adjustment workflows were introduced. Therefore, older output manifests aren't compatible with this new workflow.

Filter Your Data Before Starting the Job

Amazon SageMaker Ground Truth processes all objects in your input manifest. If you have a partially labeled data set, you might want to create a custom manifest using an Amazon S3 Select query on your input manifest. Unlabeled objects individually fail, but they don't cause the job to fail, and they might incur processing costs. Filtering out objects you don't want verified reduces your costs.

If you create a verification job using the console, you can use the filtering tools provided there. If you create jobs using the API, make filtering your data part of your workflow where needed.

Creating Custom Labeling Workflows

This document guides you through the process of setting up a workflow with a custom labeling template. To learn more about starting a labeling job, see Getting started (p. 371). In that section, when you choose the Task type, select Custom labeling task, and then follow this section's instructions to configure it.

Topics

- Step 1: Setting up your workforce (p. 510)
- Step 2: Creating your custom worker task template (p. 510)
- Step 3: Processing with AWS Lambda (p. 516)
- Demo Template: Annotation of Images with crowd-bounding-box (p. 530)
- Demo Template: Labeling Intents with crowd-classifier (p. 534)
- Custom Workflows via the API (p. 541)

For more information about creating custom labeling workflows, see Build a custom data labeling workflow with Amazon SageMaker Ground Truth.
Step 1: Setting up your workforce

In this step you use the console to establish which worker type to use and make the necessary sub-selections for the worker type. It assumes you have already completed the steps up to this point in the Getting started (p. 371) section and have chosen the Custom labeling task as the Task type.

To configure your workforce.

1. First choose an option from the Worker types. There are three types currently available:
   - **Public** uses an on-demand workforce of independent contractors, powered by Amazon Mechanical Turk. They are paid on a per-task basis.
   - **Private** uses your employees or contractors for handling data that needs to stay within your organization.
   - **Vendor** uses third party vendors that specialize in providing data labeling services, available via the AWS Marketplace.

2. If you choose the Public option, you are asked to set the number of workers per dataset object. Having more than one worker perform the same task on the same object can help increase the accuracy of your results. The default is three. You can raise or lower that depending on the accuracy you need.

   You are also asked to set a price per task by using a drop-down menu. The menu recommends price points based on how long it will take to complete the task.

   The recommended method to determine this is to first run a short test of your task with a private workforce. The test provides a realistic estimate of how long the task takes to complete. You can then select the range your estimate falls within on the Price per task menu. If your average time is more than 5 minutes, consider breaking your task into smaller units.

Next

Step 2: Creating your custom worker task template (p. 510)

Step 2: Creating your custom worker task template

A worker task template is a file used by Ground Truth to customize the worker user interface (UI), or human task UI. You can create a worker task template using HTML, CSS, JavaScript, Liquid template language, and Crowd HTML Elements. Liquid is used to automate the template, and Crowd HTML Elements can be used to include common annotation tools and provide the logic to submit to Ground Truth.

- Starting with a base template (p. 511)
- Developing templates locally (p. 511)
- Using External Assets (p. 511)
- Track your variables (p. 511)
- A simple sample (p. 512)
- Adding automation with Liquid (p. 513)
- End-to-end demos (p. 515)
- Next (p. 516)

Use the following topics to learn how you can create a worker task template. You can see a repository of example Ground Truth worker task templates on GitHub.
Starting with a base template

You can use a template editor in the Ground Truth console to start creating a template. This editor includes a number of pre-designed base templates and an HTML and Crowd HTML Element autofill feature.

To access the Ground Truth custom template editor:

1. Following the instructions in Create a Labeling Job (Console) (p. 544) and select Custom for the labeling job Task type.
2. When you select Next, you will be able to access the template editor and base templates in the Custom labeling task setup section.
3. (Optional) Select a base template from the drop-down menu under Templates. If you prefer to create a template from scratch, choose Custom from the drop down-menu for a minimal template skeleton.

Developing templates locally

While you need to be in the console to test how your template will process incoming data, you can test the look and feel of your template's HTML and custom elements in your browser by adding this code to the top of your HTML file.

Example

```
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
```

This loads the necessary code to render the custom HTML elements. Use this if you want to develop your template's look and feel in your preferred editor rather than in the console.

Remember, though, this will not parse your variables. You may want to replace them with sample content while developing locally.

Using External Assets

Amazon SageMaker Ground Truth custom templates allow external scripts and style sheets to be embedded. For example, the following code block demonstrates how you would add a style sheet located at https://www.example.com/my-enhancement-styles.css to your template.

Example

```
<script src="https://www.example.com/my-enhancement-script.js"></script>
<link rel="stylesheet" type="text/css" href="https://www.example.com/my-enhancement-styles.css">
```

If you encounter errors, ensure that your originating server is sending the correct MIME type and encoding headers with the assets.

For example, the MIME and encoding types for remote scripts are: application/javascript;CHARSET=UTF-8.

The MIME and encoding type for remote stylesheets are: text/css;CHARSET=UTF-8.

Track your variables

In the process of building the sample below, there will be a step that adds variables to it to represent the pieces of data that may change from task to task, worker to worker. If you're starting with one of the
sample templates, you will need to make sure you're aware of the variables it already uses. When you
create your pre-annotation AWS Lambda script, its output will need to contain values for any of those
variables you choose to keep.

The values you use for the variables can come from your manifest file. All the key-value pairs in your
data object are provided to your pre-annotation Lambda. If it's a simple pass-through script, matching
keys for values in your data object to variable names in your template is the easiest way to pass those
values through to the tasks forms your workers see.

A simple sample

All tasks begin and end with the `<crowd-form> </crowd-form>` elements. Like standard HTML
<form> elements, all of your form code should go between them.

For a simple tweet-analysis task, use the `<crowd-classifier>` element. It requires the following
attributes:

- `name` - the variable name to use for the result in the form output.
- `categories` - a JSON formatted array of the possible answers.
- `header` - a title for the annotation tool

As children of the `<crowd-classifier>` element, you must have three regions.

- `<classification-target>` - the text the worker will classify based on the options specified in the
categories attribute above.
- `<full-instructions>` - instructions that are available from the "View full instructions" link in the tool.
  This can be left blank, but it is recommended that you give good instructions to get better results.
- `<short-instructions>` - a more brief description of the task that appears in the tool's sidebar. This can be
  left blank, but it is recommended that you give good instructions to get better results.

A simple version of this tool would look like this.

Example of using `crowd-classifier`

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<!--crowd-form-->

<!--crowd-classifier-->

  name="tweetFeeling"
  categories="["positive","negative","neutral", "unclear"]"
  header="Which term best describes this tweet?"
>
  <!--classification-target-->
  My favorite football team won today!
  Bring on the division finals!
  <!--classification-target-->

  <!--full-instructions header="Sentiment Analysis Instructions">-->
  Try to determine the sentiment the author
  of the tweet is trying to express.
  If none seem to match, choose "cannot determine."
  <!--full-instructions-->

  <!--short-instructions-->
  Pick the term best describing the sentiment
  of the tweet.
  <!--short-instructions-->

<!--crowd-classifier-->
</crowd-form>
```
You can copy and paste the code into the editor in the Ground Truth labeling job creation workflow to preview the tool, or try out a demo of this code on CodePen.

Adding automation with Liquid

Our custom template system uses Liquid for automation. It is an open source inline markup language. In Liquid, the text between single curly braces and percent symbols is an instruction or tag that performs an operation like control flow or iteration. Text between double curly braces is a variable or object that outputs its value.

The most common use of Liquid will be to parse the data coming from your pre-annotation Lambda and pull out the relevant variables to create the task. The taskInput object returned by your Pre-annotation Lambda (p. 517) will be available as the task.input object in your templates.

The properties in your manifest's data objects are passed into your Pre-annotation Lambda (p. 517) as the event.dataObject. A simple pass-through script simply returns that object as the taskInput object. You would represent values from your manifest as variables as follows.

Example Manifest data object

```json
{
  "source": "This is a sample text for classification",
  "labels": ["angry", "sad", "happy", "inconclusive"],
  "header": "What emotion is the speaker feeling?"
}
```

Example Sample HTML using variables

```html
<crowd-classifier
     name='tweetFeeling'
     categories='{{ task.input.labels | to_json }}'
     header='{{ task.input.header }}'>
<classification-target>
```
Note the addition of "| to_json" to the labels property above. That's a filter to turn the array into a JSON representation of the array. Variable filters are explained in the next section.

The following list includes two types of Liquid tags that you may find useful to automate template input data processing. If you select one of the following tag-types, you will be redirected to the Liquid documentation.

- **Control flow**: Includes programming logic operators like `if/else`, `unless`, and `case/when`.
- **Iteration**: Enables you to run blocks of code repeatedly using statements like for loops.

For an example of an HTML template that uses Liquid elements to create a for loop, see `translation-review-and-correction.liquid.html` in GitHub.

For more information and documentation, visit the [Liquid homepage](https://liquid.readthedocs.io).

### Variable filters

In addition to the standard Liquid filters and actions, Ground Truth offers a few additional filters. Filters are applied by placing a pipe (|) character after the variable name, then specifying a filter name. Filters can be chained in the form of:

Example

```liquid
{{ <content> | <filter> | <filter> }}
```

**Autoescape and explicit escape**

By default, inputs will be HTML escaped to prevent confusion between your variable text and HTML. You can explicitly add the escape filter to make it more obvious to someone reading the source of your template that the escaping is being done.

**escape_once**

`escape_once` ensures that if you've already escaped your code, it doesn't get re-escaped on top of that. For example, so that `&` doesn't become `&amp;`.

**skip_autoescape**

`skip_autoescape` is useful when your content is meant to be used as HTML. For example, you might have a few paragraphs of text and some images in the full instructions for a bounding box.

**Use skip_autoescape sparingly**

The best practice in templates is to avoid passing in functional code or markup with `skip_autoescape` unless you are absolutely sure you have strict control over what's being passed. If you're passing user input, you could be opening your workers up to a Cross Site Scripting attack.

**to_json**

`to_json` will encode what you feed it to JSON (JavaScript Object Notation). If you feed it an object, it will serialize it.

**grant_read_access**

`grant_read_access` takes an S3 URI and encodes it into an HTTPS URL with a short-lived access token for that resource. This makes it possible to display to workers photo, audio, or video objects stored in S3 buckets that are not otherwise publicly accessible.
Example of the filters

Input

```text
auto-escape: {{ "Have you read 'James & the Giant Peach'" }}
explicit escape: {{ "Have you read 'James & the Giant Peach'" | escape }}
explicit escape_once: {{ "Have you read 'James & the Giant Peach'" | escape_once }}
skip_autoescape: {{ "Have you read 'James & the Giant Peach'" | skip_autoescape }}
to_json: {{ jsObject | to_json }}
grant_read_access: {{ "s3://mybucket/myphoto.png" | grant_read_access }}
```

Example

Output

```text
auto-escape: Have you read 'James & the Giant Peach'?
explicit escape: Have you read 'James & the Giant Peach'?
explicit escape_once: Have you read 'James & the Giant Peach'?
skip_autoescape: Have you read 'James & the Giant Peach'?
to_json: { "point_number": 8, "coords": [ 59, 76 ] }
grant_read_access: https://s3.amazonaws.com/mybucket/myphoto.png?access token and other params>
```

Example of an automated classification template.

To automate the simple text classification sample, replace the tweet text with a variable.

The text classification template is below with automation added. The changes/additions are highlighted in bold.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-classifier
    name="tweetFeeling"
    categories="['positive', 'negative', 'neutral', 'cannot determine']"
    header="Which term best describes this tweet?"
  >
    <classification-target>
      {{ task.input.source }}
    </classification-target>
    <full-instructions header="Analyzing a sentiment">
      Try to determine the feeling the author of the tweet is trying to express.
      If none seem to match, choose "other."
    </full-instructions>
    <short-instructions>
      Pick the term best describing the sentiment of the tweet.
    </short-instructions>
  </crowd-classifier>
</crowd-form>
```

The tweet text that was in the prior sample is now replaced with an object. The entry.taskInput object uses source (or another name you specify in your pre-annotation Lambda) as the property name for the text and it is inserted directly in the HTML by virtue of being between double curly braces.

End-to-end demos

You can view the following end-to-end demos which include sample Lambda function:
Next

Step 3: Processing with AWS Lambda (p. 516)

Step 3: Processing with AWS Lambda

In this step, you learn how to create and specify the two types of AWS Lambda functions that are required to create a custom labeling workflow:

- **Pre-annotation Lambda**: This function initiates for and pre-processes each data object sent to your labeling job prior to sending it to workers.
- **Post-annotation Lambda**: This function processes the results once workers submit a task. If you specify multiple workers per data object, this function may include logic to consolidate annotations.

If you are a new user of Lambda and Ground Truth, we recommend that you use the pages in this section as follows:

1. First, review Pre-annotation and Post-annotation Lambda Function Requirements (p. 516).
2. Then, use the page Required Permissions To Use AWS Lambda With Ground Truth (p. 523) to learn about security and permission requirements to use your pre-annotation and post-annotation Lambda functions in a Ground Truth custom labeling job.
3. Next, you need to visit the Lambda console or use Lambda's APIs to create your functions. Use the section Create Lambda Functions for a Custom Labeling Workflow (p. 527) to learn how to create Lambda functions.
4. To learn how to test your Lambda functions, see Test Pre-Annotation and Post-Annotation Lambda Functions (p. 527).
5. After you create pre-processing and post-processing Lambda functions, select them from the Lambda functions section that comes after the code editor for your custom HTML in the Ground Truth console. To learn how to use these functions in a CreateLabelingJob API request, see Create a Labeling Job (API) (p. 547).

For a custom labeling workflow tutorial that includes example pre-annotation and post-annotation Lambda functions, in the "Demo Template: Annotation of Images with crowd-bounding-box (p. 530)" document.

Topics
- Pre-annotation and Post-annotation Lambda Function Requirements (p. 516)
- Required Permissions To Use AWS Lambda With Ground Truth (p. 523)
- Create Lambda Functions for a Custom Labeling Workflow (p. 527)
- Test Pre-Annotation and Post-Annotation Lambda Functions (p. 527)

Pre-annotation and Post-annotation Lambda Function Requirements

Use this section to learn about the syntax of the requests sent to pre-annotation and post-annotation Lambda functions, and the response syntax that Ground Truth requires to run a custom labeling workflow.

Topics
Pre-annotation Lambda

Before a labeling task is sent to the worker, your pre-annotation Lambda function is invoked.

Ground Truth sends your Lambda function a JSON-formatted request to provide details about the labeling job and the data object. The following table contains the pre-annotation request schemas. Each parameter is described below.

Data object identified with "source-ref"

```json
{
    "version": "2018-10-16",
    "labelingJobArn": "<labelingJobArn>
    "dataObject" : {
        "source-ref": "<s3Uri>
    }
}
```

Data object identified with "source"

```json
{
    "version": "2018-10-16",
    "labelingJobArn": "<labelingJobArn>
    "dataObject" : {
        "source": "<string>
    }
}
```

- **version** (string): This is a version number used internally by Ground Truth.
- **labelingJobArn** (string): This is the Amazon Resource Name, or ARN, of your labeling job. This ARN can be used to reference the labeling job when using Ground Truth API operations such as DescribeLabelingJob.
- The **dataObject** (JSON object): The key contains a single JSON line, either from your input manifest file or sent from Amazon SNS. The JSON line objects in your manifest can be up to 100 kilobytes in size and contain a variety of data. For a very basic image annotation job, the dataObject JSON may just contain a source-ref key, identifying the image to be annotated. If the data object (for example, a line of text) is included directly in the input manifest file, the data object is identified with source. If you create a verification or adjustment job, this line may contain label data and metadata from the previous labeling job.

The following table includes code block examples of a pre-annotation request. Each parameter in these example requests is explained below the tabbed table.

Data object identified with "source-ref"

```json
{
    "version": "2018-10-16",
    "labelingJobArn": "arn:aws:sagemaker:<aws_region>:<aws_account_number>:labeling-job/<labeling_job_name>
    "dataObject" : {
        "source-ref": "s3://<input-data-bucket>/<data-object-file-name>"
    }
}
```
Example of expected return data

```json
{
  "taskInput": <json object>,
  "isHumanAnnotationRequired": <boolean> # Optional
}
```

In the previous example, the `<json object>` needs to contain all the data your custom worker task template needs. If you're doing a bounding box task where the instructions stay the same all the time, it may just be the HTTP(S) or Amazon S3 resource for your image file. If it's a sentiment analysis task and different objects may have different choices, it is the object reference as a string and the choices as an array of strings.

**Implications of isHumanAnnotationRequired**

This value is optional because it defaults to true. The primary use case for explicitly setting it is when you want to exclude this data object from being labeled by human workers.

If you have a mix of objects in your manifest, with some requiring human annotation and some not needing it, you can include a `isHumanAnnotationRequired` value in each data object. You can add logic to your pre-annotation Lambda to dynamically determine if an object requires annotation, and set this boolean value accordingly.

### Examples of Pre-annotation Lambda Functions

The following, basic pre-annotation Lambda function accesses the JSON object in `dataObject` from the initial request, and returns it in the `taskInput` parameter.

```python
import json

def lambda_handler(event, context):
    return {
        "taskInput": event['dataObject']
    }
```

Assuming the input manifest file uses "source-ref" to identify data objects, the worker task template used in the same labeling job as this pre-annotation Lambda must include a Liquid element like the following to ingest `dataObject`:

```liquid
{{ task.input.source-ref | grant_read_access }}
```

If the input manifest file used `source` to identify the data object, the work task template can ingest `dataObject` with the following:
The following pre-annotation Lambda example includes logic to identify the key used in `dataObject`, and to point to that data object using `taskObject` in the Lambda's return statement.

```python
import json
def lambda_handler(event, context):
    # Event received
    print("Received event: " + json.dumps(event, indent=2))

    # Get source if specified
    source = event['dataObject']['source'] if "source" in event['dataObject'] else None

    # Get source-ref if specified
    source_ref = event['dataObject']['source-ref'] if "source-ref" in event['dataObject'] else None

    # if source field present, take that otherwise take source-ref
    task_object = source if source is not None else source_ref

    # Build response object
    output = {
        "taskInput": {
            "taskObject": task_object,
            "humanAnnotationRequired": "true"
        }
    }

    print(output)

    # If neither source nor source-ref specified, mark the annotation failed
    if task_object is None:
        print(" Failed to pre-process {} !".format(event["labelingJobArn"]))
        output["humanAnnotationRequired"] = "false"

    return output
```

Post-annotation Lambda

When all workers have annotated the data object or when `TaskAvailabilityLifetimeInSeconds` has been reached, whichever comes first, Ground Truth sends those annotations to your post-annotation Lambda. This Lambda is generally used for Consolidate Annotations (p. 639).

**Tip**

To see an example of a post-consolidation Lambda function, see `annotation_consolidation_lambda.py` in the aws-sagemaker-ground-truth-recipe GitHub repository.

The following code block contains the post-annotation request schema. Each parameter is described in the following bulleted list.

```json
{
    "version": "2018-10-16",
    "labelingJobArn": <string>,
    "labelCategories": [<string>],
    "labelAttributeName": <string>,
    "roleArn": <string>,
    "payload": {
        "s3Uri": <string>
    }
}
```
• **version** (string): A version number used internally by Ground Truth.
• **labelingJobArn** (string): The Amazon Resource Name, or ARN, of your labeling job. This ARN can be used to reference the labeling job when using Ground Truth API operations such as DescribeLabelingJob.
• **labelCategories** (list of strings): Includes the label categories and other attributes you either specified in the console, or that you include in the label category configuration file.
• **labelAttributeName** (string): Either the name of your labeling job, or the label attribute name you specify when you create the labeling job.
• **roleArn** (string): The Amazon Resource Name (ARN) of the IAM execution role you specify when you create the labeling job.
• **payload** (JSON object): A JSON that includes an `s3Uri` key, which identifies the location of the annotation data for that data object in Amazon S3. The second code block below shows an example of this annotation file.

The following code block contains an example of a post-annotation request. Each parameter in this example request is explained below the code block.

**Example of an post-annotation Lambda request**

```json
{
    "version": "2018-10-16",
    "labelCategories": ["Ex Category1", "Ex Category2", "Ex Category3"],
    "labelAttributeName": "labeling-job-attribute-name",
    "roleArn": "arn:aws:iam::111122223333:role/role-name",
    "payload": {
        "s3Uri": "s3://DOC-EXAMPLE-BUCKET/annotations.json"
    }
}
```

**Note**

If no worker works on the data object and `TaskAvailabilityLifetimeInSeconds` has been reached, the data object is marked as failed and not included as part of post-annotation Lambda invocation.

The following code block contains the payload schema. This is the file that is indicated by the `s3Uri` parameter in the post-annotation Lambda request `payload` JSON object. For example, if the previous code block is the post-annotation Lambda request, the following annotation file is located at `s3://DOC-EXAMPLE-BUCKET/annotations.json`.

Each parameter is described in the following bulleted list.

**Example of an annotation file**

```json
[
    {
        "datasetObjectId": <string>,
        "dataObject": {
            "s3Uri": <string>,
            "content": <string>
        },
        "annotations": [{
            "workerId": <string>,
            "annotationData": {
                "content": <string>
            }
        }]
    }
]
```
• `datasetObjectId` (string): Identifies a unique ID that Ground Truth assigns to each data object you send to the labeling job.

• `dataObject` (JSON object): The data object that was labeled. If the data object is included in the input manifest file and identified using the `source` key (for example, a string), `dataObject` includes a `content` key, which identifies the data object. Otherwise, the location of the data object (for example, a link or S3 URI) is identified with `s3Uri`.

• `annotations` (list of JSON objects): This list contains a single JSON object for each annotation submitted by workers for that `dataObject`. A single JSON object contains a unique `workerId` that can be used to identify the worker that submitted that annotation. The `annotationData` key contains one of the following:
  • `content` (string): Contains the annotation data.
  • `s3Uri` (string): Contains an S3 URI that identifies the location of the annotation data.

The following table contains examples of the content that you may find in payload for different types of annotation.

### Named Entity Recognition Payload

```
[  
  {  
    "datasetObjectId": "1",  
    "dataObject": {  
      "content": "Sift 3 cups of flour into the bowl."
    },  
    "annotations": [  
      {  
        "workerId": "private.us-west-2.ef729f850a3d9d1",  
        "annotationData": {  
          "content": "{"crowd-entity-annotation":{"entities":[{"endOffset":4,\"label\":\"verb\",\"startOffset":0},{\"endOffset\":6,\"label\":\"number\",\"startOffset\":5},{\"endOffset\":20,\"label\":\"object\",\"startOffset\":15},{\"endOffset\":34,\"label\":\"object\",\"startOffset\":30}]}"
        }
      }
    ]
  }
]
```

### Semantic Segmentation Payload

```
[  
  {  
    "datasetObjectId": "2",  
    "dataObject": {  
      "s3Uri": "s3://DOC-EXAMPLE-BUCKET/gt-input-data/images/bird3.jpg"
    },  
    "annotations": [  
      {  
        "workerId": "private.us-west-2.ab1234c5678a919d0",  
        "annotationData": {  
          "content": "{"crowd-semantic-segmentation":{"inputImageProperties":\{"height\":2000,\"width\":3020\},\"labelMappings":{"\"Bird\":\{"\"color\":\"#2ca02c\"\"},\"labeledImage":\{"\"pngImageData\":\"iVBOR\...\"\}"
        }
      }
    ]
  }
]```
Bounding Box Payload

```
[
    {
        "datasetObjectId": "0",
        "dataObject": {
            "s3Uri": "s3://DOC-EXAMPLE-BUCKET/gt-input-data/images/bird1.jpg"
        },
        "annotations": [
            {
                "workerId": "private.us-west-2.ab1234c5678a919d0",
                "annotationData": {
                    "content": "{"boundingBox": [{"height":2052,"label":"Bird","left":583,"top":302,"width":1375}],"inputImageProperties": [{"height":2497,"width":3745}]"
                }
            }
        ]
    }
]
```

Your post-annotation Lambda function may contain logic similar to the following to loop through and access all annotations contained in the request. For a full example, see annotation_consolidation_lambda.py in the aws-sagemaker-ground-truth-recipe GitHub repository. In this GitHub example, you must add your own annotation consolidation logic.

```
for i in range(len(annotations)):
    worker_id = annotations[i]['workerId']
    annotation_content = annotations[i]['annotationData'].get('content')
    annotation_s3_uri = annotations[i]['annotationData'].get('s3Uri')
    annotation = annotation_content if annotation_s3_uri is None else s3_client.get_object_from_s3(annotation_s3_uri)
    annotation_from_single_worker = json.loads(annotation)
    print('{} Received Annotations from worker [{}] is [{}]' .format(log_prefix, worker_id, annotation_from_single_worker))
```

**Tip**
When you run consolidation algorithms on the data, you can use an AWS database service to store results, or you can pass the processed results back to Ground Truth. The data you return to Ground Truth is stored in consolidated annotation manifests in the S3 bucket specified for output during the configuration of the labeling job.

In return, Ground Truth requires a response formatted like the following:

**Example of expected return data**

```
[
    {
        "datasetObjectId": <string>,
        "consolidatedAnnotation": {
            "content": {
                
```
At this point, all the data you're sending to your S3 bucket, other than the datasetObjectId, is in the content object.

When you return annotations in content, this results in an entry in your job's output manifest like the following:

**Example of label format in output manifest**

```json
{
  "source-ref"/"source": "<s3uri or content>",
  "<labelAttributeName>": {
    # ... label content from you
  },
  "<labelAttributeName>-metadata": {
    # This will be added by Ground Truth
    "job_name": "<labelingJobName>",
    "type": "groundTruth/custom",
    "human-annotated": "yes",
    "creation_date": <date> # Timestamp of when received from Post-labeling Lambda
  }
}
```

Because of the potentially complex nature of a custom template and the data it collects, Ground Truth does not offer further processing of the data.

**Required Permissions To Use AWS Lambda With Ground Truth**

You may need to configure some or all the following to create and use AWS Lambda with Ground Truth.

- You need to grant an IAM role or user (collectively, an IAM entity) permission to create the pre-annotation and post-annotation Lambda functions using AWS Lambda, and to choose them when creating the labeling job.
- The IAM execution role specified when the labeling job is configured needs permission to invoke the pre-annotation and post-annotation Lambda functions.
- The post-annotation Lambda functions may need permission to access Amazon S3.

Use the following sections to learn how to create the IAM entities and grant permissions described above.

**Topics**
- Grant Permission to Create and Select an AWS Lambda Function (p. 524)
Grant Permission to Create and Select an AWS Lambda Function

If you do not require granular permissions to develop pre-annotation and post-annotation Lambda functions, you can attach the AWS managed policy AWSLambda_FullAccess to an IAM user or role. This policy grants broad permissions to use all Lambda features, as well as permission to perform actions in other AWS services with which Lambda interacts.

To create a more granular policy for security-sensitive use cases, refer to the documentation Identity-based IAM policies for Lambda in the to AWS Lambda Developer Guide to learn how to create an IAM policy that fits your use case.

Policies to Use the Lambda Console

If you want to grant an IAM entity permission to use the Lambda console, see Using the Lambda console in the AWS Lambda Developer Guide.

Additionally, if you want the user to be able to access and deploy the Ground Truth starter pre-annotation and post-annotation functions using the AWS Serverless Application Repository in the Lambda console, you must specify the `<aws-region>` where you want to deploy the functions (this should be the same AWS Region used to create the labeling job), and add the following policy to the IAM role.

```
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "VisualEditor0",
            "Effect": "Allow",
            "Action": [
                "serverlessrepo:ListApplicationVersions",
                "serverlessrepo:GetApplication",
                "serverlessrepo:CreateCloudFormationTemplate"
            ],
        },
        {
            "Sid": "VisualEditor1",
            "Effect": "Allow",
            "Action": "serverlessrepo:SearchApplications",
            "Resource": "*"
        }
    ]
}
```

Policies to See Lambda Functions in the Ground Truth Console

To grant an IAM entity permission to view Lambda functions in the Ground Truth console when the user is creating a custom labeling job, the entity must have the permissions described in Grant IAM Permission to Use the Amazon SageMaker Ground Truth Console (p. 651), including the permissions described in the section Custom Labeling Workflow Permissions (p. 654).

Grant IAM Execution Role Permission to Invoke AWS Lambda Functions

If you add the IAM managed policy AmazonSageMakerGroundTruthExecution to the IAM execution role used to create the labeling job, this role has permission to list and invoke Lambda functions with one
of the following strings in the function name: GtRecipe, SageMaker, Sagemaker, sagemaker, or LabelingFunction.

If the pre-annotation or post-annotation Lambda function names do not include one of the terms in the preceding paragraph, or if you require more granular permission than those in the AmazonSageMakerGroundTruthExecution managed policy, you can add a policy similar to the following to give the execution role permission to invoke pre-annotation and post-annotation functions.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": "lambda:InvokeFunction",
            "Resource": [
            ]
        }
    ]
}
```

Grant Post-Annotation Lambda Permissions to Access Annotation

As described in Post-annotation Lambda (p. 519), the post-annotation Lambda request includes the location of the annotation data in Amazon S3. This location is identified by the s3Uri string in the payload object. To process the annotations as they come in, even for a simple pass through function, you need to assign the necessary permissions to the post-annotation Lambda execution role to read files from the Amazon S3.

There are many ways that you can configure your Lambda to access annotation data in Amazon S3. Two common ways are:

- Allow the Lambda execution role to assume the SageMaker execution role identified in roleArn in the post-annotation Lambda request. This SageMaker execution role is the one used to create the labeling job, and has access to the Amazon S3 output bucket where the annotation data is stored.
- Grant the Lambda execution role permission to access the Amazon S3 output bucket directly.

Use the following sections to learn how to configure these options.

Grant Lambda Permission to Assume SageMaker Execution Role

To allow a Lambda function to assume a SageMaker execution role, you must attach a policy to the Lambda function's execution role, and modify the trust relationship of the SageMaker execution role to allow Lambda to assume it.

1. Attach the following IAM policy to your Lambda function's execution role to assume the SageMaker execution role identified in Resource. Replace 222222222222 with an AWS account ID. Replace sm-execution-role with the name of the assumed role.

```json
{
    "Version": "2012-10-17",
    "Statement": {
        "Effect": "Allow",
        "Action": "sts:AssumeRole",
```
2. Modify the trust policy of the SageMaker execution role to include the following Statement. Replace `222222222222` with an AWS account ID. Replace `my-lambda-execution-role` with the name of the assumed role.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Principal": {
        "AWS": "arn:aws:iam::222222222222:role/my-lambda-execution-role"
      },
      "Action": "sts:AssumeRole"
    }
  ]
}
```

**Grant Lambda Execution Role Permission to Access S3**

You can add a policy similar to the following to the post-annotation Lambda function execution role to give it S3 read permissions. Replace `DOC-EXAMPLE-BUCKET` with the name of the output bucket you specify when you create a labeling job.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["s3:GetObject"],
      "Resource": "arn:aws:s3:::DOC-EXAMPLE-BUCKET/*"
    }
  ]
}
```

To add S3 read permissions to a Lambda execution role in the Lambda console, use the following procedure.

**Add S3 read permissions to post-annotation Lambda:**

1. Open the Functions page in the Lambda console.
2. Choose the name of the post-annotation function.
3. Choose Configuration and then choose Permissions.
4. Select the Role name and the summary page for that role opens in the IAM console in a new tab.
5. Select Attach policies.
6. Do one of the following:
   - Search for and select AmazonS3ReadOnlyAccess to give the function permission to read all buckets and objects in the account.
   - If you require more granular permissions, select Create policy and use the policy example in the preceding section to create a policy. Note that you must navigate back to the execution role summary page after you create the policy.
7. If you used the AmazonS3ReadOnlyAccess managed policy, select **Attach policy**.

If you created a new policy, navigate back to the Lambda execution role summary page and attach the policy you just created.

**Create Lambda Functions for a Custom Labeling Workflow**

You can create a Lambda function using the Lambda console, the AWS CLI, or an AWS SDK in a supported programming language of your choice. Use the AWS Lambda Developer Guide to learn more about each of these options:

- To learn how to create a Lambda function using the console, see [Create a Lambda function with the console](#).
- To learn how to create a Lambda function using the AWS CLI, see [Using AWS Lambda with the AWS Command Line Interface](#).
- Select the relevant section in the table of contents to learn more about working with Lambda in the language of your choice. For example, select [Working with Python](#) to learn more about using Lambda with the AWS SDK for Python (Boto3).

Ground Truth provides pre-annotation and post-annotation templates through an AWS Serverless Application Repository (SAR) **recipe**. Use the following procedure to select the Ground Truth recipe in the Lambda console.

**Use the Ground Truth SAR recipe to create pre-annotation and post-annotation Lambda functions:**

1. Open the **Functions** page on the Lambda console.
2. Select **Create function**.
3. Select **Browse serverless app repository**.
4. In the search text box, enter `aws-sagemaker-ground-truth-recipe` and select that app.
5. Select **Deploy**. The app may take a couple of minutes to deploy.

Once the app deploys, two functions appear in the **Functions** section of the Lambda console: `serverlessrepo-aws-sagemaker-GtRecipePreHumanTaskFunc-<id>` and `serverlessrepo-aws-sagemaker-GtRecipeAnnotationConsol-<id>`.

6. Select one of these functions and add your custom logic in the **Code** section.
7. When you are finished making changes, select **Deploy** to deploy them.

**Test Pre-Annotation and Post-Annotation Lambda Functions**

You can test your pre-annotation and post annotation Lambda functions in the Lambda console. If you are a new user of Lambda, you can learn how to test, or **invoke**, your Lambda functions in the console using the **Create a Lambda function** tutorial with the console in the AWS Lambda Developer Guide.

You can use the sections on this page to learn how to test the Ground Truth pre-annotation and post-annotation templates provided through an AWS Serverless Application Repository (SAR).

**Topics**

- Prerequisites (p. 528)
- Test the Pre-annotation Lambda Function (p. 528)
- Test the Post-Annotation Lambda Function (p. 529)
Prerequisites

You must do the following to use the tests described on this page.

- You need access to the Lambda console, and you need permission to create and invoke Lambda functions. To learn how to set up these permissions, see Grant Permission to Create and Select an AWS Lambda Function (p. 524).
- If you have not deployed the Ground Truth SAR recipe, use the procedure in Create Lambda Functions for a Custom Labeling Workflow (p. 527) to do so.
- To test the post-annotation Lambda function, you must have a data file in Amazon S3 with sample annotation data. For a simple test, you can copy and paste the following code into a file and save it as sample-annotations.json and upload this file to Amazon S3. Note the S3 URI of this file—you need this information to configure the post-annotation Lambda test.

```json
[{
"datasetObjectId": "0",
"dataObject": {
"content": "To train a machine learning model, you need a large, high-quality, labeled dataset. Ground Truth helps you build high-quality training datasets for your machine learning models."},
"annotations": [
{"workerId": "private.us-west-2.0123456789", "annotationData": {
"content": "{\"crowd-entity-annotation\": {\"entities\": [\n{"endOffset": 8, \"label\": \"verb\", \"startOffset": 3}, {\"endOffset": 27, \"label\": \"adjective\", \"startOffset": 11}, {\"endOffset": 33, \"label\": \"object\", \"startOffset": 28}, {\"endOffset": 51, \"label\": \"adjective\", \"startOffset": 46}, {\"endOffset": 65, \"label\": \"adjective\", \"startOffset": 53}, {\"endOffset": 74, \"label\": \"adjective\", \"startOffset": 69}, {\"endOffset": 82, \"label\": \"adjective\", \"startOffset": 75}, {\"endOffset": 102, \"label\": \"verb\", \"startOffset": 97}, {\"endOffset": 112, \"label\": \"verb\", \"startOffset": 107}, {\"endOffset": 125, \"label\": \"adjective\", \"startOffset": 113}, {\"endOffset": 134, \"label\": \"adjective\", \"startOffset": 126}, {\"endOffset": 143, \"label\": \"object\", \"startOffset": 135}, {\"endOffset": 169, \"label\": \"adjective\", \"startOffset": 153}, {\"endOffset": 176, \"label\": \"object\", \"startOffset": 170}\n\n}]}
],
"datasetObjectId": "1",
"dataObject": {
"content": "Sift 3 cups of flour into the bowl.\n"},
"annotations": [
{"workerId": "private.us-west-2.0123456789", "annotationData": {
"content": "{\"crowd-entity-annotation\": {\"entities\": [\n{"endOffset": 6, \"label\": \"number\", \"startOffset": 5}, {\"endOffset": 20, \"label\": \"object\", \"startOffset": 15}, {\"endOffset": 34, \"label\": \"object\", \"startOffset": 30}\n\n}]}
],
"datasetObjectId": "2",
"dataObject": {
"content": "Jen purchased 10 shares of the stock on January 1st, 2020.\n"},
"annotations": [
{"workerId": "private.us-west-2.0123456789", "annotationData": {
"content": "{\"crowd-entity-annotation\": {\"entities\": [\n{"endOffset": 13, \"label\": \"person\", \"startOffset": 0}, {\"endOffset": 14, \"label\": \"verb\", \"startOffset": 13}, {\"endOffset": 16, \"label\": \"number\", \"startOffset": 14}, {\"endOffset": 58, \"label\": \"date\", \"startOffset": 48}\n\n}]}
],
"datasetObjectId": "3",
"dataObject": {
"content": "The narrative was interesting, however the character development was weak.\n"},
"annotations": [
{"workerId": "private.us-west-2.0123456789", "annotationData": {
"content": "{\"crowd-entity-annotation\": {\"entities\": [\n{"endOffset": 29, \"label\": \"adjective\", \"startOffset": 18}, {\"endOffset": 73, \"label\": \"adjective\", \"startOffset": 69}\n\n}]}
]
]
}

- You must use the directions in Grant Post-Annotation Lambda Permissions to Access Annotation (p. 525) to give your post-annotation Lambda function’s execution role permission to assume the SageMaker execution role you use to create the labeling job. The post-annotation Lambda function uses the SageMaker execution role to access the annotation data file, sample-annotations.json, in S3.

Test the Pre-annotation Lambda Function

Use the following procedure to test the pre-annotation Lambda function created when you deployed the Ground Truth AWS Serverless Application Repository (SAR) recipe.

Test the Ground Truth SAR recipe pre-annotation Lambda function

1. Open the Functions page in the Lambda console.
2. Select the pre-annotation function that was deployed from the Ground Truth SAR recipe. The name of this function is similar to serverlessrepo-aws-sagemaker-GtRecipePreHumanTaskFunc-<id>.

3. In the Code source section, select the arrow next to Test.

4. Select Configure test event.

5. Keep the Create new test event option selected.


7. Give your test an Event name.

8. Select Create.

9. Select the arrow next to Test again and you should see that the test you created is selected, which is indicated with a dot by the event name. If it is not selected, select it.

10. Select Test to run the test.

After you run the test, you can see the Execution results. In the Function logs, you should see a response similar to the following:

```
START RequestId: cd117d38-8365-4e1a-bffb-0dcd631a878f Version: $LATEST
Received event: {
  "version": "2018-10-16",
  "dataObject": {
    "source-ref": "s3://sagemakerexample/object_to_annotate.jpg"
  }
}
{'taskInput': {'taskObject': 's3://sagemakerexample/object_to_annotate.jpg'}, 'isHumanAnnotationRequired': 'true'}
END RequestId: cd117d38-8365-4e1a-bffb-0dcd631a878f
REPORT RequestId: cd117d38-8365-4e1a-bffb-0dcd631a878f Duration: 0.42 ms Billed Duration: 1 ms Memory Size: 128 MB Max Memory Used: 43 MB
```

In this response, we can see the Lambda function's output matches the required pre-annotation response syntax:

```
{'taskInput': {'taskObject': 's3://sagemakerexample/object_to_annotate.jpg'}, 'isHumanAnnotationRequired': 'true'}
```

Test the Post-Annotation Lambda Function

Use the following procedure to test the post-annotation Lambda function created when you deployed the Ground Truth AWS Serverless Application Repository (SAR) recipe.

**Test the Ground Truth SAR recipe post-annotation Lambda**

1. Open the Functions page in the Lambda console.

2. Select the post-annotation function that was deployed from the Ground Truth SAR recipe. The name of this function is similar to serverlessrepo-aws-sagemaker-GtRecipeAnnotationConsol-<id>.

3. In the Code source section, select the arrow next to Test.

4. Select Configure test event.

5. Keep the Create new test event option selected.


7. Give your test an Event name.

8. Modify the template code provided as follows:
• Replace the Amazon Resource Name (ARN) in `roleArn` with the ARN of the SageMaker execution role you used to create the labeling job.
• Replace the S3 URI in `s3Uri` with the URI of the `sample-annotations.json` file you added to Amazon S3.

After you make these modifications, your test should look similar to the following:

```json
{
   "version": "2018-10-16",
   "labelAttributeName": "example-attribute",
   "roleArn": "arn:aws:iam::222222222222:role/sm-execution-role",
   "payload": {
      "s3Uri": "s3://your-bucket/sample-annotations.json"
   }
}
```

9. Select **Create**.
10. Select the arrow next to **Test** again and you should see that the test you created is selected, which is indicated with a dot by the event name. If it is not selected, select it.
11. Select the **Test** to run the test.

After you run the test, you should see a **-- Consolidated Output --** section in the **Function Logs**, which contains a list of all annotations included in `sample-annotations.json`.

**Demo Template: Annotation of Images with crowd-bounding-box**

When you chose to use a custom template as your task type in the Amazon SageMaker Ground Truth console, you reach the **Custom labeling task panel**. There you can choose from multiple base templates. The templates represent some of the most common tasks and provide a sample to work from as you create your customized labeling task's template. If you are not using the console, or as an additional recourse, see **Amazon SageMaker Ground Truth Sample Task UIs** for a repository of demo templates for a variety of labeling job task types.

This demonstration works with the **BoundingBox** template. The demonstration also works with the AWS Lambda functions needed for processing your data before and after the task. In the Github repository above, to find templates that work with AWS Lambda functions, look for `{{ task.input.<property name> }}` in the template.

**Topics**

- Starter Bounding Box custom template (p. 530)
- Your own Bounding Box custom template (p. 531)
- Your manifest file (p. 532)
- Your pre-annotation Lambda function (p. 533)
- Your post-annotation Lambda function (p. 533)
- The output of your labeling job (p. 534)

**Starter Bounding Box custom template**

This is the starter bounding box template that is provided.
Your own Bounding Box custom template

As an example, assume you have a large collection of animal photos in which you know the kind of animal in an image from a prior image-classification job. Now you want to have a bounding box drawn around it.

In the starter sample, there are three variables: taskObject, header, and labels.

Each of these would be represented in different parts of the bounding box.

- **taskObject** is an HTTP(S) URL or S3 URI for the photo to be annotated. The added | grant_read_access is a filter that will convert an S3 URI to an HTTPS URL with short-lived access to that resource. If you're using an HTTP(S) URL, it's not needed.
- **header** is the text above the photo to be labeled, something like "Draw a box around the bird in the photo."
• labels is an array, represented as ['item1', 'item2', ...]. These are labels that can be assigned by the worker to the different boxes they draw. You can have one or many.

Each of the variable names come from the JSON object in the response from your pre-annotation Lambda. The names above are merely suggested, Use whatever variable names make sense to you and will promote code readability among your team.

Only use variables when necessary
If a field will not change, you can remove that variable from the template and replace it with that text, otherwise you have to repeat that text as a value in each object in your manifest or code it into your pre-annotation Lambda function.

Example: Final Customized Bounding Box Template
To keep things simple, this template will have one variable, one label, and very basic instructions. Assuming your manifest has an "animal" property in each data object, that value can be re-used in two parts of the template.

Note the re-use of {{ task.input.animal }} throughout the template. If your manifest had all of the animal names beginning with a capital letter, you could use {{ task.input.animal | downcase }}, incorporating one of Liquid's built-in filters in sentences where it needed to be presented lowercase.

Your manifest file
Your manifest file should provide the variable values you're using in your template. You can do some transformation of your manifest data in your pre-annotation Lambda, but if you don't need to, you maintain a lower risk of errors and your Lambda will run faster. Here's a sample manifest file for the template.

["source-ref": "<S3 image URI>", "animal": "horse"}
{"source-ref": "<S3 image URI>", "animal": "bird"}
{"source-ref": "<S3 image URI>", "animal": "dog"}
{"source-ref": "<S3 image URI>", "animal": "cat"}
Your pre-annotation Lambda function

As part of the job set-up, provide the ARN of an AWS Lambda function that can be called to process your manifest entries and pass them to the template engine.

**Naming your Lambda function**

The best practice in naming your function is to use one of the following four strings as part of the function name: SageMaker, Sagemaker, sagemaker, or LabelingFunction. This applies to both your pre-annotation and post-annotation functions.

When you're using the console, if you have AWS Lambda functions that are owned by your account, a drop-down list of functions meeting the naming requirements will be provided to choose one.

In this very basic example, you're just passing through the information from the manifest without doing any additional processing on it. This sample pre-annotation function is written for Python 3.7.

```python
import json

def lambda_handler(event, context):
    return {
        "taskInput": event['dataObject']
    }
```

The JSON object from your manifest will be provided as a child of the `event` object. The properties inside the `taskInput` object will be available as variables to your template, so simply setting the value of `taskInput` to `event['dataObject']` will pass all the values from your manifest object to your template without having to copy them individually. If you wish to send more values to the template, you can add them to the `taskInput` object.

Your post-annotation Lambda function

As part of the job set-up, provide the ARN of an AWS Lambda function that can be called to process the form data when a worker completes a task. This can be as simple or complex as you want. If you want to do answer consolidation and scoring as it comes in, you can apply the scoring and/or consolidation algorithms of your choice. If you want to store the raw data for offline processing, that is an option.

**Provide permissions to your post-annotation Lambda**

The annotation data will be in a file designated by the `s3Uri` string in the `payload` object. To process the annotations as they come in, even for a simple pass through function, you need to assign S3Readonly access to your Lambda so it can read the annotation files.

In the Console page for creating your Lambda, scroll to the **Execution role** panel. Select **Create a new role from one or more templates**. Give the role a name. From the **Policy templates** drop-down, choose **Amazon S3 object read-only permissions**. Save the Lambda and the role will be saved and selected.

The following sample is in Python 2.7.

```python
import json
import boto3
from urlparse import urlparse

def lambda_handler(event, context):
    consolidated_labels = []

    parsed_url = urlparse(event['payload']['s3Uri']);
    s3 = boto3.client('s3')
    textFile = s3.get_object(Bucket = parsed_url.netloc, Key = parsed_url.path[1:])
    filecont = textFile['Body'].read()
    annotations = json.loads(filecont);

    for dataset in annotations:
        for annotation in dataset['annotations']:
```
The post-annotation Lambda will often receive batches of task results in the event object. That batch will be the payload object the Lambda should iterate through. What you send back will be an object meeting the API contract (p. 516).

The output of your labeling job

You'll find the output of the job in a folder named after your labeling job in the target S3 bucket you specified. It will be in a subfolder named manifests.

For a bounding box task, the output you find in the output manifest will look a bit like the demo below. The example has been cleaned up for printing. The actual output will be a single line per record.

Example : JSON in your output manifest

```json
{
"source-ref":"<URL>",
"<label attribute name>":
{
"workerId":"<URL>",
"imageSource":"<image URL>",
"boxesInfo":{"boundingBox":[["height":878, "label":"bird ", "left":208, "top":6, "width":809]},"inputImageProperties":{"height":924, "width":1280}}],
"<label attribute name>-metadata":
{
"type":"groundTruth/custom",
"job_name":"<Labeling job name>",
"human-annotated":"yes"
},
"animal" : "bird"
}
```

Note how the additional animal attribute from your original manifest is passed to the output manifest on the same level as the source-ref and labeling data. Any properties from your input manifest, whether they were used in your template or not, will be passed to the output manifest.

Demo Template: Labeling Intents with crowd-classifier

If you choose a custom template, you'll reach the Custom labeling task panel. There you can select from multiple starter templates that represent some of the more common tasks. The templates provide a starting point to work from in building your customized labeling task's template.

In this demonstration, you work with the Intent Detection template, which uses the crowd-classifier (p. 734) element, and the AWS Lambda functions needed for processing your data before and after the task.
Starter Intent Detection custom template

This is the intent detection template that is provided as a starting point.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-classifier
    name="intent"
    categories="{{ task.input.labels | to_json | escape }}"
    header="Pick the most relevant intention expressed by the below text"
  >
    <classification-target>
      {{ task.input.utterance }}
    </classification-target>
  
    <full-instructions header="Intent Detection Instructions">
      <p>Select the most relevant intention expressed by the text.</p>
      <div>
        <p><strong>Example: </strong>I would like to return a pair of shoes</p>
        <p><strong>Intent: </strong>Return</p>
      </div>
    </full-instructions>

    <short-instructions>
      Pick the most relevant intention expressed by the text
    </short-instructions>

</crowd-classifier>
</crowd-form>
```

The custom templates use the **Liquid template language**, and each of the items between double curly braces is a variable. The pre-annotation AWS Lambda function should provide an object named `taskInput` and that object's properties can be accessed as `{{ task.input.<property name> }}` in your template.

Your Intent Detection custom template

In the starter template, there are two variables: the `task.input.labels` property in the `crowd-classifier` element opening tag and the `task.input.utterance` in the `classification-target` region's content.

Unless you need to offer different sets of labels with different utterances, avoiding a variable and just using text will save processing time and creates less possibility of error. The template used in this demonstration will remove that variable, but variables and filters like `to_json` are explained in more detail in the **crowd-bounding-box demonstration** article.

Styling Your Elements

Two parts of these custom elements that sometimes get overlooked are the `<full-instructions>` and `<short-instructions>` regions. Good instructions generate good results.
In the elements that include these regions, the `<short-instructions>` appear automatically in the "Instructions" pane on the left of the worker's screen. The `<full-instructions>` are linked from the "View full instructions" link near the top of that pane. Clicking the link opens a modal pane with more detailed instructions.

You can not only use HTML, CSS, and JavaScript in these sections, you are encouraged to if you believe you can provide a strong set of instructions and examples that will help workers complete your tasks with better speed and accuracy.

**Example Try out a sample with JSFiddle**

![JSFiddle](image.png)

Try out an example `<crowd-classifier>` task. The example is rendered by JSFiddle, therefore all the template variables are replaced with hard-coded values. Click the "View full instructions" link to see a set of examples with extended CSS styling. You can fork the project to experiment with your own changes to the CSS, adding sample images, or adding extended JavaScript functionality.

**Example : Final Customized Intent Detection Template**

This uses the example `<crowd-classifier>` task, but with a variable for the `<classification-target>`. If you are trying to keep a consistent CSS design among a series of different labeling jobs, you can include an external stylesheet using a `<link rel...>` element the same way you'd do in any other HTML document.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-classifier
    name="intent"
    categories="['buy', 'eat', 'watch', 'browse', 'leave']"
    header="Pick the most relevant intent expressed by the text below"
  >
  <classification-target>
```
In the statements and questions provided in this exercise, what category of action is the speaker interested in doing?

<table>
<thead>
<tr>
<th>Example Utterance</th>
<th>Good Choice</th>
</tr>
</thead>
<tbody>
<tr>
<td>When is the Seahawks game on?</td>
<td>watch, browse</td>
</tr>
<tr>
<td>When is the Seahawks game on?</td>
<td>buy, eat, watch</td>
</tr>
</tbody>
</table>

What is the speaker expressing they would like to do next?
Example: Your manifest file

If you are preparing your manifest file manually for a text-classification task like this, have your data formatted in the following manner.

```json
["source": "Roses are red"]
["source": "Violets are Blue"]
["source": "Ground Truth is the best"]
["source": "And so are you"]
```

This differs from the manifest file used for the "Demo Template: Annotation of Images with crowd-bounding-box (p. 530)" demonstration in that source-ref was used as the property name instead of source. The use of source-ref designates S3 URIs for images or other files that must be converted to HTTP. Otherwise, source should be used like it is with the text strings above.
Your pre-annotation Lambda function

As part of the job set-up, provide the ARN of an AWS Lambda that can be called to process your manifest entries and pass them to the template engine.

This Lambda function is required to have one of the following four strings as part of the function name: SageMaker, Sagemaker, sagemaker, or LabelingFunction.

This applies to both your pre-annotation and post-annotation Lambdas.

When you're using the console, if you have Lambdas that are owned by your account, a drop-down list of functions meeting the naming requirements will be provided to choose one.

In this very basic sample, where you have only one variable, it's primarily a pass-through function. Here's a sample pre-labeling Lambda using Python 3.7.

```python
import json

def lambda_handler(event, context):
    return {
        "taskInput": event['dataObject']
    }
```

The dataObject property of the event contains the properties from a data object in your manifest.

In this demonstration, which is a simple pass through, you just pass that straight through as the taskInput value. If you add properties with those values to the event['dataObject'] object, they will be available to your HTML template as Liquid variables with the format `{{ task.input.<property name> }}`.

Your post-annotation Lambda function

As part of the job set up, provide the ARN of an Lambda function that can be called to process the form data when a worker completes a task. This can be as simple or complex as you want. If you want to do answer-consolidation and scoring as data comes in, you can apply the scoring or consolidation algorithms of your choice. If you want to store the raw data for offline processing, that is an option.

**Set permissions for your post-annotation Lambda function**

The annotation data will be in a file designated by the s3Uri string in the payload object. To process the annotations as they come in, even for a simple pass through function, you need to assign S3ReadOnly access to your Lambda so it can read the annotation files.

In the Console page for creating your Lambda, scroll to the Execution role panel. Select Create a new role from one or more templates. Give the role a name. From the Policy templates drop-down, choose Amazon S3 object read-only permissions. Save the Lambda and the role will be saved and selected.

The following sample is for Python 3.7.

```python
import json
import boto3
from urllib.parse import urlparse

def lambda_handler(event, context):
    consolidated_labels = []

    parsed_url = urlparse(event['payload']['s3Uri']);
    s3 = boto3.client('s3')
    textFile = s3.get_object(Bucket = parsed_url.netloc, Key = parsed_url.path[1:])
    filecont = textFile['Body'].read()
    annotations = json.loads(filecont);

    for dataset in annotations:
        consolidated_labels.append(dataset)
```

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for annotation in dataset['annotations']:
    new_annotation = json.loads(annotation['annotationData']['content'])
    label = {
        'datasetObjectId': dataset['datasetObjectId'],
        'consolidatedAnnotation': {
            'content': {
                event['labelAttributeName']: {
                    'workerId': annotation['workerId'],
                    'result': new_annotation,
                    'labeledContent': dataset['dataObject']
                }
            }
        }
    }
    consolidated_labels.append(label)
return consolidated_labels

Your labeling job output

The post-annotation Lambda will often receive batches of task results in the event object. That batch will be the payload object the Lambda should iterate through.

You'll find the output of the job in a folder named after your labeling job in the target S3 bucket you specified. It will be in a subfolder named manifests.

For an intent detection task, the output in the output manifest will look a bit like the demo below. The example has been cleaned up and spaced out to be easier for humans to read. The actual output will be more compressed for machine reading.

Example: JSON in your output manifest

```json
[
    {
        "datasetObjectId": "<Number representing item's place in the manifest>",
        "consolidatedAnnotation": {
            "content": {
                "<name of labeling job>": {
                    "workerId": "private.us-east-1.XXXXXXXXXXXXXXXXXXX",
                    "result": {
                        "intent": {
                            "label": "<label chosen by worker>
                        
                    },
                    "labeledContent": {
                        "content": "<text content that was labeled>
                    }
                }
            }
        }
    },
    {
        "datasetObjectId": "<Number representing item's place in the manifest>",
        "consolidatedAnnotation": {
            "content": {
                "<name of labeling job>": {
                    "workerId": "private.us-east-1.XXXXXXXXXXXXXXXXXXX",
                    "result": {
                        "intent": {
                            "label": "<label chosen by worker>
                        
                    },
                    "labeledContent": {
                        "content": "<text content that was labeled>
                    }
                }
            }
        }
    }
]```
This should help you create and use your own custom template.

**Custom Workflows via the API**

When you have created your custom UI template (Step 2) and processing Lambda functions (Step 3), you should place the template in an Amazon S3 bucket with a file name format of: `<FileName>.liquid.html`

Use the `CreateLabelingJob` action to configure your task. You'll use the location of a custom template (Step 2: Creating your custom worker task template (p. 510)) stored in a `<filename>.liquid.html` file on S3 as the value for the `UiTemplateS3Uri` field in the `UiConfig` object within the `HumanTaskConfig` object.

For the AWS Lambda tasks described in Step 3: Processing with AWS Lambda (p. 516), the post-annotation task's ARN will be used as the value for the `AnnotationConsolidationLambdaArn` field, and the pre-annotation task will be used as the value for the `PreHumanTaskLambdaArn`.

**Create a Labeling Job**

You can create a labeling job in the Amazon SageMaker console and by using an AWS SDK in your preferred language to run `CreateLabelingJob`. After a labeling job has been created, you can track worker metrics (for private workforces) and your labeling job status using `CloudWatch`.

Before you create a labeling job it is recommended that you review the following pages, as applicable:

- You can specify our input data using an automatic data setup in the console, or an input manifest file in either the console or when using `CreateLabelingJob` API. For automated data setup, see Automated Data Setup (p. 574). To learn how to create an input manifest file, see Use an Input Manifest File (p. 573).
- Review labeling job input data quotas: Input Data Quotas (p. 580).

After you have chosen your task type, use the topics on this page to learn how to create a labeling job.

If you are a new Ground Truth user, we recommend that you start by walking through the demo in Getting started (p. 371).

**Important**

Ground Truth requires all S3 buckets that contain labeling job input image data to have a CORS policy attached. To learn more, see CORS Permission Requirement (p. 649).
Topics

- Built-in Task Types (p. 542)
- Creating Instruction Pages (p. 542)
- Create a Labeling Job (Console) (p. 544)
- Create a Labeling Job (API) (p. 547)
- Create a Streaming Labeling Job (p. 552)
- Create a Labeling Category Configuration File with Label Category and Frame Attributes (p. 557)

Built-in Task Types

Amazon SageMaker Ground Truth has several built-in task types. Ground Truth provides a worker task template for built-in task types. Additionally, some built-in task types support Automate Data Labeling (p. 640). The following topics describe each built-in task type and demo the worker task templates that are provided by Ground Truth in the console. To learn how to create a labeling job in the console using one of these task types, select the task type page.

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<tr>
<th>Label Images</th>
<th>Label Text</th>
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<th>Label 3D Point Clouds</th>
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<tr>
<td>• Verify and Adjust Labels (p. 502)</td>
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</tr>
</tbody>
</table>

Note

Each of the video frame and 3D point cloud task types has an adjustment task type that you use to verify and adjust labels from a previous labeling job. Select a video frame or 3D point cloud task type page above to learn how to adjust labels created using that task type.

Creating Instruction Pages

Create custom instructions for labeling jobs to improve your worker’s accuracy in completing their task. You can modify the default instructions that are provided in the console or you can create your own. The instructions are shown to the worker on the page where they complete their labeling task.

There are two kinds of instructions:

- Short instructions—instructions that are shown on the same webpage where the worker completes their task. These instructions should provide an easy reference to show the worker the correct way to label an object.
- Full instructions—instructions that are shown on a dialog box that overlays the page where the worker completes their task. We recommend that you provide detailed instructions for completing the task with multiple examples showing edge cases and other difficult situations for labeling objects.
Create instructions in the console when you are creating your labeling job. Start with the existing instructions for the task and use the editor to modify them to suit your labeling job.

**Note**

Once you create your labeling job, it will automatically start and you will not be able to modify your worker instructions. If you need to change your worker instructions, stop the labeling job that you created, clone it, and modify your worker instructions before creating a new job. You can clone a labeling job in the console by selecting the labeling job and then selecting **Clone** in the **Actions** menu.

To clone a labeling job using the Amazon SageMaker API or your preferred Amazon SageMaker SDK, make a new request to the `CreateLabelingJob` operation with the same specifications as your original job after modifying your worker instructions.

### Short Instructions

Short instructions appear on the same web page that workers use to label your data object. For example, the following is the editing page for a bounding box task. The short instructions panel is on the left.

Keep in mind that a worker will only spend seconds looking at the short instructions. Workers must be able to scan and understand your information quickly. In all cases it should take less time to understand the instructions than it takes to complete the task. Keep these points in mind:

- Your instructions should be clear and simple.
• Pictures are better than words. Create a simple illustration of your task that your workers can
immediately understand.
• If you must use words, use short, concise examples.
• Your short instructions are more important than your full instructions.

The Amazon SageMaker Ground Truth console provides an editor so that you can create your short
instructions. Replace the placeholder text and images with instructions for your task. Preview the
worker’s task page by choosing Preview. The preview will open in a new window, be sure to turn off pop-
up blocking so that the window will show.

Full Instructions

You can provide additional instructions for your workers in a dialog box that overlays the page where
workers label your data objects. Use full instructions to explain more complex tasks and to show workers
the proper way to label edge cases or other difficult objects.

You can create full instructions using an editor in the Ground Truth console. As with quick instructions,
keep the following in mind:

• Workers will want detailed instruction the first few times that the complete your task. Any information
  that they must have should be in the quick instructions.
• Pictures are more important than words.
• Text should be concise.
• Full instructions should supplement the short instructions. Don’t repeat information that appears in
  the short instructions.

The Ground Truth console provides an editor so that you can create your full instructions. Replace the
placeholder text and images with instructions for your task. Preview the full instruction page by choosing
Preview. The preview will open in a new window, be sure to turn off pop-up blocking so that the window
will show.

Add example images to your instructions

Images provide useful examples for your workers. To add a publicly accessible image to your instructions:

• Place the cursor where the image should go in the instructions editor.
• Click the image icon in the editor toolbar.
• Enter the URL of your image.

If your instruction image in Amazon S3 is not publicly accessible:

• As the image URL, enter: {{ 'https://s3.amazonaws.com/your-bucket-name/image-file-
  name' | grant_read_access }}.
• This renders the image URL with a short-lived, one-time access code appended so the worker’s browser
can display it. A broken image icon is displayed in the instructions editor, but previewing the tool
displays the image in the rendered preview.

Create a Labeling Job (Console)

You can use the Amazon SageMaker console to create a labeling job for all of the Ground Truth built-in
task types and custom labeling workflows. For built-in task types, we recommend that you use this page
alongside the page for your task type. Each task type page includes specific details on creating a labeling
job using that task type.
You need to provide the following to create a labeling job in the SageMaker console:

- An input manifest file in Amazon S3. You can place your input dataset in Amazon S3 and automatically generate a manifest file using the Ground Truth console (not supported for 3D point cloud labeling jobs).

  Alternatively, you can manually create an input manifest file. To learn how, see Input Data (p. 572).
- An Amazon S3 bucket to store your output data.
- An IAM role with permission to access your resources in Amazon S3 and with a SageMaker execution policy attached. For a general solution, you can attach the managed policy, AmazonSageMakerFullAccess, to an IAM role and include sagemaker in your bucket name.

  For more granular policies, see the section called “IAM Permissions” (p. 650).
- 3D point cloud task types have additional security considerations. Learn more.
- A work team. You create a work team from a workforce made up of Amazon Mechanical Turk workers, vendors, or your own private workers. To learn more, see Create and Manage Workforces (p. 694).

  You cannot use the Mechanical Turk workforce for 3D point cloud or video frame labeling jobs.
- If you are using a custom labeling workflow, you must save a worker task template in Amazon S3 and provide an Amazon S3 URI for that template. For more information, see Step 2: Creating your custom worker task template (p. 510).
- (Optional) An AWS KMS key ARN if you want SageMaker to encrypt the output of your labeling job using your own AWS KMS encryption key instead of the default Amazon S3 service key.
- (Optional) Existing labels for the dataset you use for your labeling job. Use this option if you want workers to adjust, or approve and reject labels.
- If you want to create an adjustment or verification labeling job, you must have an output manifest file in Amazon S3 that contains the labels you want adjusted or verified. This option is only supported for bounding box and semantic segmentation image labeling jobs and 3D point cloud and video frame labeling jobs. It is recommended that you use the instructions on Verify and Adjust Labels (p. 502) to create a verification or adjustment labeling job.

  **Important**
  Your work team, input manifest file, output bucket, and other resources in Amazon S3 must be in the same AWS Region you use to create your labeling job.

When you create a labeling job using the SageMaker console, you add worker instructions and labels to the worker UI that Ground Truth provides. You can preview and interact with the worker UI while creating your labeling job in the console. You can also see a preview of the worker UI on your built-in task type page.

### To create a labeling job (console)

2. In the left navigation pane, choose **Labeling jobs**.
3. On the **Labeling jobs** page, choose **Create labeling job**.
4. For **Job name**, enter a name for your labeling job.
5. (Optional) If you want to identify your labels with a key, select **I want to specify a label attribute name different from the labeling job name**. If you do not select this option, the labeling job name you specified in the previous step will be used to identify your labels in your output manifest file.
6. Choose a data setup to setup to set up a connection between your input dataset and Ground Truth.

   - For **Automated data setup**:
     - Follow the instructions in Automated Data Setup (p. 574) for image, text, and video clip labeling jobs.
• Follow the instructions in Automated Video Frame Input Data Setup (p. 611) for video frame labeling jobs.

• For Manual data setup:
  • For Input dataset location, provide the location in Amazon S3 in which your input manifest file is located. For example, if your input manifest file, manifest.json, is located in example-bucket, enter s3://example-bucket/manifest.json.
  • For Output dataset location, provide the location in Amazon S3 where you want Ground Truth to store the output data from your labeling job.

7. For IAM Role, choose an existing IAM role or create an IAM role with permission to access your resources in Amazon S3, to write to the output Amazon S3 bucket specified above, and with a SageMaker execution policy attached.

8. (Optional) For Additional configuration, you can specify how much of your dataset you want workers to label, and if you want SageMaker to encrypt the output data for your labeling job using an AWS KMS encryption key. To encrypt your output data, you must have the required AWS KMS permissions attached to the IAM role you provided in the previous step. For more details, see the section called “IAM Permissions” (p. 650).

9. In the Task type section, under Task category, use the dropdown list to select your task category.

10. In Task selection, choose your task type.

11. (Optional) Provide tags for your labeling job to make it easier to find in the console later.

12. Choose Next.

13. In the Workers section, choose the type of workforce you would like to use. For more details about your workforce options see Create and Manage Workforces (p. 694).

14. (Optional) After you've selected your workforce, specify the Task timeout. This is the maximum amount of time a worker has to work on a task.

   For 3D point cloud annotation tasks, the default task timeout is 3 days. The default timeout for text and image classification and label verification labeling jobs is 5 minutes. The default timeout for all other labeling jobs is 60 minutes.

15. (Optional) For bounding box, semantic segmentation, video frame, and 3D point cloud task types, you can select Display existing labels if you want to display labels for your input data set for workers to verify or adjust.

   For bounding box and semantic segmentation labeling jobs, this will create an adjustment labeling job.

   For 3D point cloud and video frame labeling jobs:

   • Select Adjustment to create an adjustment labeling job. When you select this option, you can add new labels but you cannot remove or edit existing labels from the previous job. Optionally, you can choose label category attributes and frame attributes that you want workers to edit. To make an attribute editable, select the check box Allow workers to edit this attribute for that attribute.

   Optionally, you can add new label category and frame attributes.

   • Select Verification to create an adjustment labeling job. When you select this option, you cannot add, modify, or remove existing labels from the previous job. Optionally, you can choose label category attributes and frame attributes that you want workers to edit. To make an attribute editable, select the check box Allow workers to edit this attribute for that attribute.

   We recommend that you can add new label category attributes to the labels that you want workers to verify, or add one or more frame attributes to have workers provide information about the entire frame.

For more information, see Verify and Adjust Labels (p. 502).
16. Configure your workers' UI:

- If you are using a built-in task type, specify workers instructions and labels.
  - For image classification and text classification (single and multi-label) you must specify at least two label categories. For all other built-in task types, you must specify at least one label category.
  - (Optional) If you are creating a 3D point cloud or video frame labeling job, you can specify label category attributes (not supported for 3D point cloud semantic segmentation) and frame attributes. Label category attributes can be assigned to one or more labels. Frame attributes will appear on each point cloud or video frame workers label. To learn more, see Worker User Interface (UI) (p. 469) for 3D point cloud and Worker User Interface (UI) (p. 421) for video frame.

- (Optional) Add **Additional instructions** to help your worker complete your task.

- If you are creating a custom labeling workflow you must:
  - Enter a custom template in the code box. Custom templates can be created using a combination of HTML, the Liquid templating language and our pre-built web components. Optionally, you can choose a base-template from the drop-down menu to get started.
  - Specify pre-annotation and post-annotation lambda functions. To learn how to create these functions, see Step 3: Processing with AWS Lambda (p. 516).

17. (Optional) You can select See preview to preview your worker instructions, labels, and interact with the worker UI. Make sure the pop-up blocker of the browser is disabled before generating the preview.

18. Choose **Create**.

After you've successfully created your labeling job, you are redirected to the **Labeling jobs** page. The status of the labeling job you just created is **In progress**. This status progressively updates as workers complete your tasks. When all tasks are successfully completed, the status changes to **Completed**.

If an issue occurs while creating the labeling job, its status changes to **Failed**.

To view more details about the job, choose the labeling job name.

**Next Steps**

After your labeling job status changes to **Completed**, you can view your output data in the Amazon S3 bucket that you specified while creating that labeling job. For details about the format of your output data, see **Output Data** (p. 614).

**Create a Labeling Job (API)**

To create a labeling job using the Amazon SageMaker API, you use the **CreateLabelingJob** operation. For specific instructions on creating a labeling job for a built-in task type, see that task type page. To learn how to create a streaming labeling job, which is a labeling job that runs perpetually, see Create a Streaming Labeling Job (p. 552).

To use the **CreateLabelingJob** operation, you need the following:

- A worker task template (UiTemplateS3Uri) or human task UI ARN (HumanTaskUiArn) in Amazon S3.
- For 3D point cloud jobs, video object detection and tracking jobs, and NER jobs, use the ARN listed in HumanTaskUiArn for your task type.
- If you are using a built-in task type other than 3D point cloud tasks, you can add your worker instructions to one of the pre-built templates and save the template (using a .html or .liquid extension) in your S3 bucket. Find the pre-build templates on your task type page.
• If you are using a custom labeling workflow, you can create a custom template and save the template in your S3 bucket. To learn how to build a custom worker template, see Step 2: Creating your custom worker task template (p. 510). For custom HTML elements that you can use to customize your template, see Crowd HTML Elements Reference (p. 720). For a repository of demo templates for a variety of labeling tasks, see Amazon SageMaker Ground Truth Sample Task UIs.

• An input manifest file that specifies your input data in Amazon S3. Specify the location of your input manifest file in ManifestS3Uri. For information about creating an input manifest, see Input Data (p. 572). If you create a streaming labeling job, this is optional. To learn how to create a streaming labeling job, see Create a Streaming Labeling Job (p. 552).

• An Amazon S3 bucket to store your output data. You specify this bucket, and optionally, a prefix in S3OutputPath.

• A label category configuration file. Each label category name must be unique. Specify the location of this file in Amazon S3 using the LabelCategoryConfigS3Uri parameter. The format and label categories for this file depend on the task type you use:
  • For image classification and text classification (single and multi-label) you must specify at least two label categories. For all other task types, the minimum number of label categories required is one.
  • For named entity recognition tasks, you must provide worker instructions in this file. See Provide Worker Instructions in a Label Category Configuration File (p. 399) for details and an example.
  • For 3D point cloud and video frame task type, use the format in Create a Labeling Category Configuration File with Label Category and Frame Attributes (p. 557).
  • For all other built-in task types and custom tasks, your label category configuration file must be a JSON file in the following format. Identify the labels you want to use by replacing label_1, label_2,...,label_n with your label categories.

```json
{
   "document-version": "2018-11-28",
   "labels": [
      {"label": "label_1"},
      {"label": "label_2"},
      ...
      {"label": "label_n"}
   ]
}
```

• An AWS Identity and Access Management (IAM) role with the AmazonSageMakerGroundTruthExecution managed IAM policy attached and with permissions to access your S3 buckets. Specify this role in RoleArn. To learn more about this policy, see Use IAM Managed Policies with Ground Truth (p. 650). If you require more granular permissions, see the section called "IAM Permissions" (p. 650).

If your input or output bucket name does not contain sagemaker, you can attach a policy similar to the following to the role that is passed to the CreateLabelingJob operation.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": ["s3:GetObject"],
         "Resource": ["arn:aws:s3:::my_input_bucket/*"]
      },
      {
         "Effect": "Allow",
         "Action": [
```
• A pre-annotation and post-annotation (or annotation-consolidation) AWS Lambda function Amazon Resource Name (ARN) to process your input and output data.

• Lambda functions are predefined in each AWS Region for built-in task types. To find the pre-annotation Lambda ARN for your Region, see PreHumanTaskLambdaArn. To find the annotation-consolidation Lambda ARN for your Region, see AnnotationConsolidationLambdaArn.

• For custom labeling workflows, you must provide a custom pre- and post-annotation Lambda ARN. To learn how to create these Lambda functions, see Step 3: Processing with AWS Lambda (p. 516).

• A work team ARN that you specify in WorkteamArn. You receive a work team ARN when you subscribe to a vendor workforce or create a private workteam. If you are creating a labeling job for a video frame or point cloud task type, you cannot use the Amazon Mechanical Turk workforce. For all other task types, to use the Mechanical Turk workforce, use the following ARN. Replace region with the AWS Region you are using to create the labeling job.

  arn:aws:sagemaker:region:394669845002:workteam/public-crowd/default

If you use the Amazon Mechanical Turk workforce, use the ContentClassifiers parameter in DataAttributes of InputConfig to declare that your content is free of personally identifiable information and adult content.

Ground Truth requires that your input data is free of personally identifiable information (PII) if you use the Mechanical Turk workforce. If you use Mechanical Turk and do not specify that your input data is free of PII using the FreeOfPersonallyIdentifiableInformation flag, your labeling job will fail. Use the FreeOfAdultContent flag to declare that your input data is free of adult content. SageMaker may restrict the Amazon Mechanical Turk workers that can view your task if it contains adult content.

To learn more about work teams and workforces, see Create and Manage Workforces (p. 694).

• If you use the Mechanical Turk workforce, you must specify the price you’ll pay workers for performing a single task in PublicWorkforceTaskPrice.

• To configure the task, you must provide a task description and title using TaskDescription and TaskTitle respectively. Optionally, you can provide time limits that control how long the workers have to work on an individual task (TaskTimeLimitInSeconds) and how long tasks remain in the worker portal, available to workers (TaskAvailabilityLifetimeInSeconds).

• (Optional) For some task types, you can have multiple workers label a single data object by inputting a number greater than one for the NumberOfHumanWorkersPerDataObject parameter. For more information about annotation consolidation, see Consolidate Annotations (p. 639).

• (Optional) To create an automated data labeling job, specify one of the ARNs listed in LabelingJobAlgorithmSpecificationArn in LabelingJobAlgorithmsConfig. This ARN identifies the algorithm used in the automated data labeling job. The task type associated with this ARN must match the task type of the PreHumanTaskLambdaArn and AnnotationConsolidationLambdaArn you specify. Automated data labeling is supported for the following task types: image classification, bounding box, semantic segmentation, and text classification. The minimum number of objects allowed for automated data labeling is 1,250, and we strongly suggest providing a minimum of 5,000 objects. To learn more about automated data labeling jobs, see Automate Data Labeling (p. 640).

• (Optional) You can provide StoppingConditions that cause the labeling job to stop if one the conditions is met. You can use stopping conditions to control the cost of the labeling job.
Examples

The following code examples demonstrate how to create a labeling job using `CreateLabelingJob`. For additional examples, we recommend you use one of the Ground Truth Labeling Jobs Jupyter notebooks in the SageMaker Examples section of a SageMaker notebook instance. To learn how to use a notebook example from the SageMaker Examples, see Example Notebooks (p. 306). You can also see these example notebooks on GitHub in the SageMaker Examples repository.

AWS SDK for Python (Boto3)

The following is an example of an AWS Python SDK (Boto3) request to create a labeling job for a built-in task type in the US East (N. Virginia) Region using a private workforce. Replace all red-italized text with your labeling job resources and specifications.

```python
response = client.create_labeling_job(
    LabelingJobName="example-labeling-job",
    LabelAttributeName="label",
    InputConfig={
        'DataSource': {
            'S3DataSource': {
                'ManifestS3Uri': "s3://bucket/path/manifest-with-input-data.json"
            }
        },
        'DataAttributes': {
            'ContentClassifiers': [
                "FreeOfPersonallyIdentifiableInformation","FreeOfAdultContent",
            ]
        }
    },
    OutputConfig={
        'S3OutputPath': "s3://bucket/path/file-to-store-output-data",
        'KmsKeyId': "string"
    },
    RoleArn="arn:aws:iam::*:role/*",
    LabelCategoryConfigS3Uri="s3://bucket/path/label-categories.json",
    StoppingConditions={
        'MaxHumanLabeledObjectCount': 123,
        'MaxPercentageOfInputDatasetLabeled': 123
    },
    HumanTaskConfig={
        'WorkteamArn': "arn:aws:sagemaker:region::*:workteam/private-crowd/*",
        'UiConfig': {
            'UiTemplateS3Uri': "s3://bucket/path/custom-worker-task-template.html"
        },
        'TaskKeywords': ["Images","Classification","Multi-label"],
        'TaskTitle': "Multi-label image classification task",
        'TaskDescription': "Select all labels that apply to the images shown",
        'NumberOfHumanWorkersPerDataObject': 1,
        'TaskTimeLimitInSeconds': 3600,
        'TaskAvailabilityLifetimeInSeconds': 21600,
        'MaxConcurrentTaskCount': 1000,
        'AnnotationConsolidationConfig': {
            'AnnotationConsolidationLambdaArn': "arn:aws:lambda:us-east-1:432418664414:function:ACS-
        },
    },
    Tags=[
        {
            'Key': "string",
```
AWS CLI

The following is an example of an AWS CLI request to create a labeling job for a built-in task type in the US East (N. Virginia) Region using the Amazon Mechanical Turk workforce. For more information, see `start-human-loop` in the AWS CLI Command Reference. Replace all *red-italized text* with your labeling job resources and specifications.

```bash
$ aws --region us-east-1 sagemaker create-labeling-job \
--labeling-job-name "example-labeling-job" \
--label-attribute-name "label" \
--role-arn "arn:aws:iam::account-id:role/role-name" \
--input-config '{
    "DataAttributes": {
        "ContentClassifiers": [
            "FreeOfPersonallyIdentifiableInformation",
            "FreeOfAdultContent"
        ],
    },
    "DataSource": {
        "S3DataSource": {
            "ManifestS3Uri": "s3://bucket/path/manifest-with-input-data.json"
        }
    }
} \
--output-config '{
    "KmsKeyId": '',
    "S3OutputPath": "s3://bucket/path/file-to-store-output-data"
} \
--human-task-config '{
    "AnnotationConsolidationConfig": {
        "AnnotationConsolidationLambdaArn": "arn:aws:lambda:us-east-1:432418664414:function:ACS-
    },
    "TaskAvailabilityLifetimeInSeconds": 21600,
    "TaskTimeLimitInSeconds": 3600,
    "NumberOfHumanWorkersPerDataObject": 1,
    "WorkteamArn": "arn:aws:sagemaker:us-east-1:394669845002:workteam/public-crowd/default",
    "PublicWorkforceTaskPrice": {
        "AmountInUsd": {
            "Dollars": 0,
            "TenthFractionsOfACent": 6,
            "Cents": 3
        }
    },
    "TaskDescription": "Select all labels that apply to the images shown",
    "MaxConcurrentTaskCount": 1000,
    "TaskTitle": "Multi-label image classification task",
    "TaskKeywords": [
        "Images",
        "Classification",
        "Multi-label"
    ],
    "UiConfig": {
        "UiTemplateS3Uri": "s3://bucket/path/custom-worker-task-template.html"
    }
}
```

Create a Labeling Job

For more information about this operation, see CreateLabelingJob. For information about how to use other language-specific SDKs, see See Also in the CreateLabelingJobs topic.

Create a Streaming Labeling Job

Streaming labeling jobs enable you to send individual data objects in real time to a perpetually running, streaming labeling job. To create a streaming labeling job, you must create an Amazon SNS input topic and specify this topic in CreateLabelingJob parameters InputConfig of SnsDataSource. Optionally, you can also create an Amazon SNS output topic and specify it in OutputConfig if you want to receive label data in real time.

Important
If you are a new user of Ground Truth streaming labeling jobs, it is recommended that you review Ground Truth Streaming Labeling Jobs (p. 576) before creating a streaming labeling job.

Use the following sections to create the resources that you need and can use to create a streaming labeling job:

- Learn how to create SNS topics with the permissions required for Ground Truth streaming labeling jobs by following the steps in Create Amazon SNS Input and Output Topics (p. 552). Your SNS topics must be created in the same AWS Region as your labeling job.
- See Subscribe an Endpoint to Your Amazon SNS Output Topic (p. 554) to learn how to set up an endpoint to receive labeling task output data at a specified endpoint each time a labeling task is completed.
- To learn how to configure your Amazon S3 bucket to send notifications to your Amazon SNS input topic, see Set up Amazon S3 Bucket Event Notifications (p. 555).
- Optionally, add data objects that you want to have labeled as soon as the labeling job starts to your input manifest. For more information, see Create a Manifest File (Optional) (p. 555).
- There are other resources required to create a labeling job, such as an IAM role, Amazon S3 bucket, a worker task template and label categories. These are described in the Ground Truth documentation on creating a labeling job. For more information, see Create a Labeling Job (p. 541).

Important
When you create a labeling job you must provide an IAM execution role. Attach the AWS managed policy AmazonSageMakerGroundTruthExecution to this role to ensure it has required permissions to execute your labeling job.

When you submit a request to create a streaming labeling job, the state of your labeling job is Initializing. Once the labeling job is active, the state changes to InProgress. Do not send new data objects to your labeling job or attempt to stop your labeling job while it is in the Initializing state. Once the state changes to InProgress, you can start sending new data objects using Amazon SNS and the Amazon S3 configuration.

Topics
- Create Amazon SNS Input and Output Topics (p. 552)
- Set up Amazon S3 Bucket Event Notifications (p. 555)
- Create a Manifest File (Optional) (p. 555)
- Example: Use SageMaker API To Create Streaming Labeling Job (p. 555)
- Stop a Streaming Labeling Job (p. 556)

Create Amazon SNS Input and Output Topics

You need to create an Amazon SNS input to create a streaming labeling job. Optionally, you may provide an Amazon SNS output topic.
When you create an Amazon SNS topic to use in your streaming labeling job, note down the topic Amazon Resource Name (ARN). The ARN will be the input values for the parameter SnsTopicArn in InputConfig and OutputConfig when you create a labeling job.

Create an Input Topic

Your input topic is used to send new data objects to Ground Truth. To create an input topic, follow the instructions in Creating an Amazon SNS topic in the Amazon Simple Notification Service Developer Guide.

Note down your input topic ARN and use it as input for the CreateLabelingJob parameter SnsTopicArn in InputConfig.

Create an Output Topic

If you provide an output topic, it is used to send notifications when a data object is labeled. When you create a topic, you have the option to add an encryption key. Use this option to add an AWS Key Management Service customer managed key to your topic to encrypt the output data of your labeling job before it is published to your output topic.

To create an output topic, follow the instructions in Creating an Amazon SNS topic in the Amazon Simple Notification Service Developer Guide.

If you add encryption, you must attach additional permission to the topic. See Add Encryption to Your Output Topic (Optional) (p. 553) for more information.

Important
To add a customer managed key to your output topic while creating a topic in the console, do not use the (Default) alias/aws/sns option. Select a customer managed key that you created.

Note down your input topic ARN and use it in your CreateLabelingJob request in the parameter SnsTopicArn in OutputConfig.

Add Encryption to Your Output Topic (Optional)

To encrypt messages published to your output topic, you need to provide an AWS KMS customer managed key to your topic. Modify the following policy and add it to your customer managed key to give Ground Truth permission to encrypt output data before publishing it to your output topic.

Replace <account_id> with the ID of the account that you are using to create your topic. To learn how to find your AWS account ID, see Finding Your AWS Account ID.

```json
{
  "Id": "key-console-policy",
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "Enable IAM User Permissions",
      "Effect": "Allow",
      "Principal": {
        "AWS": "arn:aws:iam::<account_id>:root"
      },
      "Action": "kms:*",
      "Resource": "*"
    },
    {
      "Sid": "Allow access for Key Administrators",
      "Effect": "Allow",
      "Principal": {
        "AWS": "arn:aws:iam::<account_id>:role/Admin"
      }
    }
  ]
}
```
Additionally, you must modify and add the following policy to the execution role that you use to create your labeling job (the input value for `RoleArn`).

Replace `<account_id>` with the ID of the account that you are using to create your topic. Replace `<region>` with the AWS Region you are using to create your labeling job. Replace `<key_id>` with your customer managed key ID.

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "sid1",
      "Effect": "Allow",
      "Action": [
        "kms:Decrypt",
        "kms:GenerateDataKey"
      ],
      "Resource": "arn:aws:kms:<region>:<account_id>:key/<key_id>"
    }
  ]
}
```

For more information on creating and securing keys, see Creating Keys and Using Key Policies in the AWS Key Management Service Developer Guide.

**Subscribe an Endpoint to Your Amazon SNS Output Topic**

When a worker completes a labeling job task from a Ground Truth streaming labeling job, Ground Truth uses your output topic to publish output data to one or more endpoints that you specify. To receive notifications when a worker finishes a labeling task, you must subscribe an endpoint to your Amazon SNS output topic.

To learn how to add endpoints to your output topic, see Subscribing to an Amazon SNS topic in the Amazon Simple Notification Service Developer Guide.

To learn more about the output data format that is published to these endpoints, see Output Data (p. 614).

**Important**

If you do not subscribe an endpoint to your Amazon SNS output topic, you will not receive notifications when new data objects are labeled.
Set up Amazon S3 Bucket Event Notifications

You can add an event notification to your Amazon S3 bucket using the Amazon S3 console, API, and language specific AWS SDKs, or the AWS Command Line Interface. Set up this event to send notifications to the same Amazon SNS input topic that you specify using SnsTopicArn in InputConfig when you create a labeling job. Do not set up event notifications using the same Amazon S3 location that you specified for S3OutputPath in OutputConfig – doing so may result in unwanted data objects being processed by Ground Truth for labeling.

You decide the types of events that you want to send to your Amazon SNS topic. Ground Truth creates a labeling job when you send object creation events.

The event structure sent to your Amazon SNS input topic must be a JSON message formatted using the same structure found in Event message structure.

To see examples of how you can set up an event notification for your Amazon S3 bucket using the Amazon S3 console, AWS SDK for .NET, and AWS SDK for Java, follow this walkthrough, Walkthrough: Configure a bucket for notifications (SNS topic or SQS queue) in the Amazon Simple Storage Service User Guide.

Create a Manifest File (Optional)

When you create a streaming labeling job, you have the one time option to add objects (such as images or text) to an input manifest file that you specify in ManifestS3Uri of CreateLabelingJob. When the streaming labeling job starts, these objects are sent to workers or added to the Amazon SQS queue if the total number of objects exceed MaxConcurrentTaskCount. The results are added to the Amazon S3 path that you specify when creating the labeling job periodically as workers complete labeling tasks. Output data is sent to any endpoint that you subscribe to your output topic.

If you want to provide initial objects to be labeled, create a manifest file that identifies these objects and place it in Amazon S3. Specify the S3 URI of this manifest file in ManifestS3Uri within InputConfig.

To learn how to format your manifest file, see Input Data (p. 572). To use the SageMaker console to automatically generate a manifest file (not supported for 3D point cloud task types), see Automated Data Setup (p. 574).

Example: Use SageMaker API To Create Streaming Labeling Job

The following is an example of an AWS Python SDK (Boto3) request that you can use to start a streaming labeling job for a built-in task type in the US East (N. Virginia) Region. For more details about each parameter below see CreateLabelingJob. To learn how you can create a labeling job using this API and associated language specific SDKs, see Create a Labeling Job (API).

In this example, note the following parameters:

- SnsDataSource – This parameter appears in InputConfig and OutputConfig and is used to identify your input and output Amazon SNS topics respectively. To create a streaming labeling job, you are required to provide an Amazon SNS input topic. Optionally, you can also provide an Amazon SNS output topic.
- S3DataSource – This parameter is optional. Use this parameter if you want to include an input manifest file of data objects that you want labeled as soon as the labeling job starts.
- StoppingConditions – This parameter is ignored when you create a streaming labeling job. To learn more about stopping a streaming labeling job, see Stop a Streaming Labeling Job (p. 556).
- Streaming labeling jobs do not support automated data labeling. Do not include the LabelingJobAlgorithmsConfig parameter.

```python
response = client.create_labeling_job(
```
LabelingJobName= 'example-labeling-job',
LabelAttributeName='label',
InputConfig={
  'DataSource': {
    'S3DataSource': {
      'ManifestS3Uri': 's3://bucket/path/manifest-with-input-data.json'
    },
    'SnsDataSource': {
      'SnsTopicArn': 'arn:aws:sns:us-east-1:123456789012:your-sns-input-topic'
    }
  },
  'DataAttributes': {
    'ContentClassifiers': ['FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent']
  }
},
OutputConfig={
  'S3OutputPath': 's3://bucket/path/file-to-store-output-data',
  'KmsKeyId': 'string',
  'SnsTopicArn': 'arn:aws:sns:us-east-1:123456789012:your-sns-output-topic'
},
RoleArn='arn:aws:iam::*:role/*',
LabelCategoryConfigS3Uri='s3://bucket/path/label-categories.json',
HumanTaskConfig={
  'WorkteamArn': 'arn:aws:sagemaker:us-east-1:*:workteam/private-crowd/*',
  'UiConfig': {
    'UiTemplateS3Uri': 's3://bucket/path/custom-worker-task-template.html'
  },
  'TaskKeywords': [],
  'TaskTitle': 'Multi-label image classification task',
  'TaskDescription': 'Select all labels that apply to the images shown',
  'NumberOfHumanWorkersPerDataObject': 123,
  'TaskTimeLimitInSeconds': 123,
  'TaskAvailabilityLifetimeInSeconds': 123,
  'MaxConcurrentTaskCount': 123,
  'AnnotationConsolidationConfig': {
    'AnnotationConsolidationLambdaArn': 'arn:aws:lambda:us-east-1:432418664414:function:ACS-tasktype'
  },
  Tags=[
    {
      'Key': 'string',
      'Value': 'string'
    }
  ]
},
Stop a Streaming Labeling Job

You can manually stop your streaming labeling job using the operation StopLabelingJob.

If your labeling job remains idle for over 10 days, it is automatically stopped by Ground Truth. In this context, a labeling job is considered idle if no objects are sent to the Amazon SNS input topic and no objects remain in your Amazon SQS queue, waiting to be labeled. For example, if no data objects are fed to the Amazon SNS input topic and all the objects fed to the labeling job are already labeled, Ground Truth starts a timer. After the timer starts, if no items are received within a 10 day period, the labeling job is stopped.

If this 10 day limit poses a problem for your business use case, please contact AWS Support.
When a labeling job is stopped, its status is STOPPING while Ground Truth cleans up labeling job resources and unsubscribes your Amazon SNS topic from your Amazon SQS queue. The Amazon SQS is not deleted by Ground Truth because this queue may contain unprocessed data objects. You should manually delete the queue if you want to avoid incurring additional charges from Amazon SQS. To learn more, see Amazon SQS pricing.

Create a Labeling Category Configuration File with Label Category and Frame Attributes

When you create a 3D point cloud or video frame labeling job using the Amazon SageMaker API operation CreateLabelingJob, you use a label category configuration file to specify your labels and worker instructions. Optionally, you can also provide the following in your label category attribute file:

- You can provide **label category attributes** for video frame and 3D point cloud object tracking and object detection task types. Workers can use one or more attributes to give more information about an object. For example, you may want to use the attribute *occluded* to have workers identify when an object is partially obstructed. You can either specify a label category attribute for a single label using the `categoryAttributes` parameter, or for all labels using the `categoryGlobalAttributes` parameter.

- You can provide **frame attributes** for video frame and 3D point cloud object tracking and object detection task types using `frameAttributes`. When you create a frame attribute, it appears on each frame or point cloud in the worker task. In video frame labeling jobs, these are attributes that workers assign to an entire video frame. For 3D point cloud labeling jobs, these attributes are applied to a single point cloud. Use frame attributes to have workers provide more information about the scene in a specific frame or point cloud.

- For video frame labeling jobs, you use the label category configuration file to specify the task type (bounding box, polyline, polygon, or keypoint) sent to workers.

For workers, specifying values for label category attributes and frame attributes will be optional.

**Important**
You should only provide a label attribute name in `auditLabelAttributeName` if you are running an audit job to verify or adjust labels. Use this parameter to input the `LabelAttributeName` used in the labeling job that generated the annotations you want your worker to adjust. When you create a labeling job in the console, if you did not specify a label attribute name, the Name of your job is used as the LabelAttributeName.

**Topics**
- Label Category Configuration File Schema (p. 557)
- Example: Label Category Configuration Files for 3D Point Cloud Labeling Jobs (p. 564)
- Example: Label Category Configuration Files for Video Frame Labeling Jobs (p. 568)
- Creating Worker Instructions (p. 571)

**Label Category Configuration File Schema**

The following table lists elements you can and must include in your label category configuration file.

**Note**
The parameter `annotationType` is only supported for video frame labeling jobs.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>frameAttributes</td>
<td>No</td>
<td>A list of JSON objects.</td>
<td>Use this parameter to create a frame attribute</td>
</tr>
<tr>
<td>Parameter</td>
<td>Required</td>
<td>Accepted Values</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>----------</td>
<td>-------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Required Parameters in each JSON Object:</strong></td>
<td>name, type, description</td>
</tr>
<tr>
<td></td>
<td></td>
<td>min and maximum are required if type is &quot;number&quot;</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Optional Parameters in each JSON Object:</strong></td>
<td>enum, editsAllowed, isRequired</td>
</tr>
<tr>
<td>categoryGlobalAttributes</td>
<td>A list of JSON objects.</td>
<td>Use this parameter to create label category attributes that are applied to all labels you specify in labels. See the third table in this section for more information.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Required Parameters in each JSON Object:</strong></td>
<td>name, type</td>
</tr>
<tr>
<td></td>
<td></td>
<td>min and maximum are required if type is &quot;number&quot;</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Optional Parameters in each JSON Object:</strong></td>
<td>description, enum, editsAllowed, isRequired</td>
</tr>
<tr>
<td>labels</td>
<td>Yes</td>
<td>A list of up to 30 JSON objects</td>
<td>Use this parameter to specify your labels, or classes. Add one label for each class.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Required Parameters in each JSON Object:</strong></td>
<td>label</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Optional Parameters in each JSON Object:</strong></td>
<td>categoryAttributes, editsAllowed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Use editsAllowed to specify whether or not a label can be edited in an adjustment labeling job. Set editsAllowed to &quot;none&quot; for verification labeling jobs.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>See the following table for more information.</td>
<td></td>
</tr>
<tr>
<td>Parameter</td>
<td>Required</td>
<td>Accepted Values</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------------------</td>
<td>----------</td>
<td>-----------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>annotationType (only supported for video frame labeling jobs)</td>
<td>No</td>
<td>String</td>
<td>Use this to specify the task type for your video frame labeling jobs. For example, for a polygon video frame object detection task, choose Polygon. If you do not specify an annotationType when you create a video frame labeling job, Ground Truth will use BoundingBox by default.</td>
</tr>
<tr>
<td>instructions</td>
<td>No</td>
<td>A JSON object</td>
<td>Use this parameter to add worker instructions to help your workers complete their tasks. For more information about worker instructions, see Worker Instructions (p. 470). Short instructions must be under 255 characters and long instruction must be under 2,048 characters. For more information, see Creating Worker Instructions (p. 571).</td>
</tr>
<tr>
<td>auditLabelAttributeName</td>
<td>Required for adjustment and verification task types</td>
<td>String</td>
<td>Enter the LabelAttributeName used in the labeling job you want to adjust annotations of. Only use this parameter if you are creating an adjustment job for video frame and 3D point cloud object detection, object tracking, or 3D point cloud semantic segmentation.</td>
</tr>
</tbody>
</table>

The following table describes the parameters that you can and must use to create a list of Labels. Each parameter should be included in a JSON object.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>label</td>
<td>Yes</td>
<td>String</td>
<td>The name of the label category that is displayed to workers. Each label category name must be unique.</td>
</tr>
<tr>
<td>categoryAttributes</td>
<td>No</td>
<td>A list of JSON objects. Required Parameters in each JSON Object: name, type minimum and maximum required if type is &quot;number&quot; Optional Parameters in each JSON Object: description, enum, editsAllowed, isRequired Use this parameter to add label category attributes to specific labels you specify in labels. To add one or more label category attributes to a label, include the categoryAttributes JSON object in the same labels JSON object as that label. See the following table for more information.</td>
<td></td>
</tr>
<tr>
<td>editsAllowed</td>
<td>No</td>
<td>String</td>
<td>Specifies whether or not a label can be edited by workers. Supported Values: &quot;none&quot;: no modifications are not allowed. or &quot;any&quot; (Default): all modifications are allowed. For video frame or 3D point cloud adjustment labeling jobs, add this parameter to one or more JSON objects in the labels list to specify whether or not a worker can edit a label. For 3D point cloud and video frame verification labeling jobs, add this parameter with the value &quot;none&quot; to each JSON object in the labels list. This will make all labels uneditable.</td>
</tr>
</tbody>
</table>

The following table describes the parameters that you can and must use to create a frame attributes using frameAttributes and label category attribute using the categoryGlobalAttributes and categoryAttributes parameters.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>name</td>
<td>Yes</td>
<td>String</td>
<td>Use this parameter to assign a name to your label category or frame attribute. This is the attribute name that workers see. Each label category attribute name in your label category configuration file must be unique. Global label category attributes and label specific label category attributes cannot have the same name.</td>
</tr>
<tr>
<td>type</td>
<td>Yes</td>
<td>String</td>
<td>Use this parameter to define the label category or frame attribute type. If you specify &quot;string&quot; for type and provide an enum value for this attribute, workers will be able to choose from one of the choices you provide. If you specify &quot;string&quot; for type and do not provide an enum value, workers can enter free form text. If you specify number for type, worker can enter a number between the minimum and maximum numbers you specify.</td>
</tr>
<tr>
<td>enum</td>
<td>No</td>
<td>List of strings</td>
<td>Use this parameter to define options that workers can choose from for this label category or frame attribute. Workers can choose one value specified in enum. For example, if you specify [&quot;foo&quot;, &quot;buzz&quot;,</td>
</tr>
<tr>
<td>Parameter</td>
<td>Required</td>
<td>Accepted Values</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------</td>
<td>----------</td>
<td>-----------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>&quot;bar&quot;] for enum, workers can choose one of foo, buzz, or bar.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>You must specify &quot;string&quot; for type to use an enum list.</td>
</tr>
<tr>
<td>description</td>
<td>frameAttributes: String Yes</td>
<td>categoryAttributes or categoryGlobalAttributes: No</td>
<td>Use this parameter to add a description of the label category or frame attribute. You can use this field to give workers more information about the attribute. This field is only required for frame attributes.</td>
</tr>
<tr>
<td>minimum and maximum</td>
<td>Required if attribute type is &quot;number&quot;</td>
<td>Integers</td>
<td>Use these parameters to specify minimum and maximum (inclusive) values workers can enter for numeric label category or frame attributes. You must specify &quot;number&quot; for type to use minimum and maximum.</td>
</tr>
<tr>
<td>editsAllowed</td>
<td>No</td>
<td>String</td>
<td>Specifies whether or not a label category or frame attribute can be edited by workers. For video frame or 3D point cloud adjustment and verification labeling jobs, add this parameter to label category and frame attribute JSON objects to specify whether or not a worker can edit an attribute.</td>
</tr>
</tbody>
</table>
### Parameter

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>isRequired</td>
<td>No</td>
<td>Boolean</td>
<td>Specifies whether workers are required to annotate an attribute. Workers cannot submit the job until all required attributes are annotated.</td>
</tr>
</tbody>
</table>

### Label and label category attribute quotas

You can specify up to 10 label category attributes per class. This 10-attribute quotas includes global label category attributes. For example, if you create four global label category attributes, and then assign three label category attributes to label X, that label will have $4+3=7$ label category attributes in total. For all label category and label category attribute limits, refer to the following table.

<table>
<thead>
<tr>
<th>Type</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labels (Labels)</td>
<td>1</td>
<td>30</td>
</tr>
<tr>
<td>Label name character quota</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Label category attributes per label (sum of categoryAttributes and categoryGlobalAttributes)</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Free form text entry label category attributes per label (sum of categoryAttributes and categoryGlobalAttributes)</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Frame attributes</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Free form text entry attributes in frameAttributes</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>Attribute name character quota (name)</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Attribute description character quota (description)</td>
<td>0</td>
<td>128</td>
</tr>
<tr>
<td>Attribute type characters quota (type)</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Allowed values in the enum list for a string attribute</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>Character quota for a value in enum list</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>Maximum characters in free form text response for free form text frameAttributes</td>
<td>0</td>
<td>1000</td>
</tr>
</tbody>
</table>
Create a Labeling Job

<table>
<thead>
<tr>
<th>Type</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum characters in free form text response for free form text categoryAttributes and categoryGlobalAttributes</td>
<td>0</td>
<td>80</td>
</tr>
</tbody>
</table>

Example: Label Category Configuration Files for 3D Point Cloud Labeling Jobs

Select a tab in the following tables to see examples of 3D point cloud label category configuration files for object detection, object tracking, semantic segmentation, adjustment, and verification labeling jobs.

3D Point Cloud Object Tracking and Object Detection

The following is an example of a label category configuration file that includes label category attributes for a 3D point cloud object detection or object tracking labeling job. This example includes a two frame attributes, which will be added to all point clouds submitted to the labeling job. The Car label will include four label category attributes—X, Y, Z, and the global attribute, W.

```json
{
    "documentVersion": "2020-03-01",
    "frameAttributes": [
        {
            "name": "count players",
            "description": "How many players do you see in the scene?",
            "type": "number"
        },
        {
            "name": "select one",
            "description": "Describe the scene",
            "type": "string",
            "enum": ["clear", "blurry"],
            "isRequired": true
        }
    ],
    "categoryGlobalAttributes": [
        {
            "name": "W",
            "description": "label-attributes-for-all-labels",
            "type": "string",
            "enum": ["foo", "buzz", "biz"]
        }
    ],
    "labels": [
        {
            "label": "Car",
            "categoryAttributes": [
                {
                    "name": "X",
                    "description": "Enter a number",
                    "type": "number",
                },
                {
                    "name": "Y",
                    "description": "Select an option",
                    "type": "string",
                    "enum": ["y1", "y2"]
                },
                {
                    "name": "Z",
                    "description": "Submit a free-form response",
                    "type": "string",
                }
            ]
        }
    ]
}
```
3D Point Cloud Semantic Segmentation

The following is an example of a label category configuration file for a 3D point cloud semantic segmentation labeling job.

Label category attributes are not supported for 3D point cloud semantic segmentation task types. Frame attributes are supported. If you provide label category attributes for a semantic segmentation labeling job, they will be ignored.

```json
{
  "documentVersion": "2020-03-01",
  "frameAttributes": [
    {
      "name": "count players",
      "description": "How many players do you see in the scene?",
      "type": "number"
    },
    {
      "name": "select one",
      "description": "Describe the scene",
      "type": "string",
      "enum": ["clear", "blurry"]
    }
  ],
  "labels": [
    {
      "label": "Car"
    },
    {
      "label": "Pedestrian"
    },
    {
      "label": "Cyclist"
    }
  ],
  "instructions": {
    "shortInstruction": "Select the appropriate label and paint all objects in the point cloud that it applies to the same color",
    "fullInstruction": "<html markup>"
  }
}
```

Select a tab in the following table to see an example of a label category configuration file for 3D point cloud verification or adjustment labeling jobs.

3D Point Cloud Adjustment

The following is an example of a label category configuration file for a 3D point cloud object detection or object tracking adjustment labeling job. For 3D point cloud semantic segmentation adjustment labeling jobs, categoryGlobalAttributes and categoryAttributes are not supported.
You must include `auditLabelAttributeName` to specify the label attribute name of the previous labeling job that you use to create the adjustment labeling job. Optionally, you can use the `editsAllowed` parameter to specify whether or not a label or frame attribute can be edited.

```json
{
  "documentVersion": "2020-03-01",
  "frameAttributes": [
    {
      "name": "count players",
      "description": "How many players do you see in the scene?",
      "type": "number"
    },
    {
      "name": "select one",
      "editsAllowed": "none",
      "description": "describe the scene",
      "type": "string",
      "enum": ["clear", "blurry"]
    }
  ],
  "categoryGlobalAttributes": [
    {
      "name": "W",
      "editsAllowed": "any",
      "description": "label-attributes-for-all-labels",
      "type": "string",
      "enum": ["foo", "buzz", "biz"]
    }
  ],
  "labels": [
    {
      "label": "Car",
      "editsAllowed": "any",
      "categoryAttributes": [
        {
          "name": "X",
          "description": "enter a number",
          "type": "number"
        },
        {
          "name": "Y",
          "description": "select an option",
          "type": "string",
          "enum": ["y1", "y2"],
          "editsAllowed": "any"
        },
        {
          "name": "Z",
          "description": "submit a free-form response",
          "type": "string",
          "editsAllowed": "none"
        }
      ]
    },
    {
      "label": "Pedestrian",
      "categoryAttributes": [...]}
  ],
  "instructions": {"shortInstruction": "Draw a tight Cuboid", "fullInstruction": "<html markup>",
  // include auditLabelAttributeName for label adjustment jobs
  "auditLabelAttributeName": "myPrevJobLabelAttributeName"
}
```
3D Point Cloud Verification

The following is an example of a label category configuration file you may use for a 3D point cloud object detection or object tracking verification labeling job. For a 3D point cloud semantic segmentation verification labeling job, categoryGlobalAttributes and categoryAttributes are not supported.

You must include auditLabelAttributeName to specify the label attribute name of the previous labeling job that you use to create the verification labeling job. Additionally, you must use the editsAllowed parameter to specify that no labels can be edited.

```json
{
    "documentVersion": "2020-03-01",
    "frameAttributes": [
        {
            "name": "count players",
            "editsAllowed": "any",
            "description": "How many players do you see in the scene?",
            "type": "number"
        },
        {
            "name": "select one",
            "editsAllowed": "any",
            "description": "describe the scene",
            "type": "string",
            "enum": ["clear", "blurry"
        }
    ],
    "categoryGlobalAttributes": [
        {
            "name": "W",
            "editsAllowed": "none",
            "description": "label-attributes-for-all-labels",
            "type": "string",
            "enum": ["foo", "buzz", "biz"],
        }
    ],
    "labels": [
        {
            "label": "Car",
            "editsAllowed": "none",
            "categoryAttributes": [
                {
                    "name": "X",
                    "description": "enter a number",
                    "type": "number",
                    "editsAllowed": "none"
                },
                {
                    "name": "Y",
                    "description": "select an option",
                    "type": "string",
                    "enum": ["y1", "y2"],
                    "editsAllowed": "any"
                },
                {
                    "name": "Z",
                    "description": "submit a free-form response",
                    "type": "string",
                    "editsAllowed": "none"
                }
            ]
        }
    ]
}
```
Example: Label Category Configuration Files for Video Frame Labeling Jobs

The annotation tools available to your worker and task type used depends on the value you specify for annotationType. For example, if you want workers to use key points to track changes in the pose of specific objects across multiple frames, you would specify Keypoint for the annotationType. If you do not specify an annotation type, BoundingBox will be used by default.

The following is an example of a video frame keypoint label category configuration file with label category attributes. This example includes two frame attributes, which will be added to all frames submitted to the labeling job. The Car label will include four label category attributes—X, Y, Z, and the global attribute, W.

```json
{
  "documentVersion": "2020-03-01",
  "frameAttributes": [
    {
      "name": "count players",
      "description": "How many players do you see in the scene?",
      "type": "number"
    },
    {
      "name": "select one",
      "description": "Describe the scene",
      "type": "string",
      "enum": ["clear", "blurry"]
    }
  ],
  "categoryGlobalAttributes": [
    {
      "name": "W",
      "description": "label-attributes-for-all-labels",
      "type": "string",
      "enum": ["foo", "buz", "buz2"]
    }
  ],
  "labels": [
    {
      "label": "Car",
      "categoryAttributes": [
        {
          "name": "X",
          "description": "Enter a number",
          "type": "number"
        },
        {
          "name": "Y",
          "description": "Select an option",
          "type": "string",
          "enum": ["y1", "y2"]
        }
      ]
    }
  ]
}
```
Select a tab from the following table to see examples of label category configuration files for video frame adjustment and verification labeling jobs.

**Video Frame Adjustment**

The following is an example of a label category configuration file you may use for a video frame adjustment labeling job.

You must include `auditLabelAttributeName` to specify the label attribute name of the previous labeling job that you use to create the verification labeling job. Optionally, you can use the `editsAllowed` parameter to specify whether or not labels, label category attributes, or frame attributes can be edited.

```json
{
    "documentVersion": "2020-03-01",
    "frameAttributes": [
        {
            "name": "count players",
            "editsAllowed": "none",
            "description": "How many players to you see in the scene?",
            "type": "number"
        },
        {
            "name": "select one",
            "description": "describe the scene",
            "type": "string",
            "enum": ["clear", "blurry"]
        }
    ],
    "categoryGlobalAttributes": [
        {
            "name": "W",
            "editsAllowed": "any",
            "description": "label-attributes-for-all-labels",
            "type": "string",
            "enum": ["foo", "buz", "buz2"]
        }
    ],
    "labels": [
        {
            "label": "Car",
            "editsAllowed": "any",
            "categoryAttributes": [
                {
                    "name": "X",
                    "description": "enter a number",
                    "type": "number",
                    "editsAllowed": "any"
                }
            ]
        }
    ]
}
```
Video Frame Verification

The following is an example of a label category configuration file for a video frame labeling job.

You must include `auditLabelAttributeName` to specify the label attribute name of the previous labeling job that you use to create the verification labeling job. Additionally, you must use the `editsAllowed` parameter to specify that no labels can be edited.

```json
{
  "documentVersion": "2020-03-01",
  "frameAttributes": [
    {
      "name": "count players",
      "editsAllowed": "none",
      "description": "How many players do you see in the scene?",
      "type": "number"
    },
    {
      "name": "select one",
      "editsAllowed": "any",
      "description": "describe the scene",
      "type": "string",
      "enum": ["clear", "blurry"]
    }
  ],
  "categoryGlobalAttributes": [
    {
      "name": "W",
      "editsAllowed": "none",
      "description": "label-attributes-for-all-labels",
      "type": "string",
      "enum": ["foo", "buz", "buz2"]
    }
  ],
  "labels": [
    {
      "name": "Y",
      "description": "select an option",
      "type": "string",
      "enum": ["y1", "y2"],
      "editsAllowed": "any"
    },
    {
      "name": "Z",
      "description": "submit a free-form response",
      "type": "string",
      "editsAllowed": "none"
    }
  ]
}
```
Creating Worker Instructions

Create custom instructions for labeling jobs to improve your worker's accuracy in completing their task. Your instructions are accessible when workers select the Instructions menu option in the worker UI. Short instructions must be under 255 characters and long instruction must be under 2,048 characters.

There are two kinds of instructions:

- **Short instructions** – These instructions are shown to workers when they select Instructions in the worker UI menu. They should provide an easy reference to show the worker the correct way to label an object.

- **Full instructions** – These instructions are shown when workers select More Instructions in instructions the pop-up window. We recommend that you provide detailed instructions for completing the task with multiple examples showing edge cases and other difficult situations for labeling objects.

For 3D point cloud and video frame labeling jobs, you can add worker instructions to your label category configuration file. You can use a single string to create instructions or you can add HTML mark up to customize the appearance of your instructions and add images. Make sure that any images you include in your instructions are publicly available, or if your instructions are in Amazon S3, that your workers have read-access so that they can view them.
Use Input and Output Data

The input data that you provide to Amazon SageMaker Ground Truth is sent to your workers for labeling. You choose the data to send to your workers by creating a single manifest file that defines all of the data that requires labeling or by sending input data objects to an ongoing, streaming labeling job to be labeled in real time.

The output data is the result of your labeling job. The output data file, or augmented manifest file, contains label data for each object you send to the labeling job and metadata about the label assigned to data objects.

When you use image classification (single and multi-label), text classification (single and multi-label), object detection, and semantic segmentation built in task types to create a labeling job, you can use the resulting augmented manifest file to launch a SageMaker training job. For a demonstration of how to use an augmented manifest to train an object detection machine learning model with Amazon SageMaker, see object_detection_augmented_manifest_training.ipynb. For more information, see Provide Dataset Metadata to Training Jobs with an Augmented Manifest File (p. 2700).

Topics
- Input Data (p. 572)
- 3D Point Cloud Input Data (p. 584)
- Video Frame Input Data (p. 608)
- Output Data (p. 614)

Input Data

The input data are the data objects that you send to your workforce to be labeled. There are two ways to send data objects to Ground Truth for labeling:

- Send a list of data objects that require labeling using an input manifest file.
- Send individual data objects in real time to a perpetually running, streaming labeling job.

If you have a dataset that needs to be labeled one time, and you do not require an ongoing labeling job, create a standard labeling job using an input manifest file.

If you want to regularly send new data objects to your labeling job after it has started, create a streaming labeling job. When you create a streaming labeling job, you can optionally use an input manifest file to specify a group of data that you want labeled immediately when the job starts. You can continuously send new data objects to a streaming labeling job as long as it is active.

Note

Streaming labeling jobs are only supported through the SageMaker API. You cannot create a streaming labeling job using the SageMaker console.

The following task types have special input data requirements and options:

- For 3D point cloud labeling job input data requirements, see 3D Point Cloud Input Data (p. 584).
- For video frame labeling job input data requirements, see Video Frame Input Data (p. 608).

Topics
- Use an Input Manifest File (p. 573)
- Automated Data Setup (p. 574)
- Supported Data Formats (p. 575)
- Ground Truth Streaming Labeling Jobs (p. 576)
Use an Input Manifest File

Each line in an input manifest file is an entry containing an object, or a reference to an object, to label. An entry can also contain labels from previous jobs and for some task types, additional information.

Input data and the manifest file must be stored in Amazon Simple Storage Service (Amazon S3). Each has specific storage and access requirements, as follows:

- The Amazon S3 bucket that contains the input data must be in the same AWS Region in which you are running Amazon SageMaker Ground Truth. You must give Amazon SageMaker access to the data stored in the Amazon S3 bucket so that it can read it. For more information about Amazon S3 buckets, see Working with Amazon S3 buckets.
- The manifest file must be in the same AWS Region as the data files, but it doesn't need to be in the same location as the data files. It can be stored in any Amazon S3 bucket that is accessible to the AWS Identity and Access Management (IAM) role that you assigned to Ground Truth when you created the labeling job.

**Note**

3D point cloud and video frame task types have different input manifest requirements and attributes. For 3D point cloud task types, refer to Create an Input Manifest File for a 3D Point Cloud Labeling Job (p. 586). For video frame task types, refer to Create a Video Frame Input Manifest File (p. 613).

The manifest is a UTF-8 encoded file in which each line is a complete and valid JSON object. Each line is delimited by a standard line break, \n or \r\n. Because each line must be a valid JSON object, you can't have unescaped line break characters. For more information about data format, see JSON Lines.

Each JSON object in the manifest file can be no larger than 100,000 characters. No single attribute within an object can be larger than 20,000 characters. Attribute names can't begin with $ (dollar sign).

Each JSON object in the manifest file must contain one of the following keys: source-ref or source. The value of the keys are interpreted as follows:

- **source-ref** – The source of the object is the Amazon S3 object specified in the value. Use this value when the object is a binary object, such as an image.
- **source** – The source of the object is the value. Use this value when the object is a text value.

The following is an example of a manifest file for files stored in an Amazon S3 bucket:

```json
{"source-ref": "s3 bucket location 1"},
{"source-ref": "s3 bucket location 2"}, 
...
{"source-ref": "s3 bucket location n"}
```

Use the source-ref key for image files for bounding box, image classification (single and multi-label), semantic segmentation, and video clips for video classification labeling jobs. 3D point cloud and video frame labeling jobs also use the source-ref key but these labeling jobs require additional information in the input manifest file. For more information see 3D Point Cloud Input Data (p. 584) and Video Frame Input Data (p. 608).

The following is an example of a manifest file with the input data stored in the manifest:
Use the `source` key for single and multi-label text classification and named entity recognition labeling jobs.

You can include other key-value pairs in the manifest file. These pairs are passed to the output file unchanged. This is useful when you want to pass information between your applications. For more information, see Output Data (p. 614).

Automated Data Setup

You can use the automated data setup to create manifest files for your labeling jobs in the Ground Truth console using images, videos, video frames, text (.txt) files, and comma-separated value (.csv) files stored in Amazon S3. When you use automated data setup, you specify an Amazon S3 location where your input data is stored and the input data type, and Ground Truth looks for the files that match that type in the location you specify.

**Note**

Ground Truth does not use an AWS KMS key to access your input data or write the input manifest file in the Amazon S3 location that you specify. The IAM user or role that creates the labeling job must have permissions to access your input data objects in Amazon S3.

Before using the following procedure, ensure that your input images or files are correctly formatted:

- **Image files** – Image files must comply with the size and resolution limits listed in the tables found in Input File Size Quota (p. 580).
- **Text files** – Text data can be stored in one or more .txt files. Each item that you want labeled must be separated by a standard line break.
- **CSV files** – Text data can be stored in one or more .csv files. Each item that you want labeled must be in a separate row.
- **Videos** – Video files can be any of the following formats: .mp4, .ogg, and .webm. If you want to extract video frames from your video files for object detection or object tracking, see Provide Video Files (p. 610).
- **Video frames** – Video frames are images extracted from a video. All images extracted from a single video are referred to as a sequence of video frames. Each sequence of video frames must have unique prefix keys in Amazon S3. See Provide Video Frames (p. 609). For this data type, see Automated Video Frame Input Data Setup (p. 611)

**Important**

For video frame object detection and video frame object tracking labeling jobs, see Automated Video Frame Input Data Setup (p. 611) to learn how to use the automated data setup.

Use these instructions to automatically set up your input dataset connection with Ground Truth.

**Automatically connect your data in Amazon S3 with Ground Truth**

   
   This link puts you in the North Virginia (us-east-1) AWS Region. If your input data is in an Amazon S3 bucket in another Region, switch to that Region. To change your AWS Region, on the navigation bar, choose the name of the currently displayed Region.

2. Select Create labeling job.

3. Enter a Job name.
4. In the section **Input data setup**, select **Automated data setup**.
5. Enter an Amazon S3 URI for **S3 location for input datasets**.
6. Specify your **S3 location for output datasets**. This is where your output data is stored.
7. Choose your **Data type** using the dropdown list.
8. Use the drop down menu under **IAM Role** to select an execution role. If you select **Create a new role**, specify the Amazon S3 buckets that you want grant this role permission to access. This role must have permission to access the S3 buckets you specified in Steps 5 and 6.
9. Select **Complete data setup**.

The following GIF demonstrates how to use the automated data setup for image data. This example will create a file, dataset-\texttt{YYMMDDTHHHMMSS}.manifest in the Amazon S3 bucket example-groundtruth-images where \texttt{YYMMDDTHHHMMSS} indicates the year (YY), month (MM), day (DD) and time in hours (HH), minutes (mm) and seconds (ss), that the input manifest file was created.

### Supported Data Formats

When you create an input manifest file for a **built-in task types** manually, your input data must be in one of the following support file formats for the respective input data type. To learn about automated data setup, see Automated Data Setup (p. 574).

**Tip**

When you use the automated data setup, additional data formats can be used to generate an input manifest file for video frame and text based task types.

<table>
<thead>
<tr>
<th>Task Types</th>
<th>Input Data Type</th>
<th>Support Formats</th>
<th>Example Input Manifest Line</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bounding Box, Semantic Segmentation, Image Classification (Single Label and Multi-label), Verify and Adjust Labels</td>
<td>Image</td>
<td>.jpg, .jpeg, .png</td>
<td>{&quot;source-ref&quot;: &quot;s3://DOC-EXAMPLE-BUCKET1/example-image.png&quot;}</td>
</tr>
<tr>
<td>Named Entity Recognition, Text Classification (Single and Multi-Label)</td>
<td>Text</td>
<td>Raw text</td>
<td>{&quot;source&quot;: &quot;Lorem ipsum dolor sit amet&quot;}</td>
</tr>
<tr>
<td>Video Classification</td>
<td>Video clips</td>
<td>.mp4, .ogg, and .webm</td>
<td>{&quot;source-ref&quot;: &quot;s3://example-video.mp4&quot;}</td>
</tr>
<tr>
<td>Video Frame Object Detection, Video Frame Object Tracking (bounding boxes, polylines, polygons or keypoint)</td>
<td>Video frames and video frame sequence files (for Object Tracking)</td>
<td>Video frames: .jpg, .jpeg, .png</td>
<td>Refer to Create a Video Frame Input Manifest File (p. 613).</td>
</tr>
<tr>
<td>3D Point Cloud Semantic Segmentation, 3D Point Cloud Object Detection,</td>
<td>Point clouds and point cloud sequence files (for Object Tracking)</td>
<td><strong>Point clouds</strong>: Binary pack format and ASCII. For more information see Accepted Raw 3D Data Formats (p. 584).</td>
<td>Refer to Create an Input Manifest File for a 3D Point Cloud Labeling Job (p. 586).</td>
</tr>
</tbody>
</table>
Ground Truth Streaming Labeling Jobs

If you want to perpetually send new data objects to Amazon SageMaker Ground Truth to be labeled, use a streaming labeling job. Streaming labeling jobs allow you to:

- Send new dataset objects to workers in real time using a perpetually running labeling job. Workers continuously receive new data objects to label as long as the labeling job is active and new objects are being sent to it.
- Gain visibility into the number of objects that have been queued and are waiting to be labeled. Use this information to control the flow of data objects sent to your labeling job.
- Receive label data for individual data objects in real time as workers finish labeling them.

Ground Truth streaming labeling jobs remain active until they are manually stopped or have been idle for more than 10 days. You can intermittently send new data objects to workers while the labeling job is active.

If you are a new user of Ground Truth streaming labeling jobs, it is recommended that you review How It Works (p. 576).

Use Create a Streaming Labeling Job (p. 552) to learn how to create a streaming labeling job.

Note
Ground Truth streaming labeling jobs are only supported through the SageMaker API.

Topics
- How It Works (p. 576)
- Send Data to a Streaming Labeling Job (p. 576)
- Manage Labeling Requests with an Amazon SQS Queue (p. 578)
- Receive Output Data from a Streaming Labeling Job (p. 578)
- Duplicate Message Handling (p. 578)

How It Works

When you create a Ground Truth streaming labeling job, the job remains active until it is manually stopped, remains idle for more than 10 days, or is unable to access input data sources. You can intermittently send new data objects to workers while it is active. A worker can continue to receive new data objects in real time as long as the total number of tasks currently available to the worker is less than the value in MaxConcurrentTaskCount. Otherwise, the data object is sent to a queue that Ground Truth creates on your behalf in Amazon Simple Queue Service (Amazon SQS) for later processing. These tasks are sent to workers as soon as the total number of tasks currently available to a worker falls below MaxConcurrentTaskCount. If a data object is not sent to a worker after 14 days, it expires. You can view the number of tasks pending in the queue and adjust the number of objects you send to the labeling job. For example, you may decrease the speed at which you send objects to the labeling job if the backlog of pending objects moves above a threshold.

Send Data to a Streaming Labeling Job

You can optionally submit input data to a streaming labeling job one time when you create the labeling job using an input manifest file. Once the labeling job has started and the state is InProgress, you
can submit new data objects to your labeling job in real time using your Amazon SNS input topic and Amazon S3 event notifications.

**Submit Data Objects When you Start the Labeling Job (One Time):**

- **Use an Input Manifest File** – You can optionally specify an input manifest file Amazon S3 URI in `ManifestS3Uri` when you create the streaming labeling job. Ground Truth sends each data object in the manifest file to workers for labeling as soon as the labeling job starts. To learn more, see Create a Manifest File (Optional) (p. 555).

After you submit a request to create the streaming labeling job, its status will be **Initializing**. Once the labeling job is active, the state changes to **InProgress** and you can start using the real-time options to submit additional data objects for labeling.

**Submit Data Objects in Real Time:**

- **Send data objects using Amazon SNS messages** – You can send Ground Truth new data objects to label by sending an Amazon SNS message. You will send this message to an Amazon SNS input topic that you create and specify when you create your streaming labeling job. For more information, see Send Data Objects Using Amazon SNS (p. 577).

- **Send data objects by placing them in an Amazon S3 bucket** – Each time you add a new data object to an Amazon S3 bucket, you can prompt Ground Truth to process that object for labeling. To do this, you add an event notification to the bucket so that it notifies your Amazon SNS input topic each time a new object is added to (or created in) that bucket. For more information, see Send Data Objects using Amazon S3 (p. 578). This option is not available for text-based labeling jobs such as text classification and named entity recognition.

  **Important**
  If you use the Amazon S3 configuration, do not use the same Amazon S3 location for your input data configuration and your output data. You specify the S3 prefix for your output data when you create a labeling job.

**Send Data Objects Using Amazon SNS**

You can send data objects to your streaming labeling job using Amazon Simple Notification Service (Amazon SNS). Amazon SNS is a web service that coordinates and manages the delivery of messages to and from endpoints (for example, an email address or AWS Lambda function). An Amazon SNS topic acts as a communication channel between two or more endpoints. You use Amazon SNS to send, or publish, new data objects to the topic specified in the `CreateLabelingJob` parameter `SnsTopicArn` in `InputConfig`. The format of these messages is the same as a single line from an input manifest file.

For example, you may send a piece of text to an active text classification labeling job by publishing it to your input topic. The message that you publish may look similar to the following:

```json
{"source": "Lorem ipsum dolor sit amet"}
```

To send a new image object to an image classification labeling job, your message may look similar to the following:

```json
{"source-ref": "s3://awsexamplebucket/example-image.jpg"}
```

**Note**

You can also include custom deduplication IDs and deduplication keys in your Amazon SNS messages. To learn more, see Duplicate Message Handling (p. 578).

When Ground Truth creates your streaming labeling job, it subscribes to your Amazon SNS input topic.
Send Data Objects using Amazon S3

You can send one or more new data objects to a streaming labeling job by placing them in an Amazon S3 bucket that is configured with an Amazon SNS event notification. You can set up an event to notify your Amazon SNS input topic anytime a new object is created in your bucket. You must specify this same Amazon SNS input topic in the `CreateLabelingJob` parameter `SnsTopicArn` in `InputConfig`.

Anytime you configure an Amazon S3 bucket to send notifications to Amazon SNS, Ground Truth will publish a test event, "s3:TestEvent", to ensure that the topic exists and that the owner of the Amazon S3 bucket specified has permission to publish to the specified topic. It is recommended that you set up your Amazon S3 connection with Amazon SNS before starting a streaming labeling job. If you do not, this test event may register as a data object and be sent to Ground Truth for labeling.

**Important**
- If you use the Amazon S3 configuration, do not use the same Amazon S3 location for your input data configuration and your output data. You specify the S3 prefix for your output data when you create a labeling job.
- For image-based labeling jobs, Ground Truth requires all S3 buckets to have a CORS policy attached. To learn more, see CORS Permission Requirement (p. 649).

Once you have configured your Amazon S3 bucket and created your labeling job, you can add objects to your bucket and Ground Truth either sends that object to workers or places it on your Amazon SQS queue.

To learn more, see Set up Amazon S3 Bucket Event Notifications (p. 555).

**Important**
- This option is not available for text-based labeling jobs such as text classification and named entity recognition.

Manage Labeling Requests with an Amazon SQS Queue

When Ground Truth creates your streaming labeling job, it creates an Amazon SQS queue in the AWS account used to create the labeling job. The queue name is `GroundTruth-labeling_job_name` where `labeling_job_name` is the name of your labeling job, in lowercase letters. When you send data objects to your labeling job, Ground Truth either sends the data objects directly to workers or places the task in your queue to be processed at a later time. If a data object is not sent to a worker after 14 days, it expires and is removed from the queue. You can setup an alarm in Amazon SQS to detect when objects expire and use this mechanism to control the volume of objects you send to your labeling job.

**Important**
- Modifying, deleting, or sending objects directly to the Amazon SQS queue associated with your streaming labeling job may lead to job failures.

Receive Output Data from a Streaming Labeling Job

Your Amazon S3 output bucket is periodically updated with new output data from your streaming labeling job.

Optionally, you can specify an Amazon SNS output topic. Each time a worker submits a labeled object, a notification with the output data is sent to that topic. You can subscribe an endpoint to your SNS output topic to receive notifications or trigger events when you receive output data from a labeling task. Use an Amazon SNS output topic if you want to do real time chaining to another streaming job and receive an Amazon SNS notifications each time a data object is submitted by a worker.

To learn more, see Subscribe an Endpoint to Your Amazon SNS Output Topic (p. 554).

Duplicate Message Handling

For data objects sent in real time, Ground Truth guarantees idempotency by ensuring each unique object is only sent for labeling once, even if the input message referring to that object is received multiple
times (duplicate messages). To do this, each data object sent to a streaming labeling job is assigned a deduplication ID, which is identified with a deduplication key.

If you send your requests to label data objects directly through your Amazon SNS input topic using Amazon SNS messages, you can optionally choose a custom deduplication key and deduplication IDs for your objects. For more information, see Specify A Deduplication Key and ID in an Amazon SNS Message (p. 579).

If you do not provide your own deduplication key, or if you use the Amazon S3 configuration to send data objects to your labeling job, Ground Truth uses one of the following for the deduplication ID:

- For messages sent directly to your Amazon SNS input topic, Ground Truth uses the SNS message ID.
- For messages that come from an Amazon S3 configuration, Ground Truth creates a deduplication ID by combining the Amazon S3 URI of the object with the sequencer token in the message.

Specify A Deduplication Key and ID in an Amazon SNS Message

When you send a data object to your streaming labeling job using an Amazon SNS message, you have the option to specify your deduplication key and deduplication ID in one of the following ways. In all of these scenarios, identify your deduplication key with dataset-objectid-attribute-name.

Bring Your Own Deduplication Key and ID

Create your own deduplication key and deduplication ID by configuring your Amazon SNS message as follows. Replace byo-key with your key and UniqueId with the deduplication ID for that data object.

```json
{
   "source-ref": "s3://bucket/prefix/object1",
   "dataset-objectid-attribute-name": "byo-key",
   "byo-key": "UniqueId"
}
```

Your deduplication key can be up to 140 characters. Supported patterns include: "^[a-zA-Z0-9](-*[a-zA-Z0-9])*".

Your deduplication ID can be up to 1,024 characters. Supported patterns include: ^((https|s3)://([^/]+)?(.*))$.

Use an Existing Key for your Deduplication Key

You can use an existing key in your message as the deduplication key. When you do this, the value associated with that key is used for the deduplication ID.

For example, you can specify use the source-ref key as your deduplication key by formatting your message as follows:

```json
{
   "source-ref": "s3://bucket/prefix/object1",
   "dataset-objectid-attribute-name": "source-ref"
}
```

In this example, Ground Truth uses "s3://bucket/prefix/object1" for the deduplication id.

Find Deduplication Key and ID in Your Output Data

You can see the deduplication key and ID in your output data. The deduplication key is identified by dataset-objectid-attribute-name.
When you use your own custom deduplication key, your output contains something similar to the following:

```
"dataset-objectid-attribute-name": "byo-key",
"byo-key": "UniqueId",
```

When you do not specify a key, you can find the deduplication ID that Ground Truth assigned to your data object as follows. The `$label-attribute-name-object-id` parameter identifies your deduplication ID.

```
{
  "source-ref":"s3://bucket/prefix/object1",
  "dataset-objectid-attribute-name":"$label-attribute-name-object-id"
  "label-attribute-name" :0,
  "label-attribute-name-metadata": {...},
  "$label-attribute-name-object-id":"<service-generated-key>"
}
```

For `<service-generated-key>`, if the data object came through an Amazon S3 configuration, Ground Truth adds a unique value used by the service and emits a new field keyed by `$sequencer` which shows the Amazon S3 sequencer used. If object was fed to SNS directly, Ground Truth use the SNS message ID.

**Note**

Do not use the `$` character in your label attribute name.

### Input Data Quotas

Input datasets used in semantic segmentation labeling jobs have a quota of 20,000 items. For all other labeling job types, the dataset size quota is 100,000 items. To request an increase to the quota for labeling jobs other than semantic segmentation jobs, review the procedures in [AWS Service Quotas](https://aws.amazon.com/servicequotas) to request a quota increase.

Input image data for active and non-active learning labeling jobs must not exceed size and resolution quotas. *Active learning* refers to labeling job that use automated data labeling. *Non-active learning* refers to labeling jobs that don't use automated data labeling.

Additional quotas apply for label categories for all task types, and for input data and labeling category attributes for 3D point cloud and video frame task types.

### Input File Size Quota

Input files can't exceed the following size- quotas for both active and non-active learning labeling jobs. There is no input file size quota for videos used in *video classification* labeling jobs.

<table>
<thead>
<tr>
<th>Labeling Job Task Type</th>
<th>Input File Size Quota</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image classification</td>
<td>40 MB</td>
</tr>
<tr>
<td>Bounding box (Object detection)</td>
<td>40 MB</td>
</tr>
<tr>
<td>Semantic segmentation</td>
<td>40 MB</td>
</tr>
<tr>
<td>Bounding box (Object detection) label adjustment</td>
<td>40 MB</td>
</tr>
<tr>
<td>Semantic segmentation label adjustment</td>
<td>40 MB</td>
</tr>
<tr>
<td>Bounding box (Object detection) label verification</td>
<td>40 MB</td>
</tr>
<tr>
<td>Semantic segmentation label verification</td>
<td>40 MB</td>
</tr>
</tbody>
</table>
Input Image Resolution Quotas

Image file resolution refers to the number of pixels in an image, and determines the amount of detail an image holds. Image resolution quotas differ depending on the labeling job type and the SageMaker built-in algorithm used. The following table lists the resolution quotas for images used in active and non-active learning labeling jobs.

<table>
<thead>
<tr>
<th>Labeling Job Task Type</th>
<th>Resolution Quota - Non Active Learning</th>
<th>Resolution Quota - Active Learning</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image classification</td>
<td>100 million pixels</td>
<td>3840 x 2160 pixels (4 K)</td>
</tr>
<tr>
<td>Bounding box (Object detection)</td>
<td>100 million pixels</td>
<td>3840 x 2160 pixels (4 K)</td>
</tr>
<tr>
<td>Semantic segmentation</td>
<td>100 million pixels</td>
<td>1920 x 1080 pixels (1080 p)</td>
</tr>
<tr>
<td>Object detection label adjustment</td>
<td>100 million pixels</td>
<td>3840 x 2160 pixels (4 K)</td>
</tr>
<tr>
<td>Semantic segmentation label adjustment</td>
<td>100 million pixels</td>
<td>1920 x 1080 pixels (1080 p)</td>
</tr>
<tr>
<td>Object detection label verification</td>
<td>100 million pixels</td>
<td>Not available</td>
</tr>
<tr>
<td>Semantic segmentation label verification</td>
<td>100 million pixels</td>
<td>Not available</td>
</tr>
</tbody>
</table>

Label Category Quotas

Each labeling job task type has a quota for the number of label categories you can specify. Workers select label categories to create annotations. For example, you may specify label categories car, pedestrian, and biker when creating a bounding box labeling job and workers will select the car category before drawing bounding boxes around cars.

**Important**

Label category names cannot exceed 256 characters.
All label categories must be unique. You cannot specify duplicate label categories.

The following label category limits apply to labeling jobs. Quotas for label categories depend on whether you use the SageMaker API operation CreateLabelingJob or the console to create a labeling job.

<table>
<thead>
<tr>
<th>Labeling Job Task Type</th>
<th>Label Category Quota - API</th>
<th>Label Category Quota - Console</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image classification (Multi-label)</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Image classification (Single label)</td>
<td>Unlimited</td>
<td>30</td>
</tr>
<tr>
<td>Bounding box (Object detection)</td>
<td>50</td>
<td>50</td>
</tr>
<tr>
<td>Label verification</td>
<td>Unlimited</td>
<td>30</td>
</tr>
<tr>
<td>Semantic segmentation (with active learning)</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>Semantic segmentation (without active learning)</td>
<td>Unlimited</td>
<td>10</td>
</tr>
</tbody>
</table>
Use Input and Output Data

Labeling Job Task Type | Label Category Quota - API | Label Category Quota - Console
--- | --- | ---
Named entity recognition | Unlimited | 30
Text classification (Multi-label) | 50 | 50
Text classification (Single label) | Unlimited | 30
Video classification | 30 | 30
Video frame object detection | 30 | 30
Video frame object tracking | 30 | 30
3D point cloud object detection | 30 | 30
3D point cloud object tracking | 30 | 30
3D point cloud semantic segmentation | 30 | 30

3D Point Cloud and Video Frame Labeling Job Quotas

The following quotas apply for 3D point cloud and video frame labeling job input data.

<table>
<thead>
<tr>
<th>Labeling Job Task Type</th>
<th>Input Data Quota</th>
</tr>
</thead>
<tbody>
<tr>
<td>Video frame object detection</td>
<td>2,000 video frames (images) per sequence</td>
</tr>
<tr>
<td>Video frame object detection</td>
<td>10 video frame sequences per manifest file</td>
</tr>
<tr>
<td>Video frame object tracking</td>
<td>2,000 video frames (images) per sequence</td>
</tr>
<tr>
<td>Video frame object tracking</td>
<td>10 video frame sequences per manifest file</td>
</tr>
<tr>
<td>3D point cloud object detection</td>
<td>100,000 point cloud frames per labeling job</td>
</tr>
<tr>
<td>3D point cloud object tracking</td>
<td>100,000 point cloud frame sequences per labeling job</td>
</tr>
<tr>
<td>3D point cloud object tracking</td>
<td>500 point cloud frames in each sequence file</td>
</tr>
</tbody>
</table>

When you create a video frame or 3D point cloud labeling job, you can add one or more label category attributes to each label category that you specify to have workers provide more information about an annotation.

Each label category attribute has a single label category attribute name, and a list of one or more options (values) to choose from. To learn more, see Worker User Interface (UI) (p. 469) for 3D point cloud labeling jobs and Worker User Interface (UI) (p. 421) for video frame labeling jobs.

The following quotas apply to the number of label category attributes names and values you can specify for labeling jobs.
Filter and Select Data for Labeling

You can use the Amazon SageMaker console to select a portion of your dataset for labeling. The data must be stored in an Amazon S3 bucket. You have three options:

- Use the full dataset.
- Choose a randomly selected sample of the dataset.
- Specify a subset of the dataset using a query.

The following options are available in the Labeling jobs section of the SageMaker console after selecting Create labeling job. To learn how to create a labeling job in the console, see Getting started (p. 371). To configure the dataset that you use for labeling, in the Job overview section, choose Additional configuration.

Use the Full Dataset

When you choose to use the Full dataset, you must provide a manifest file for your data objects. You can provide the path of the Amazon S3 bucket that contains the manifest file or use the SageMaker console to create the file. To learn how to create a manifest file using the console, see Automated Data Setup (p. 574).

Choose a Random Sample

When you want to label a random subset of your data, select Random sample. The dataset is stored in the Amazon S3 bucket specified in the Input dataset location field.

After you have specified the percentage of data objects that you want to include in the sample, choose Create subset. SageMaker randomly picks the data objects for your labeling job. After the objects are selected, choose Use this subset.

SageMaker creates a manifest file for the selected data objects. It also modifies the value in the Input dataset location field to point to the new manifest file.

Specify a Subset

You can specify a subset of your data objects using an Amazon S3 SELECT query on the object file names.

The SELECT statement of the SQL query is defined for you. You provide the WHERE clause to specify which data objects should be returned.

For more information about the Amazon S3 SELECT statement, see Selecting Content from Objects. Choose Create subset to start the selection, and then choose Use this subset to use the selected data.

SageMaker creates a manifest file for the selected data objects. It also updates the value in the Input dataset location field to point to the new manifest file.

<table>
<thead>
<tr>
<th>Labeling Job Task Type</th>
<th>Label Category Attribute (name) Quota</th>
<th>Label Category Attribute Values Quota</th>
</tr>
</thead>
<tbody>
<tr>
<td>Video frame object tracking</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>3D point cloud object detection</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>3D point cloud object tracking</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>3D point cloud semantic segmentation</td>
<td>10</td>
<td>10</td>
</tr>
</tbody>
</table>
3D Point Cloud Input Data

To create a 3D point cloud labeling job, you must create an input manifest file. Use this topic to learn the formatting requirements of the input manifest file for each task type. To learn about the raw input data formats Ground Truth accepts for 3D point cloud labeling jobs, see the section Accepted Raw 3D Data Formats (p. 584).

Use your labeling job task type to choose a topics on Create an Input Manifest File for a 3D Point Cloud Labeling Job (p. 586) to learn about the formatting requirements for each line of your input manifest file.

Topics
- Accepted Raw 3D Data Formats (p. 584)
- Create an Input Manifest File for a 3D Point Cloud Labeling Job (p. 586)
- Understand Coordinate Systems and Sensor Fusion (p. 599)

Accepted Raw 3D Data Formats

Ground Truth uses your 3D point cloud data to render a 3D scenes that workers annotate. This section describes the raw data formats that are accepted for point cloud data and sensor fusion data for a point cloud frame. To learn how to create an input manifest file to connect your raw input data files with Ground Truth, see Create an Input Manifest File for a 3D Point Cloud Labeling Job (p. 586).

For each frame, Ground Truth supports Compact Binary Pack Format (.bin) and ASCII (.txt) files. These files contain information about the location (x, y, and z coordinates) of all points that make up that frame, and, optionally, information about the pixel color of each point for colored point clouds. When you create a 3D point cloud labeling job input manifest file, you can specify the format of your raw data in the format parameter.

The following table lists elements that Ground Truth supports in point cloud frame files to describe individual points.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>x</td>
<td>The x coordinate of the point.</td>
</tr>
<tr>
<td>y</td>
<td>The y coordinate of the point.</td>
</tr>
<tr>
<td>z</td>
<td>The z coordinate of the point.</td>
</tr>
<tr>
<td>i</td>
<td>The intensity of the point.</td>
</tr>
<tr>
<td>r</td>
<td>The red color channel component. An 8-bit value (0-255).</td>
</tr>
<tr>
<td>g</td>
<td>The green color channel component. An 8-bit value (0-255)</td>
</tr>
<tr>
<td>b</td>
<td>The blue color channel component. An 8-bit value (0-255)</td>
</tr>
</tbody>
</table>

Ground Truth assumes the following about your input data:
- All of the positional coordinates (x, y, z) are in meters.
- All the pose headings (qx, qy, qz, qw) are measured in Spatial Quaternions.
Compact Binary Pack Format

The Compact Binary Pack Format represents a point cloud as an ordered set of a stream of points. Each point in the stream is an ordered binary pack of 4-byte float values in some variant of the form xyzirgb. The x, y, and z elements are required and additional information about that pixel can be included in a variety of ways using i, r, g, and b.

To use a binary file to input point cloud frame data to a Ground Truth 3D point cloud labeling job, enter binary/ in the format parameter for your input manifest file and replace with the order of elements in each binary pack. For example, you may enter one of the following for the format parameter.

- `binary/xyzi` – When you use this format, your point element stream would be in the following order: x1y1z1i1x2y2z2i2...
- `binary/xyzrgb` – When you use this format, your point element stream would be in the following order: x1y1z1r1g1b1x2y2z2r2g2b2...
- `binary/xyzirgb` – When you use this format, your point element stream would be in the following order: x1y1z1i1r1g1b1x2y2z2i2r2g2b2...

When you use a binary file for your point cloud frame data, if you do not enter a value for format, the default pack format binary/xyzi is used.

ASCII Format

The ASCII format uses a text file to represent a point cloud, where each line in the ASCII point cloud file represents a single point. Each point is a line the text file and contains white space separated values, each of which is a 4-byte float ASCII values. The x, y, and z elements are required for each point and additional information about that point can be included in a variety of ways using i, r, g, and b.

To use a text file to input point cloud frame data to a Ground Truth 3D point cloud labeling job, enter text/ in the format parameter for your input manifest file and replace with the order of point elements on each line.

For example, if you enter text/xyzi for format, your text file for each point cloud frame should look similar to the following:

```
x1 y1 z1 i1
x2 y2 z2 i2
...
```

If you enter text/xyzrgb, your text file should look similar to the following:

```
x1 y1 z1 r1 g1 b1
x2 y2 z2 r2 g2 b1
...
```

When you use a text file for your point cloud frame data, if you do not enter a value for format, the default format text/xyzi will be used.

Point Cloud Resolution Limits

Ground Truth does not have a resolution limit for 3D point cloud frames. However, we recommend that you limit each point cloud frame to 500K points for optimal performance. When Ground Truth renders the 3D point cloud visualization, it must be viewable on your workers' computers, which depends on workers' computer hardware. Point cloud frames that are larger than 1 million points may not render on standard machines, or may take too long to load.
Create an Input Manifest File for a 3D Point Cloud Labeling Job

When you create a labeling job, you provide an input manifest file where each line of the manifest describes a unit of task to be completed by annotators. The format of your input manifest file depends on your task type.

- If you are creating a 3D point cloud **object detection** or **semantic segmentation** labeling job, each line in your input manifest file contains information about a single 3D point cloud frame. This is called a **point cloud frame input manifest**. To learn more, see Create a Point Cloud Frame Input Manifest File (p. 586).

- If you are creating a 3D point cloud **object tracking** labeling job, each line of your input manifest file contains a sequence of 3D point cloud frames and associated data. This is called a **point cloud sequence input manifest**. To learn more, see Create a Point Cloud Sequence Input Manifest File (p. 592).

Create a Point Cloud Frame Input Manifest File

The manifest is a UTF-8 encoded file in which each line is a complete and valid JSON object. Each line is delimited by a standard line break, \n or \n\n. Because each line must be a valid JSON object, you can't have unescaped line break characters. In the single-frame input manifest file, each line in the manifest contains data for a single point cloud frame. The point cloud frame data can either be stored in binary or ASCII format (see Accepted Raw 3D Data Formats (p. 584)). This is the manifest file formatting required for 3D point cloud object detection and semantic segmentation. Optionally, you can also provide camera sensor fusion data for each point cloud frame.

Ground Truth supports point cloud and video camera sensor fusion in the **world coordinate system** (p. 599) for all modalities. If you can obtain your 3D sensor extrinsic (like a LiDAR extrinsic), we recommend that you transform 3D point cloud frames into the world coordinate system using the extrinsic. For more information, see Sensor Fusion (p. 601).

However, if you cannot obtain a point cloud in world coordinate system, you can provide coordinates in the original coordinate system that the data was captured in. If you are providing camera data for sensor fusion, it is recommended that you provide LiDAR sensor and camera pose in the world coordinate system.

To create a single-frame input manifest file, you will identify the location of each point cloud frame that you want workers to label using the **source-ref** key. Additionally, you must use the **source-ref-metadata** key to identify the format of your dataset, a timestamp for that frame, and, optionally, sensor fusion data and video camera images.

The following example demonstrates the syntax used for an input manifest file for a single-frame point cloud labeling job. The example includes two point cloud frames. For details about each parameter, see the table following this example.

**Important**

Each line in your input manifest file must be in **JSON Lines** format. The following code block shows an input manifest file with two JSON objects. Each JSON object is used to point to and provide details about a single point cloud frame. The JSON objects have been expanded for readability, but you must minimize each JSON object to fit on a single line when creating an input manifest file. An example is provided under this code block.

```
{
"source-ref": "s3://awsexamplebucket/examplefolder/frame1.bin",
"source-ref-metadata":{
   "format": "binary/xyzi",
   "unix-timestamp": 1566861644.759115,
   "ego-vehicle-pose":{
      "position": {
         "x": -2.7161461413869947,
         "y": 116.25822288149078,
```

586
"z": 1.8348751887989483,
"heading": {
"qx": -0.02111296123795955,
"qy": -0.006495469416730261,
"qz": -0.000024565904865688,
"qw": 0.9997181192298087
},
"prefix": "s3://awsexamplebucket/lidar_singleframe_dataset/someprefix/",
"images": [
{
"image-path": "images/frame300.bin_camera0.jpg",
"unix-timestamp": 1566861644.759115,
"fx": 847.7962624528487,
"fy": 850.034093791985,
"cx": 576.2129134707038,
"cy": 317.2423573573745,
"k1": 0,
"k2": 0,
"k3": 0,
"k4": 0,
"p1": 0,
"p2": 0,
"skew": 0,
"position": {
"x": -2.2722515189268138,
"y": 116.86003310568965,
"z": 1.454614668542299
},
"heading": {
"qx": 0.7594754093069037,
"qy": 0.02181790885672969,
"qz": -0.02461725233103356,
"qw": -0.6496916273040025
},
"camera-model": "pinhole"
}]
]

"source-ref": "s3://awsexamplebucket/examplefolder/frame2.bin",
"source-ref-metadata":{
"format": "binary/xyzi",
"unix-timestamp": 1566861632.759133,
"ego-vehicle-pose":{
"position": {
"x": -2.7161461413869947,
"y": 116.25822288149078,
"z": 1.8348751887989483
},
"heading": {
"qx": 0.7594754093069037,
"qy": 0.02181790885672969,
"qz": -0.02461725233103356,
"qw": -0.6496916273040025
}
},
"prefix": "s3://awsexamplebucket/lidar_singleframe_dataset/someprefix/",
"images": [
{
"image-path": "images/frame300.bin_camera0.jpg",
"unix-timestamp": 1566861644.759115,
"fx": 847.7962624528487,
"fy": 850.034093791985,
"cx": 576.2129134707038,
When you create an input manifest file, you must collapse your JSON objects to fit on a single line. For example, the code block above would appear as follows in an input manifest file:

```
{"source-ref":"s3://awsexamplebucket/examplefolder/frame1.bin","source-ref-metadata":
{"format":"binary/xyzi","unix-timestamp":1566861644.759115,"ego-vehicle-pose":{"position":
{"x":-2.7161461413869947,"y":116.2582228140078,"z":1.8348751887989483},"heading":
{"qx":-0.02111296123795955,"qy":-0.006495469416730261,"qz":-0.008024565904865688,"qw":0.9997181912290868},"prefix":"s3://awsexamplebucket/lidar_singleframe_dataset/someprefix/"},"images":
[{"image-path":"images/frame300.bin_camera0.jpg","unix-timestamp":1566861644.759115,"fx":847.7962624528487,"fy":850.0340893791985,"cx":576.2129134707038,"cy":317.2423573573745,"k1":0,"k2":0,"k3":0,"k4":0,"p1":0,"p2":0,"skew":0,"position":
{"x":-2.272215189268138,"y":116.86003310568965,"z":1.45641668542299},
"heading":
{"qx":0.75914754093069037,"qy":0.02181790885672969,"qz":-0.0246172523310356,"qw":-0.6496916273040025},
"camera-model":"pinhole"}]
}]
```

The following table shows the parameters you can include in your input manifest file:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>source-ref</td>
<td>Yes</td>
<td>String</td>
<td>The Amazon S3 location of a single point cloud frame.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Accepted string value format:</strong> s3://bucket-name//folder-name//point-cloud-frame-file</td>
<td></td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>source-ref-metadata</td>
<td>Yes</td>
<td>JSON object</td>
<td>Use this parameter to include additional information about the point cloud in source-ref, and to provide camera data for sensor fusion.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Accepted</strong></td>
<td>Parameters: format, unix-timestamp, ego-vehicle-pose, position, prefix, images</td>
</tr>
<tr>
<td>format</td>
<td>No</td>
<td><strong>String</strong></td>
<td>Use this parameter to specify the format of your point cloud data. For more information, see [Accepted Raw 3D Data Formats](p. 584).</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Accepted string values</strong>:</td>
<td>&quot;binary/xyz&quot;, &quot;binary/xyzl&quot;, &quot;binary/xyzrgb&quot;, &quot;binary/xyzirgb&quot;, &quot;text/xyz&quot;, &quot;text/xyzl&quot;, &quot;text/xyzrgb&quot;, &quot;text/xyzirgb&quot;</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Default Values</strong>:</td>
<td>When the file identified in source-ref has a .bin extension, binary/xyzl</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>When the file identified in source-ref has a .txt extension, text/xyzl</td>
</tr>
<tr>
<td>unix-timestamp</td>
<td>Yes</td>
<td>Number</td>
<td>The unix timestamp is the number of seconds since January 1st, 1970 until the UTC time that the data was collected by a sensor.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>A unix timestamp.</strong></td>
<td></td>
</tr>
<tr>
<td>ego-vehicle-pose</td>
<td>No</td>
<td>JSON object</td>
<td>The pose of the device used to collect the point cloud data. For more information about this parameter, see [Include Vehicle Pose Information in Your Input Manifest](p. 590).</td>
</tr>
</tbody>
</table>
Use Input and Output Data

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
</table>
| prefix    | No       | String          | The location in Amazon S3 where your metadata, such as camera images, is stored for this frame. The prefix must end with a forward slash: /.
| images    | No       | List            | A list of parameters describing color camera images used for sensor fusion. You can include up to 8 images in this list. For more information about the parameters required for each image, see Include Camera Data in Your Input Manifest (p. 591). |

Include Vehicle Pose Information in Your Input Manifest

Use the ego-vehicle location to provide information about the location of the vehicle used to capture point cloud data. Ground Truth use this information to compute LiDAR extrinsic matrix.

Ground Truth uses extrinsic matrices to project labels to and from the 3D scene and 2D images. For more information, see Sensor Fusion (p. 601).

The following table provides more information about the position and orientation (heading) parameters that are required when you provide ego-vehicle information.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>position</td>
<td>Yes</td>
<td>JSON object</td>
<td>The translation vector of the ego vehicle in the world coordinate system.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Required Parameters: x, y, and z. Enter numbers for these parameters.</td>
<td></td>
</tr>
<tr>
<td>heading</td>
<td>Yes</td>
<td>JSON Object</td>
<td>The orientation of the frame of reference of the device or sensor mounted on the vehicle sensing the surrounding, measured in quaternions, (qx, qy, qz, qw) in the a coordinate system.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Required Parameters: qx, qy, qz, and qw. Enter numbers for these parameters.</td>
<td></td>
</tr>
</tbody>
</table>
Include Camera Data in Your Input Manifest

If you want to include video camera data with a frame, use the following parameters to provide information about each image. The **Required** column below applies when the images parameter is included in the input manifest file under `source-ref-metadata`. You are not required to include images in your input manifest file.

If you include camera images, you must include information about the camera position and heading used to capture the images in the world coordinate system.

If your images are distorted, Ground Truth can automatically undistort them using information you provide about the image in your input manifest file, including distortion coefficients ($k_1$, $k_2$, $k_3$, $k_4$, $p_1$, $p_1$), the camera model and the camera intrinsic matrix. The intrinsic matrix is made up of focal length ($f_x$, $f_y$), and the principal point ($c_x$, $c_y$). See [Intrinsic Matrix](#) to learn how Ground Truth uses the camera intrinsic. If distortion coefficients are not included, Ground Truth will not undistort an image.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>image-path</td>
<td>Yes</td>
<td>String</td>
<td>The relative location, in Amazon S3 of your image file. This relative path will be appended to the path you specify in prefix.</td>
</tr>
<tr>
<td>unix-timestamp</td>
<td>Yes</td>
<td>Number</td>
<td>The unix timestamp is the number of seconds since January 1st, 1970 until the UTC time that the data was collected by a camera.</td>
</tr>
<tr>
<td>camera-model</td>
<td>No</td>
<td>String:</td>
<td>The model of the camera used to capture the image. This information is used to undistort camera images.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Accepted Values:</td>
<td>''pinhole'', ''fisheye''</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Default:</td>
<td>''pinhole''</td>
</tr>
<tr>
<td>$f_x$, $f_y$</td>
<td>Yes</td>
<td>Numbers</td>
<td>The focal length of the camera, in the $x$ ($f_x$) and $y$ ($f_y$) directions.</td>
</tr>
<tr>
<td>$c_x$, $c_y$</td>
<td>Yes</td>
<td>Numbers</td>
<td>The $x$ ($c_x$) and $y$ ($c_y$) coordinates of the principal point.</td>
</tr>
<tr>
<td>$k_1$, $k_2$, $k_3$, $k_4$</td>
<td>No</td>
<td>Number</td>
<td>Radial distortion coefficients. Supported for both <em>fisheye</em> and <em>pinhole</em> camera models.</td>
</tr>
<tr>
<td>$p_1$, $p_2$</td>
<td>No</td>
<td>Number</td>
<td>Tangential distortion coefficients. Supported</td>
</tr>
</tbody>
</table>
### Use Input and Output Data

#### Parameter

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>skew</td>
<td>No</td>
<td>Number</td>
<td>A parameter to measure the skew of an image.</td>
</tr>
<tr>
<td>position</td>
<td>Yes</td>
<td>JSON object</td>
<td>The location or origin of the frame of reference of the camera mounted on the vehicle capturing images.</td>
</tr>
<tr>
<td>heading</td>
<td>Yes</td>
<td>JSON Object</td>
<td>The orientation of the frame of reference of the camera mounted on the vehicle capturing images, measured using quaternions, ((qx, qy, qz, qw)), in the world coordinate system.</td>
</tr>
</tbody>
</table>

#### Point Cloud Frame Limits

You can include up to 100,000 point cloud frames in your input manifest file. 3D point cloud labeling job have longer pre-processing times than other Ground Truth task types. For more information, see Job Pre-processing Time (p. 468).

#### Create a Point Cloud Sequence Input Manifest

The manifest is a UTF-8 encoded file in which each line is a complete and valid JSON object. Each line is delimited by a standard line break, \n or \n\n. Because each line must be a valid JSON object, you can't have unescaped line break characters. In the point cloud sequence input manifest file, each line in the manifest contains a sequence of point cloud frames. The point cloud data for each frame in the sequence can either be stored in binary or ASCII format. For more information, see Accepted Raw 3D Data Formats (p. 584). This is the manifest file formatting required for 3D point cloud object tracking. Optionally, you can also provide point attribute and camera sensor fusion data for each point cloud frame. When you create a sequence input manifest file, you must provide LiDAR and video camera sensor fusion data in a world coordinate system (p. 599).

The following example demonstrates the syntax used for an input manifest file when each line in the manifest is a sequence file. Each line in your input manifest file must be in JSON Lines format.

```json
{"source-ref": "s3://awsexamplebucket/example-folder/seq1.json"}
{"source-ref": "s3://awsexamplebucket/example-folder/seq2.json"}
```

The data for each sequence of point cloud frames needs to be stored in a JSON data object. The following is an example of the format you use for a sequence file. Information about each frame is included as a JSON object and is listed in the \frames list. This is an example of a sequence file with two point cloud frame files, \texttt{frame300.bin} and \texttt{frame303.bin}. The \ldots is used to indicated where you should include information for additional frames. Add a JSON object for each frame in the sequence.

The following code block includes a JSON object for a single sequence file. The JSON object has been expanded for readability.
The following table provides details about the top-level parameters of a sequence file. For detailed information about the parameters required for individual frames in the sequence file, see Parameters for Individual Point Cloud Frames (p. 594).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>seq-no</td>
<td>Yes</td>
<td>Integer</td>
<td>The ordered number of the sequence.</td>
</tr>
</tbody>
</table>
| prefix        | Yes      | String          | The Amazon S3 location where the sequence files are located. The prefix must end with a forward slash: /.
| number-of-frames | Yes    | Integer         | The total number of frames included in the sequence file. This number must match the total number of frames listed in the frames parameter in the next row. |
| frames        | Yes      | List of JSON objects | A list of frame data. The length of the list must equal number-of-frames. In the worker UI, frames in a sequence will be the same as the order of frames in this array. For details about the format of each frame, see Parameters for Individual Point Cloud Frames (p. 594). |

Parameters for Individual Point Cloud Frames

The following table shows the parameters you can include in your input manifest file.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>frame-no</td>
<td>No</td>
<td>Integer</td>
<td>A frame number. This is an optional identifier specified by the customer to identify the frame within a sequence. It is not used by Ground Truth.</td>
</tr>
<tr>
<td>Parameter</td>
<td>Required</td>
<td>Accepted Values</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------</td>
<td>----------</td>
<td>-----------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>unix-timestamp</td>
<td>Yes</td>
<td>Number</td>
<td>The unix timestamp is the number of seconds since January 1st, 1970 until the UTC time that the data was collected by a sensor. The timestamp for each frame must be different and timestamps must be sequential because they are used for cuboid interpolation. Ideally, this should be the real timestamp when the data was collected. If this is not available, you must use an incremental sequence of timestamps, where the first frame in your sequence file corresponds to the first timestamp in the sequence.</td>
</tr>
<tr>
<td>frame</td>
<td>Yes</td>
<td>String</td>
<td>The relative location, in Amazon S3 of your sequence file. This relative path will be appended to the path you specify in prefix. Example of format <code>&lt;folder-name&gt;/&lt;sequence-file.json&gt;</code></td>
</tr>
<tr>
<td>Parameter</td>
<td>Required</td>
<td>Accepted Values</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>----------</td>
<td>--------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>format</td>
<td>No</td>
<td>String</td>
<td>Use this parameter to specify the format of your point cloud data. For more information, see Accepted Raw 3D Data Formats (p. 584).</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Accepted string values: &quot;binary/xyz&quot;, &quot;binary/xyzirgb&quot;, &quot;binary/xyzrgb&quot;, &quot;binary/xyzirgb&quot;, &quot;text/xyz&quot;, &quot;text/xyzirgb&quot;, &quot;text/xyzrgb&quot;, &quot;text/xyzirgb&quot;</td>
<td></td>
</tr>
<tr>
<td>ego-vehicle-pose</td>
<td>No</td>
<td>JSON object</td>
<td>The pose of the device used to collect the point cloud data. For more information about this parameter, see Include Vehicle Pose Information in Your Input Manifest (p. 597).</td>
</tr>
<tr>
<td>prefix</td>
<td>No</td>
<td>String</td>
<td>The location in Amazon S3 where your metadata, such as camera images, is stored for this frame. The prefix must end with a forward slash: /.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Accepted string value format:</td>
<td></td>
</tr>
<tr>
<td>images</td>
<td>No</td>
<td>List</td>
<td>A list parameters describing color camera images used for sensor fusion. You can include up to 8 images in this list. For more information about the parameters required for each image, see Include Camera Data in Your Input Manifest (p. 597).</td>
</tr>
<tr>
<td></td>
<td></td>
<td>s3://&lt;bucket-name&gt;/&lt;folder-name&gt;/</td>
<td></td>
</tr>
</tbody>
</table>
Include Vehicle Pose Information in Your Input Manifest

Use the ego-vehicle location to provide information about the pose of the vehicle used to capture point cloud data. Ground Truth uses this information to compute LiDAR extrinsic matrices.

Ground Truth uses extrinsic matrices to project labels to and from the 3D scene and 2D images. For more information, see Sensor Fusion (p. 601).

The following table provides more information about the position and orientation (heading) parameters that are required when you provide ego-vehicle information.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>position</td>
<td>Yes</td>
<td>JSON object</td>
<td>The translation vector of the ego vehicle in the world coordinate system.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Required Parameters:</strong></td>
<td>x, y, and z. Enter numbers for these parameters.</td>
</tr>
<tr>
<td>heading</td>
<td>Yes</td>
<td>JSON Object</td>
<td>The orientation of the frame of reference of the device or sensor mounted on the vehicle sensing the surrounding, measured in quaternions, ((q_x, q_y, q_z, q_w)) in the a coordinate system.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Required Parameters:</strong></td>
<td>q_x, q_y, q_z, and q_w. Enter numbers for these parameters.</td>
</tr>
</tbody>
</table>

Include Camera Data in Your Input Manifest

If you want to include color camera data with a frame, use the following parameters to provide information about each image. The Required column in the following table applies when the images parameter is included in the input manifest file. You are not required to include images in your input manifest file.

If you include camera images, you must include information about the position and orientation (heading) of the camera used to capture the images.

If your images are distorted, Ground Truth can automatically undistort them using information you provide about the image in your input manifest file, including distortion coefficients \((k_1, k_2, k_3, k_4, p_1, p_1)\), camera model and focal length \((f_x, f_y)\), and the principal point \((c_x, c_y)\). To learn more about these coefficients and undistorting images, see Camera calibration With OpenCV. If distortion coefficients are not included, Ground Truth will not undistort an image.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>image-path</td>
<td>Yes</td>
<td>String</td>
<td>The relative location, in Amazon S3 of your image file. This relative path will be appended to the path you specify in prefix.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Example of format:</strong></td>
<td>(&lt;folder-name&gt;/\text{imagefile.png}&gt;)</td>
</tr>
</tbody>
</table>

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## Parameter

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>unix-timestamp</td>
<td>Yes</td>
<td>Number</td>
<td>The timestamp of the image.</td>
</tr>
<tr>
<td>camera-model</td>
<td>No</td>
<td>String:</td>
<td>The model of the camera used to capture the image. This information is used to undistort camera images.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Accepted Values:</td>
<td>&quot;pinhole&quot;, &quot;fisheye&quot;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Default:</td>
<td>&quot;pinhole&quot;</td>
</tr>
<tr>
<td>fx, fy</td>
<td>Yes</td>
<td>Numbers</td>
<td>The focal length of the camera, in the x (fx) and y (fy) directions.</td>
</tr>
<tr>
<td>cx, cy</td>
<td>Yes</td>
<td>Numbers</td>
<td>The x (cx) and y (cy) coordinates of the principal point.</td>
</tr>
<tr>
<td>k1, k2, k3, k4</td>
<td>No</td>
<td>Number</td>
<td>Radial distortion coefficients. Supported for both fisheye and pinhole camera models.</td>
</tr>
<tr>
<td>p1, p2</td>
<td>No</td>
<td>Number</td>
<td>Tangential distortion coefficients. Supported for pinhole camera models.</td>
</tr>
<tr>
<td>skew</td>
<td>No</td>
<td>Number</td>
<td>A parameter to measure any known skew in the image.</td>
</tr>
<tr>
<td>position</td>
<td>Yes</td>
<td>JSON object</td>
<td>The location or origin of the frame of reference of the camera mounted on the vehicle capturing images.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Required Parameters:</td>
<td>x, y, and z. Enter numbers for these parameters.</td>
</tr>
<tr>
<td>heading</td>
<td>Yes</td>
<td>JSON object</td>
<td>The orientation of the frame of reference of the camera mounted on the vehicle capturing images, measured using quaternions, (qx, qy, qz, qw).</td>
</tr>
</tbody>
</table>

### Sequence File and Point Cloud Frame Limits

You can include up to 100,000 point cloud frame sequences in your input manifest file. You can include up to 500 point cloud frames in each sequence file.
Keep in mind that 3D point cloud labeling job have longer pre-processing times than other Ground Truth task types. For more information, see Job Pre-processing Time (p. 468).

**Understand Coordinate Systems and Sensor Fusion**

Point cloud data is always located in a coordinate system. This coordinate system may be local to the vehicle or the device sensing the surroundings, or it may be a world coordinate system. When you use Ground Truth 3D point cloud labeling jobs, all the annotations are generated using the coordinate system of your input data. For some labeling job task types and features, you must provide data in a world coordinate system.

In this topic, you'll learn the following:

- When you are required to provide input data in a world coordinate system or global frame of reference.
- What a world coordinate is and how you can convert point cloud data to a world coordinate system.
- How you can use your sensor and camera extrinsic matrices to provide pose data when using sensor fusion.

**Coordinate System Requirements for Labeling Jobs**

If your point cloud data was collected in a local coordinate system, you can use an extrinsic matrix of the sensor used to collect the data to convert it to a world coordinate system or a global frame of reference. If you cannot obtain an extrinsic for your point cloud data and, as a result, cannot obtain point clouds in a world coordinate system, you can provide point cloud data in a local coordinate system for 3D point cloud object detection and semantic segmentation task types.

For object tracking, you must provide point cloud data in a world coordinate system. This is because when you are tracking objects across multiple frames, the ego vehicle itself is moving in the world and so all of the frames need a point of reference.

If you include camera data for sensor fusion, it is recommended that you provide camera poses in the same world coordinate system as the 3D sensor (such as a LiDAR sensor).

**Using Point Cloud Data in a World Coordinate System**

This section explains what a world coordinate system (WCS), also referred to as a *global frame of reference*, is and explains how you can provide point cloud data in a world coordinate system.

**What is a World Coordinate System?**

A WCS or global frame of reference is a fixed universal coordinate system in which vehicle and sensor coordinate systems are placed. For example, if multiple point cloud frames are located in different coordinate systems because they were collected from two sensors, a WCS can be used to translate all of the coordinates in these point cloud frames into a single coordinate system, where all frames have the same origin, (0,0,0). This transformation is done by translating the origin of each frame to the origin of the WCS using a translation vector, and rotating the three axes (typically x, y, and z) to the right orientation using a rotation matrix. This rigid body transformation is called a *homogeneous transformation*.

A world coordinate system is important in global path planning, localization, mapping, and driving scenario simulations. Ground Truth uses the right-handed Cartesian world coordinate system such as the one defined in ISO 8855, where the x axis is forward toward the car's movement, y axis is left, and the z axis points up from the ground.

The global frame of reference depends on the data. Some datasets use the LiDAR position in the first frame as the origin. In this scenario, all the frames use the first frame as a reference and device heading and position will be near the origin in the first frame. For example, KITTI datasets have the first frame as a reference for world coordinates. Other datasets use a device position that is different from the origin.
Note that this is not the GPS/IMU coordinate system, which is typically rotated by 90 degrees along the z-axis. If your point cloud data is in a GPS/IMU coordinate system (such as OxTS in the open source AV KITTI dataset), then you need to transform the origin to a world coordinate system (typically the vehicle's reference coordinate system). You apply this transformation by multiplying your data with transformation metrics (the rotation matrix and translation vector). This will transform the data from its original coordinate system to a global reference coordinate system. Learn more about this transformation in the next section.

Convert 3D Point Cloud Data to a WCS

Ground Truth assumes that your point cloud data has already been transformed into a reference coordinate system of your choice. For example, you can choose the reference coordinate system of the sensor (such as LiDAR) as your global reference coordinate system. You can also take point clouds from various sensors and transform them from the sensor's view to the vehicle's reference coordinate system view. You use the a sensor's extrinsic matrix, made up of a rotation matrix and translation vector, to convert your point cloud data to a WCS or global frame of reference.

Collectively, the translation vector and rotation matrix can be used to make up an extrinsic matrix, which can be used to convert data from a local coordinate system to a WCS. For example, your LiDAR extrinsic matrix may be composed as follows, where R is the rotation matrix and T is the translation vector:

\[
\text{LiDAR\_extrinsic} = \begin{bmatrix} R & T \\ 0 & 0 & 0 & 1 \end{bmatrix}
\]

For example, the autonomous driving KITTI dataset includes a rotation matrix and translation vector for the LiDAR extrinsic transformation matrix for each frame. The pykitti python module can be used for loading the KITTI data, and in the dataset dataset.oxts[i].T_w_imu gives the LiDAR extrinsic transform for the i\textsuperscript{th} frame with can be multiplied with points in that frame to convert them to a world frame - np.matmul(lidar_transform_matrix, points). Multiplying a point in LiDAR frame with a LiDAR extrinsic matrix transforms it into world coordinates. Multiplying a point in the world frame with the camera extrinsic matrix gives the point coordinates in the camera's frame of reference.

The following code example demonstrates how you can convert point cloud frames from the KITTI dataset into a WCS.

```python
import pykitti
import numpy as np

basedir = '/Users/nameofuser/kitti-data'
date = '2011_09_26'
drive = '0079'

# The 'frames' argument is optional - default: None, which loads the whole dataset.
# Calibration, timestamps, and IMU data are read automatically.
# Camera and velodyne data are available via properties that create generators
# when accessed, or through getter methods that provide random access.
data = pykitti.raw(basedir, date, drive, frames=range(0, 50, 5))

i = 0

# lidar extrinsic for the ith frame
lidar_extrinsic_matrix = data.oxts[i].T_w_imu

# velodyne raw point cloud in lidar scanners own coordinate system
points = data.get_velo(i)

# transform points from lidar to global frame using lidar_extrinsic_matrix
def generate_transformed_pcd_from_point_cloud(points, lidar_extrinsic_matrix):
    tps = []
    for point in points:
        tps.append(np.matmul(lidar_extrinsic_matrix, point))
    return np.array(tps)

transformed_points = generate_transformed_pcd_from_point_cloud(points, lidar_extrinsic_matrix)
```
transformed_points = np.matmul(lidar_extrinsic_matrix, np.array([point[0],
point[1], point[2], 1], dtype=np.float32).reshape(4,1)).tolist()
    if len(point) > 3 and point[3] is not None:
        tps.append([transformed_points[0][0], transformed_points[1][0],
        transformed_points[2][0], point[3]])
    return tps

# customer transforms points from lidar to global frame using lidar_extrinsic_matrix
transformed_pcl = generate_transformed_pcd_from_point_cloud(points, lidar_extrinsic_matrix)

**Sensor Fusion**

Ground Truth supports sensor fusion of point cloud data with up to 8 video camera inputs. This feature allows human labellers to view the 3D point cloud frame side-by-side with the synchronized video frame. In addition to providing more visual context for labeling, sensor fusion allows workers to adjust annotations in the 3D scene and in 2D images and the adjustment are projected into the other view. The following video demonstrates a 3D point cloud labeling job with LiDAR and camera sensor fusion.
For best results, when using sensor fusion, your point cloud should be in a WCS. Ground Truth uses your sensor (such as LiDAR), camera, and ego vehicle pose information to compute extrinsic and intrinsic matrices for sensor fusion.

**Extrinsic Matrix**

Ground Truth uses sensor (such as LiDAR) extrinsic and camera extrinsic and intrinsic matrices to project objects to and from the point cloud data's frame of reference to the camera's frame of reference.

For example, in order to project a label from the 3D point cloud to camera image plane, Ground Truth transforms 3D points from LiDAR's own coordinate system to the camera's coordinate system. This is typically done by first transforming 3D points from LiDAR's own coordinate system to a world coordinate system (or a global reference frame) using the LiDAR extrinsic matrix. Ground Truth then uses the camera inverse extrinsic (which converts points from a global frame of reference to the camera's frame of reference) to transform the 3D points from world coordinate system obtained in previous step into the camera image plane. The LiDAR extrinsic matrix can also be used to transform 3D data into a world coordinate system. If your 3D data is already transformed into world coordinate system then the first transformation doesn't have any impact on label translation, and label translation only depends on the camera inverse extrinsic. A view matrix is used to visualize projected labels. To learn more about these transformations and the view matrix, see [Ground Truth Sensor Fusion Transformations](#).

Ground Truth computes these extrinsic matrices by using LiDAR and camera pose data that you provide: heading (in quaternions: qx, qy, qz, and qw) and position (x, y, z). For the vehicle, typically the heading and position are described in vehicle's reference frame in a world coordinate system and are called a *ego vehicle pose*. For each camera extrinsic, you can add pose information for that camera. For more information, see [Pose](#).

**Intrinsic Matrix**

Ground Truth use the camera extrinsic and intrinsic matrices to compute view metrics to transform labels to and from the 3D scene to camera images. Ground Truth computes the camera intrinsic matrix using camera focal length (fx, fy) and optical center coordinates (cx, cy) that you provide. For more information, see [Intrinsic and Distortion](#).

**Image Distortion**

Image distortion can occur for a variety of reasons. For example, images may be distorted due to barrel or fish-eye effects. Ground Truth uses intrinsic parameters along with distortion co-efficient to undistort images you provide when creating 3D point cloud labeling jobs. If a camera image is already been undistorted, all distortion coefficients should be set to 0.

For more information about the transformations Ground Truth performs to undistort images, see [Camera Calibrations: Extrinsic, Intrinsic and Distortion](#).

**Ego Vehicle**

To collect data for autonomous driving applications, the measurements used to generate point cloud data and are taken from sensors mounted on a vehicle, or the *ego vehicle*. To project label adjustments to and from the 3D scene and 2D images, Ground Truth needs your ego vehicle pose in a world coordinate system. The ego vehicle pose is comprised of position coordinates and orientation quaternion.

Ground Truth uses your ego vehicle pose to compute rotation and transformations matrices. Rotations in 3 dimensions can be represented by a sequence of 3 rotations around a sequence of axes. In theory, any three axes spanning the 3D Euclidean space are enough. In practice, the axes of rotation are chosen to be the basis vectors. The three rotations are expected to be in a global frame of reference (extrinsic). Ground Truth does not a support body centered frame of reference (intrinsic) which is attached to, and moves with, the object under rotation. To track objects, Ground Truth needs to measure from a global reference where all vehicles are moving. When using Ground Truth 3D point cloud labeling jobs, z specifies the axis of rotation (extrinsic rotation) and yaw Euler angles are in radians (rotation angle).
Pose

Ground Truth uses pose information for 3D visualizations and sensor fusion. Pose information you input through your manifest file is used to compute extrinsic matrices. If you already have an extrinsic matrix, you can use it to extract sensor and camera pose data.

For example in the autonomous driving KITTI dataset, the pykitti python module can be used for loading the KITTI data. In the dataset dataset.oxts[i].T_w_imu gives the LiDAR extrinsic transform for the i-th frame and it can be multiplied with the points to get them in a world frame - matmul(lidar_transform_matrix, points). This transform can be converted into position (translation vector) and heading (in quaternion) of LiDAR for the input manifest file JSON format. Camera extrinsic transform for cam0 in i-th frame can be calculated by

```python
inv(matmul(dataset.calib.T_cam0_velo, inv(dataset.oxts[i].T_w_imu)))
```

This can be converted into heading and position for cam0.

```python
import numpy
rotation = [[ 9.96714314e-01, -8.09890350e-02,  1.16333982e-03],
             [ 8.09967396e-02,  9.96661051e-01, -1.03090934e-02],
             [-3.24531964e-04,  1.03694477e-02,  9.99946183e-01]]
origin= [1.71104606e+00,
         5.80000039e-01,
         9.43144935e-01]

from scipy.spatial.transform import Rotation as R

# position is the origin
position = origin
r = R.from_matrix(np.asarray(rotation))

# heading in WCS using scipy
heading = r.as_quat()
print(f"pose: {position}\nheading: {heading}"
```

Position

In the input manifest file, position refers to the position of the sensor with respect to a world frame. If you are unable to put the device position in a world coordinate system, you can use LiDAR data with local coordinates. Similarly, for mounted video cameras you can specify the position and heading in a world coordinate system. For camera, if you do not have position information, please use (0, 0, 0).

The following are the fields in the position object:

1. x (float) – x coordinate of ego vehicle, sensor, or camera position in meters.
2. y (float) – y coordinate of ego vehicle, sensor, or camera position in meters.
3. z (float) – z coordinate of ego vehicle, sensor, or camera position in meters.

The following is an example of a position JSON object:

```json
{
  "position": {
    "x": 311.21505956090624,
    "y": -152.77584902657554,
    "z": -10.854137529636024
  }
}
```
**Heading**

In the input manifest file, heading is an object that represents the orientation of a device with respect to world frame. Heading values should be in quaternion. A quaternion is a representation of the orientation consistent with geodesic spherical properties. If you are unable to put the sensor heading in world coordinates, please use the identity quaternion \((q_x = 0, q_y = 0, q_z = 0, q_w = 1)\). Similarly, for cameras, specify the heading in quaternions. If you are unable to obtain extrinsic camera calibration parameters, please also use the identity quaternion.

Fields in heading object are as follows:

1. \(q_x\) (float) - x component of ego vehicle, sensor, or camera orientation.
2. \(q_y\) (float) - y component of ego vehicle, sensor, or camera orientation.
3. \(q_z\) (float) - z component of ego vehicle, sensor, or camera orientation.
4. \(q_w\) (float) - w component of ego vehicle, sensor, or camera orientation.

The following is an example of a heading JSON object:

```
{
    "heading": {
        "qy": -0.7046155108831117,
        "qx": 0.034278837280808494,
        "qz": 0.7070617895701465,
        "qw": -0.04904659893885366
    }
}
```

To learn more, see Compute Orientation Quaternions and Position (p. 605).

**Compute Orientation Quaternions and Position**

Ground Truth requires that all orientation, or heading, data be given in quaternions. A quaternion is a representation of the orientation consistent with geodesic spherical properties that can be used to approximate of rotation. Compared to Euler angles they are simpler to compose and avoid the problem of gimbal lock. Compared to rotation matrices they are more compact, more numerically stable, and more efficient.

You can compute quaternions from a rotation matrix or a transformation matrix.

If you have a rotation matrix (made up of the axis rotations) and translation vector (or origin) in world coordinate system instead of a single 4x4 rigid transformation matrix, then you can directly use the rotation matrix and translation vector to compute quaternions. Libraries like scipy and pyqaternion can help. The following code-block shows an example using these libraries to compute quaternion from a rotation matrix.

```
import numpy

rotation = [[ 9.96714314e-01, -8.0990350e-02,  1.16333982e-03],
            [ 8.09967396e-02,  9.96661051e-01, -1.03090934e-02],
            [-3.24531964e-04,  1.03694477e-02,  9.99946183e-01]]

origin = [1.71104606e+00,
          5.80000039e-01,
          9.43144955e-01]

from scipy.spatial.transform import Rotation as R

# position is the origin
position = origin
```
A UI tool like 3D Rotation Converter can also be useful.

If you have a 4x4 extrinsic transformation matrix, note that the transformation matrix is in the form \([R \ 0 \ 0 \ 1]\) where \(R\) is the rotation matrix and \(T\) is the origin translation vector. That means you can extract rotation matrix and translation vector from the transformation matrix as follows.

```python
import numpy as np
transformation = [[9.96714314e-01, -8.0990350e-02, 1.16333982e-03, 1.71104606e+00],
                  [8.09967396e-02, 9.9661051e-01, -1.03090934e-02, 5.80000039e-01],
                  [-3.24531964e-04, 1.03694477e-02, 9.99946183e-01, 9.43144935e-01],
                  [0, 0, 0, 1]]
transformation = np.array(transformation)
rotation = transformation[0:3, 0:3]
translation = transformation[0:3, 3]
from scipy.spatial.transform import Rotation as R
# position is the origin translation
position = translation
r = R.from_matrix(np.asarray(rotation))
# heading in WCS using scipy
heading = r.as_quat()
print(f"position: {position}
heading: {heading}"
)
```

With your own setup, you can compute an extrinsic transformation matrix using the GPS/IMU position and orientation (latitude, longitude, altitude and roll, pitch, yaw) with respect to the LiDAR sensor on the ego vehicle. For example, you can compute pose from KITTI raw data using `convertOxtsToPose(oxts)` to transform the oxts data into a local euclidean poses, specified by 4x4 rigid transformation matrices. You can then transform this pose transformation matrix to a global reference frame using the reference frames transformation matrix in the world coordinate system.

```c
struct Quaternion
{
    double w, x, y, z;
};

Quaternion ToQuaternion(double yaw, double pitch, double roll) // yaw (Z), pitch (Y), roll (X)
{
    // Abbreviations for the various angular functions
    double cy = cos(yaw * 0.5);
    double sy = sin(yaw * 0.5);
    double cp = cos(pitch * 0.5);
    double sp = sin(pitch * 0.5);
    double cr = cos(roll * 0.5);
    double sr = sin(roll * 0.5);

    Quaternion q;
    q.w = cr * cp * cy + sr * sp * sy;
    q.x = sr * cp * cy - cr * sp * sy;
    q.y = cr * sp * cy + sr * cp * sy;
    q.z = cr * cp * sy - sr * sp * cy;

    return q;
}
```
Ground Truth Sensor Fusion Transformations

The following sections go into greater detail about the Ground Truth sensor fusion transformations that are performed using the pose data you provide.

LiDAR Extrinsic

In order to project to and from a 3D LiDAR scene to a 2D camera image, Ground Truth computes the rigid transformation projection metrics using the ego vehicle pose and heading. Ground Truth computes rotation and translation of a world coordinates into the 3D plane by doing a simple sequence of rotations and translation.

Ground Truth computes rotation metrics using the heading quaternions as follows:

\[
M = \begin{pmatrix}
1 - 2y^2 - 2z^2 & 2xy + 2zw & 2xz - 2yw \\
2xy - 2zw & 1 - 2x^2 - 2z^2 & 2yz + 2xw \\
2xz + 2yw & 2yz - 2xw & 1 - 2x^2 - 2y^2
\end{pmatrix}
\]

Here, \([x, y, z, w]\) corresponds to parameters in the heading JSON object, \([qx, qy, qz, qw]\). Ground Truth computes the translation column vector as \(T = [\text{poseX}, \text{poseY}, \text{poseZ}]\). Then the extrinsic metrics is simply as follows:

\[
\text{LiDAR}_{\text{extrinsic}} = [R \ T; 0 \ 0 \ 0 \ 1]
\]

Camera Calibrations: Extrinsic, Intrinsic and Distortion

Geometric camera calibration, also referred to as camera resectioning, estimates the parameters of a lens and image sensor of an image or video camera. You can use these parameters to correct for lens distortion, measure the size of an object in world units, or determine the location of the camera in the scene. Camera parameters include intrinsics and distortion coefficients.

Camera Extrinsic

If the camera pose is given, then Ground Truth computes the camera extrinsic based on a rigid transformation from the 3D plane into the camera plane. The calculation is the same as the one used for the LiDAR Extrinsic (p. 607), except that Ground Truth uses camera pose (position and heading) and computes the inverse extrinsic.

\[
\text{camera}_{\text{inverse extrinsic}} = \text{inv}([Rc \ Tc; 0 \ 0 \ 0 \ 1]) \ #\text{where Rc and Tc are camera pose components}
\]

Intrinsic and Distortion

Some cameras, such as pinhole or fisheye cameras, may introduce significant distortion in photos. This distortion can be corrected using distortion coefficients and the camera focal length. To learn more, see Camera calibration With OpenCV in the OpenCV documentation.

There are two types of distortion Ground Truth can correct for: radial distortion and tangential distortion.

Radial distortion occurs when light rays bend more near the edges of a lens than they do at its optical center. The smaller the lens, the greater the distortion. The presence of the radial distortion manifests in form of the barrel or fish-eye effect and Ground Truth uses Formula 1 to undistort it.

Formula 1:

\[
x_{\text{corrected}} = x(1 + k_1r^2 + k_2r^4 + k_3r^6)
\]

\[
y_{\text{corrected}} = y(1 + k_1r^2 + k_2r^4 + k_3r^6)
\]
Tangential distortion occurs because the lenses used to take the images are not perfectly parallel to the imaging plane. This can be corrected with Formula 2.

**Formula 2:**

\[
\begin{align*}
x_{\text{corrected}} &= x + [2p_1 xy + p_2 (r^2 + 2x^2)] \\
y_{\text{corrected}} &= y + [p_1 (r^2 + 2y^2) + 2p_2 xy]
\end{align*}
\]

In the input manifest file, you can provide distortion coefficients and Ground Truth will undistort your images. All distortion coefficients are floats.

- \(k_1, k_2, k_3, k_4\) – Radial distortion coefficients. Supported for both fisheye and pinhole camera models.
- \(p_1, p_2\) – Tangential distortion coefficients. Supported for pinhole camera models.

If images are already undistorted, all distortion coefficients should be 0 in your input manifest.

In order to correctly reconstruct the corrected image, Ground Truth does a unit conversion of the images based on focal lengths. If a common focal length is used with a given aspect ratio for both axes, such as 1, in the upper formula we will have a single focal length. The matrix containing these four parameters is referred to as the **in camera intrinsic calibration matrix**.

\[
\begin{bmatrix}
x \\
y \\
w
\end{bmatrix} = \begin{bmatrix}
f_x & 0 & c_x \\
0 & f_y & c_y \\
0 & 0 & 1
\end{bmatrix} \begin{bmatrix}
X \\
Y \\
Z
\end{bmatrix}
\]

While the distortion coefficients are the same regardless of the camera resolutions used, these should be scaled with the current resolution from the calibrated resolution.

The following are float values.

- \(fx\) - focal length in x direction.
- \(fy\) - focal length in y direction.
- \(cx\) - x coordinate of principal point.
- \(cy\) - y coordinate of principal point.

Ground Truth use the camera extrinsic and camera intrinsic to compute view metrics as shown in the following code block to transform labels between the 3D scene and 2D images.

```python
def generate_view_matrix(intrinsic_matrix, extrinsic_matrix):
    intrinsic_matrix = np.c_[intrinsic_matrix, np.zeros(3)]
    view_matrix = np.matmul(intrinsic_matrix, extrinsic_matrix)
    view_matrix = np.insert(view_matrix, 2, np.array((0, 0, 0, 1)), 0)
    return view_matrix
```

**Video Frame Input Data**

When you create a video frame object detection or object tracking labeling job, you can choose video files (MP4 files) or video frames for input data. All worker tasks are created using video frames, so if you choose video files, use the Ground Truth frame extraction tool to extract video frames (images) from your video files.
For both of these options, you can use the **Automated data setup** option in the Ground Truth section of the Amazon SageMaker console to set up a connection between Ground Truth and your input data in Amazon S3 so that Ground Truth knows where to look for your input data when creating your labeling tasks. This creates and stores an input manifest file in your Amazon S3 input dataset location. To learn more, see Automated Video Frame Input Data Setup (p. 611).

Alternatively, you can manually create sequence files for each sequence of video frames that you want labeled and provide the Amazon S3 location of an input manifest file that references each of these sequences files using the `source-ref` key. To learn more, see Create a Video Frame Input Manifest File (p. 613).

**Topics**
- Choose Video Files or Video Frames for Input Data (p. 609)
- Input Data Setup (p. 610)

### Choose Video Files or Video Frames for Input Data

When you create a video frame object detection or object tracking labeling job, you can provide a sequence of video frames (images) or you can use the Amazon SageMaker console to have Ground Truth automatically extract video frames from your video files. Use the following sections to learn more about these options.

#### Provide Video Frames

Video frames are sequences of images extracted from a video file. You can create a Ground Truth labeling job to have workers label multiple sequences of video frames. Each sequence is made up of images extracted from a single video.

To create a labeling job using video frame sequences, you must store each sequence using a unique **key name prefix** in Amazon S3. In the Amazon S3 console, key name prefixes are folders. So in the Amazon S3 console, each sequence of video frames must be located in its own folder in Amazon S3.

For example, if you have two sequences of video frames, you might use the key name prefixes `sequence1/` and `sequence2/` to identify your sequences. In this example, your sequences may be located in `s3://DOC-EXAMPLE-BUCKET/video-frames/sequence1/` and `s3://DOC-EXAMPLE-BUCKET/video-frames/sequence2/`.

If you are using the Ground Truth console to create an input manifest file, all of the sequence key name prefixes should be in the same location in Amazon S3. For example, in the Amazon S3 console, each sequence could be in a folder in `s3://DOC-EXAMPLE-BUCKET/video-frames/`. In this example, your first sequence of video frames (images) may be located in `s3://DOC-EXAMPLE-BUCKET/video-frames/sequence1/` and your second sequence may be located in `s3://DOC-EXAMPLE-BUCKET/video-frames/sequence2/`.

**Important**

Even if you only have a single sequence of video frames that you want workers to label, that sequence must have a **key name prefix** in Amazon S3. If you are using the Amazon S3 console, this means that your sequence is located in a folder. It cannot be located in the root of your S3 bucket.

When creating worker tasks using sequences of video frames, Ground Truth uses one sequence per task. In each task, Ground Truth orders your video frames using **UTF-8** binary order.

For example, video frames might be in the following order in Amazon S3:

```
[0001.jpg, 0002.jpg, 0003.jpg, ..., 0011.jpg]
```
They are arranged in the same order in the worker’s task: 0001.jpg, 0002.jpg, 0003.jpg, ..., 0011.jpg.

Frames might also be ordered using a naming convention like the following:

```
[frame1.jpg, frame2.jpg, ..., frame11.jpg]
```

In this case, frame10.jpg and frame11.jpg come before frame2.jpg in the worker task. Your worker sees your video frames in the following order: frame1.jpg, frame10.jpg, frame11.jpg, frame2.jpg, ..., frame9.jpg.

**Provide Video Files**

You can use the Ground Truth frame splitting feature when creating a new labeling job in the console to extract video frames from video files (MP4 files). A series of video frames extracted from a single video file is referred to as a sequence of video frames.

You can either have Ground Truth automatically extract all frames, up to 2,000, from the video, or you can specify a frequency for frame extraction. For example, you can have Ground Truth extract every 10th frame from your videos.

You can provide up to 50 videos when you use automated data setup to extract frames, however your input manifest file cannot reference more than 10 video frame sequence files when you create a video frame object tracking and video frame object detection labeling job. If you use the automated data setup console tool to extract video frames from more than 10 video files, you will need to modify the manifest file the tool generates or create a new one to include 10 video frame sequence files or less. To learn more about these quotas, see 3D Point Cloud and Video Frame Labeling Job Quotas (p. 582).

To use the video frame extraction tool, see Automated Video Frame Input Data Setup (p. 611).

When all of your video frames have been successfully extracted from your videos, you will see the following in your S3 input dataset location:

- A key name prefix (a folder in the Amazon S3 console) named after each video. Each of these prefixes leads to:
  - A sequence of video frames extracted from the video used to name that prefix.
  - A sequence file used to identify all of the images that make up that sequence.
- An input manifest file with a .manifest extension. This identifies all of the sequence files that will be used to create your labeling job.

All of the frames extracted from a single video file are used for a labeling task. If you extract video frames from multiple video files, multiple tasks are created for your labeling job, one for each sequence of video frames.

Ground Truth stores each sequence of video frames that it extracts in your Amazon S3 location for input datasets using a unique key name prefix. In the Amazon S3 console, key name prefixes are folders.

**Input Data Setup**

When you create a video frame labeling job, you need to let Ground Truth know where to look for your input data. You can do this in one of two ways:

- You can store your input data in Amazon S3 and have Ground Truth automatically detect the input dataset used for your labeling job. See Automated Video Frame Input Data Setup (p. 611) to learn more about this option.
- You can create an input manifest file and sequence files and upload them to Amazon S3. See Manual Input Data Setup (p. 613) to learn more about this option.
Automated Video Frame Input Data Setup

You can use the Ground Truth automated data setup to automatically detect video files in your Amazon S3 bucket and extract video frames from those files. To learn how, see Provide Video Files (p. 610).

If you already have video frames in Amazon S3, you can use the automated data setup to use these video frames in your labeling job. For this option, all video frames from a single video must be stored using a unique prefix. To learn about the requirements to use this option, see Provide Video Frames (p. 609).

Select one of the following sections to learn how to set up your automatic input dataset connection with Ground Truth.

Provide Video Files and Extract Frames

Use the following procedure to connect your video files with Ground Truth and automatically extract video frames from those files for video frame object detection and object tracking labeling jobs.

Note
If you use the automated data setup console tool to extract video frames from more than 10 video files, you will need to modify the manifest file the tool generates or create a new one to include 10 video frame sequence files or less. To learn more, see Provide Video Files (p. 610).

Make sure your video files are stored in an Amazon S3 bucket in the same AWS Region that you perform the automated data setup in.

Automatically connect your video files in Amazon S3 with Ground Truth and extract video frames:


   Your input and output S3 buckets must be located in the same AWS Region that you create your labeling job in. This link puts you in the North Virginia (us-east-1) AWS Region. If your input data is in an Amazon S3 bucket in another Region, switch to that Region. To change your AWS Region, on the navigation bar, choose the name of the currently displayed Region.

2. Select Create labeling job.

3. Enter a Job name.

4. In the section Input data setup, select Automated data setup.

5. Enter an Amazon S3 URI for S3 location for input datasets. An S3 URI looks like the following: s3://DOC-EXAMPLE-BUCKET/path-to-files/. This URI should point to the Amazon S3 location where your video files are stored.

6. Specify your S3 location for output datasets. This is where your output data is stored. You can choose to store your output data in the Same location as input dataset or Specify a new location and entering the S3 URI of the location that you want to store your output data.

7. Choose Video Files for your Data type using the dropdown list.

8. Choose Yes, extract frames for object tracking and detection tasks.


   • When you choose Use all frames extracted from the video to create a labeling task, Ground Truth extracts all frames from each video in your S3 location for input datasets, up to 2,000
frames. If a video in your input dataset contains more than 2,000 frames, the first 2,000 are extracted and used for that labeling task.

- When you choose **Use every x frame from a video to create a labeling task**, Ground Truth extracts every \( x \)th frame from each video in your S3 location for input datasets.

For example, if your video is 2 seconds long, and has a frame rate of 30 frames per second, there are 60 frames in your video. If you specify 10 here, Ground Truth extracts every 10th frame from your video. This means the 1st, 10th, 20th, 30th, 40th, 50th, and 60th frames are extracted.

10. Choose or create an IAM execution role. Make sure that this role has permission to access your Amazon S3 locations for input and output data specified in steps 5 and 6.

11. Select **Complete data setup**.

**Provide Video Frames**

Use the following procedure to connect your sequences of video frames with Ground Truth for video frame object detection and object tracking labeling jobs.

Make sure your video frames are stored in an Amazon S3 bucket in the same AWS Region that you perform the automated data setup in. Each sequence of video frames should have a unique prefix. For example, if you have two sequences stored in s3://DOC-EXAMPLE-BUCKET/video-frames/sequences/, each should have a unique prefix like sequence1 and sequence2 and should both be located directly under the /sequences/ prefix. In the example above, the locations of these two sequences is: s3://DOC-EXAMPLE-BUCKET/video-frames/sequences/sequence1/ and s3://DOC-EXAMPLE-BUCKET/video-frames/sequences/sequence2/.

**Automatically connect your video frame in Amazon S3 with Ground Truth:**

1. Navigate to the **Create labeling job** page in the Amazon SageMaker console: https://console.aws.amazon.com/sagemaker/groundtruth.

   Your input and output S3 buckets must be located in the same AWS Region that you create your labeling job in. This link puts you in the North Virginia (us-east-1) AWS Region. If your input data is in an Amazon S3 bucket in another Region, switch to that Region. To change your AWS Region, on the **navigation bar**, choose the name of the currently displayed Region.

2. Select **Create labeling job**.

3. Enter a **Job name**.

4. In the section **Input data setup**, select **Automated data setup**.

5. Enter an Amazon S3 URI for **S3 location for input datasets**.

   This should be the Amazon S3 location where your sequences are stored. For example, if you have two sequences stored in s3://DOC-EXAMPLE-BUCKET/video-frames/sequences/sequence1/, s3://DOC-EXAMPLE-BUCKET/video-frames/sequences/sequence2/, enter s3://DOC-EXAMPLE-BUCKET/video-frames/sequences/here.

6. Specify your **S3 location for output datasets**. This is where your output data is stored. You can choose to store your output data in the **Same location as input dataset** or **Specify a new location** and entering the S3 URI of the location that you want to store your output data.

7. Choose **Video frames** for your **Data type** using the dropdown list.

8. Choose or create an IAM execution role. Make sure that this role has permission to access your Amazon S3 locations for input and output data specified in steps 5 and 6.

9. Select **Complete data setup**.

These procedures will create an input manifest in the Amazon S3 location for input datasets that you specified in step 5. If you are creating a labeling job using the SageMaker API or, AWS CLI, or an AWS SDK, use the Amazon S3 URI for this input manifest file as input to the parameter ManifestS3Uri.
Manual Input Data Setup

Choose the manual data setup option if you have created sequence files for each of your video frame sequences, and a manifest file listing references to those sequences files.

Create a Video Frame Input Manifest File

Ground Truth uses the input manifest file to identify the location of your input dataset when creating labeling tasks. For video frame object detection and object tracking labeling jobs, each line in the input manifest file identifies the location of a video frame sequence file. Each sequence file identifies the images included in a single sequence of video frames.

Use this page to learn how to create a video frame sequence file and an input manifest file for video frame object tracking and object detection labeling jobs.

If you want Ground Truth to automatically generate your sequence files and input manifest file, see Automated Video Frame Input Data Setup (p. 611).

Create a Video Frame Sequence Input Manifest

In the video frame sequence input manifest file, each line in the manifest is a JSON object, with a "source-ref" key that references a sequence file. Each sequence file identifies the location of a sequence of video frames. This is the manifest file formatting required for all video frame labeling jobs.

The following example demonstrates the syntax used for an input manifest file:

```json
["source-ref": "s3://DOC-EXAMPLE-BUCKET/example-folder/seq1.json"],
["source-ref": "s3://DOC-EXAMPLE-BUCKET/example-folder/seq2.json"]
```

Create a Video Frame Sequence File

The data for each sequence of video frames needs to be stored in a JSON data object. The following is an example of the format you use for a sequence file. Information about each frame is included as a JSON object and is listed in the frames list. The following JSON has been expanded for readability.

```json
{
    "seq-no": 1,
    "prefix": "s3://mybucket/prefix/video1/",
    "number-of-frames": 3,
    "frames": [
        {
            "frame-no": 1,
            "unix-timestamp": 1566861644,
            "frame": "frame0001.jpg"
        },
        {
            "frame-no": 2,
            "unix-timestamp": 1566861644,
            "frame": "frame0002.jpg"
        },
        {
            "frame-no": 3,
            "unix-timestamp": 1566861644,
            "frame": "frame0003.jpg"
        }
    ]
}
```

The following table provides details about the parameters shown in the this code example.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Required</th>
<th>Accepted Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>seq-no</td>
<td>Yes</td>
<td>Integer</td>
<td>The ordered number of the sequence.</td>
</tr>
<tr>
<td>prefix</td>
<td>Yes</td>
<td>String</td>
<td>The Amazon S3 location where the sequence files are located.</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Accepted Values:</strong></td>
<td>s3://&lt;bucket-name&gt;/&lt;prefix&gt;/</td>
</tr>
<tr>
<td>Parameter</td>
<td>Required</td>
<td>Accepted Values</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>----------</td>
<td>-----------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>number-of-frames</td>
<td>Yes</td>
<td>Integer</td>
<td>The total number of frames included in the sequence file. This number must match the total number of frames listed in the frames parameter in the next row.</td>
</tr>
<tr>
<td>frames</td>
<td>Yes</td>
<td>List of JSON objects</td>
<td>A list of frame data. The length of the list must equal number-of-frames. In the worker UI, frames in a sequence are ordered in UTF-8 binary order. To learn more about this ordering, see Provide Video Frames (p. 609).</td>
</tr>
<tr>
<td>frame-no</td>
<td>Yes</td>
<td>Integer</td>
<td>The frame order number. This will determine the order of a frame in the sequence.</td>
</tr>
<tr>
<td>unix-timestamp</td>
<td>No</td>
<td>Integer</td>
<td>The unix timestamp of a frame. The number of seconds since January 1st, 1970 until the UTC time when the frame was captured.</td>
</tr>
<tr>
<td>frame</td>
<td>Yes</td>
<td>String</td>
<td>The name of a video frame image file.</td>
</tr>
</tbody>
</table>

**Output Data**

The output from a labeling job is placed in the Amazon S3 location that you specified in the console or in the call to the CreateLabelingJob operation. Output data appears in this location when the workers have submitted one or more tasks, or when tasks expire. Note that it may take a few minutes for output data to appear in Amazon S3 after the worker submits the task or the task expires.

Each line in the output data file is identical to the manifest file with the addition of an attribute and value for the label assigned to the input object. The attribute name for the value is defined in the console or in the call to the CreateLabelingJob operation. You can't use -metadata in the label attribute name. If you are running an image semantic segmentation, 3D point cloud semantic segmentation, or 3D point cloud object tracking job, the label attribute must end with -ref. For any other type of job, the attribute name can't end with -ref.

The output of the labeling job is the value of the key-value pair with the label. The label and the value overwrites any existing JSON data in the input file with the new value.
For example, the following is the output from an image classification labeling job where the input data files were stored in an Amazon S3 `AWSDOC-EXAMPLE-BUCKET` and the label attribute name was defined as `sport`. In this example the JSON object is formatted for readability, in the actual output file the JSON object is on a single line. For more information about the data format, see JSON Lines.

```json
{
    "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/image_example.png",
    "sport": 0,
    "sport-metadata":
        {
            "class-name": "football",
            "confidence": 0.00,
            "type": "groundtruth/image-classification",
            "job-name": "identify-sport",
            "human-annotated": "yes",
            "creation-date": "2018-10-18T22:18:13.527256"
        }
}
```

The value of the label can be any valid JSON. In this case the label's value is the index of the class in the classification list. Other job types, such as bounding box, have more complex values.

Any key-value pair in the input manifest file other than the label attribute is unchanged in the output file. You can use this to pass data to your application.

The output from a labeling job can be used as the input to another labeling job. You can use this when you are chaining together labeling jobs. For example, you can send one labeling job to determine the sport that is being played. Then you send another using the same data to determine if the sport is being played indoors or outdoors. By using the output data from the first job as the manifest for the second job, you can consolidate the results of the two jobs into one output file for easier processing by your applications.

The output data file is written to the output location periodically while the job is in progress. These intermediate files contain one line for each line in the manifest file. If an object is labeled, the label is included. If the object hasn't been labeled, it is written to the intermediate output file identically to the manifest file.

**Output Directories**

Ground Truth creates several directories in your Amazon S3 output path. These directories contain the results of your labeling job and other artifacts of the job. The top-level directory for a labeling job is given the same name as your labeling job; the output directories are placed beneath it. For example, if you named your labeling job `find-people`, your output would be in the following directories:

```
s3://AWSDOC-EXAMPLE-BUCKET/find-people/activelearning
s3://AWSDOC-EXAMPLE-BUCKET/find-people/annotations
s3://AWSDOC-EXAMPLE-BUCKET/find-people/inference
s3://AWSDOC-EXAMPLE-BUCKET/find-people/manifests
s3://AWSDOC-EXAMPLE-BUCKET/find-people/training
```

Each directory contains the following output:

**Active Learning Directory**

The `activelearning` directory is only present when you are using automated data labeling. It contains the input and output validation set for automated data labeling, and the input and output folder for automatically labeled data.
Annotations Directory

The annotations directory contains all of the annotations made by the workforce. These are the responses from individual workers that have not been consolidated into a single label for the data object.

There are three subdirectories in the annotations directory.

- The first, worker-response, contains the responses from individual workers. This contains a subdirectory for each iteration, which in turn contains a subdirectory for each data object in that iteration. The worker response data for each data object is stored in a timestamped JSON file that contains the answers submitted by each worker for that data object, and if you use a private workforce, metadata about those workers. To learn more about this metadata, see Worker Metadata (p. 617).
- The second, consolidated-annotation, contains information required to consolidate the annotations in the current batch into labels for your data objects.
- The third, intermediate, contains the output manifest for the current batch with any completed labels. This file is updated as the label for each data object is completed.

Note

We recommend that you do not use files that are not mentioned in the documentation.

Inference Directory

The inference directory is only present when you are using automated data labeling. This directory contains the input and output files for the SageMaker batch transform used while labeling data objects.

Manifest Directory

The manifest directory contains the output manifest from your labeling job. There is one subdirectory in the manifest directory, output. The output directory contains the output manifest file for your labeling job. The file is named output.manifest.

Training Directory

The training directory is only present when you are using automated data labeling. This directory contains the input and output files used to train the automated data labeling model.

Confidence Score

When you have more than one worker annotate a single task, your label results from annotation consolidation. Ground Truth calculates a confidence score for each label. A confidence score is a number between 0 and 1 that indicates how confident Ground Truth is in the label. You can use the confidence score to compare labeled data objects to each other, and to identify the least or most confident labels.

You should not interpret the value of a confidence score as an absolute value, or compare confidence scores across labeling jobs. For example, if all of the confidence scores are between 0.98 and 0.998, you should only compare the data objects with each other and not rely on the high confidence scores.

You should not compare the confidence scores of human-labeled data objects and auto-labeled data objects. The confidence scores for humans are calculated using the annotation consolidation function for the task, while the confidence scores for automated labeling are calculated using a model that incorporates object features. The two models generally have different scales and average confidence.

For a bounding box labeling job, Ground Truth calculates a confidence score per box. You can compare confidence scores within one image or across images for the same labeling type (human or auto). You can’t compare confidence scores across labeling jobs.
If a single worker annotates a task (NumberOfHumanWorkersPerDataObject is set to 1 or in the console, you enter 1 for **Number of workers per dataset object**), the confidence score is set to 0.00.

**Worker Metadata**

Ground Truth provides information that you can use to track individual workers in task output data. The following data is located in the directories under the worker-response located in the Annotations Directory (p. 616):

- The **acceptanceTime** is the time that the worker accepted the task. The format of this date and time stamp is YYYY-MM-DDTHH:MM:SS.mmmZ for the year (YYYY), month (MM), day (DD), hour (HH), minute (MM), second (SS) and millisecond (mmm). The date and time are separated by a T.
- The **submissionTime** is the time that the worker submitted their annotations using the Submit button. The format of this date and time stamp is YYYY-MM-DDTHH:MM:SS.mmmZ for the year (YYYY), month (MM), day (DD), hour (HH), minute (MM), second (SS) and millisecond (mmm). The date and time are separated by a T.
- **timeSpentInSeconds** reports the total time, in seconds, that a worker actively worked on that task. This metric does not include time when a worker paused or took a break.
- The **workerId** is unique to each worker.
- If you use a **private workforce**, in workerMetadata, you see the following.
  - The **identityProviderType** is the service used to manage the private workforce.
  - The **issuer** is the Cognito user pool or OIDC Identity Provider (IdP) issuer associated with the work team assigned to this human review task.
  - A unique sub identifier refers to the worker. If you create a workforce using Amazon Cognito, you can retrieve details about this worker (such as the name or user name) using this ID using Amazon Cognito. To learn how, see Managing and Searching for User Accounts in Amazon Cognito Developer Guide.

The following is an example of the output you may see if you use Amazon Cognito to create a private workforce. This is identified in the identityProviderType.

```json
"submissionTime": "2020-12-28T18:59:38.321Z",
"acceptanceTime": "2020-12-28T18:59:15.191Z",
"timeSpentInSeconds": 40.543,
"workerId": "a12b3cdefg4h5i67",
"workerMetadata": {
  "identityData": {
    "identityProviderType": "Cognito",
    "sub": "aaaaaaaa-bbbb-cccc-dddd-eeeeeeeeeeee"
  }
}
```

The following is an example of the workerMetadata you may see if you use your own OIDC IdP to create a private workforce:

```json
"workerMetadata": {  
  "identityData": {  
    "identityProviderType": "Oidc",
    "issuer": "https://example-oidc-ipd.com/adfs",
    "sub": "aaaaaaaa-bbbb-cccc-dddd-eeeeeeeeeeee"
  }
}
```

To learn more about using private workforces, see Use a Private Workforce (p. 699).
Output Metadata

The output from each job contains metadata about the label assigned to data objects. These elements are the same for all jobs with minor variations. The following example shows the metadata elements:

```
"confidence": 0.00,
"type": "groundtruth/image-classification",
"job-name": "identify-animal-species",
"human-annotated": "yes",
"creation-date": "2020-10-18T22:18:13.527256"
```

The elements have the following meaning:

- **confidentce** – The confidence that Ground Truth has that the label is correct. For more information, see Confidence Score (p. 616).
- **type** – The type of classification job. For job types, see Built-in Task Types (p. 542).
- **job-name** – The name assigned to the job when it was created.
- **human-annotated** – Whether the data object was labeled by a human or by automated data labeling. For more information, see Automate Data Labeling (p. 640).
- **creation-date** – The date and time that the label was created.

Classification Job Output

The following are sample outputs (output manifest files) from an image classification job and a text classification job. They include the label that Ground Truth assigned to the data object, the value for the label, and metadata that describes the label.

In addition to the standard metadata elements, the metadata for a classification job includes the text value of the label's class. For more information, see Image Classification - MXNet (p. 2172).

The red, italicized text in the examples below depends on labeling job specifications and output data.

```
{  
   "source-ref":"s3://AWSDOC-EXAMPLE-BUCKET/example_image.jpg",
   "species":"0",
   "species-metadata":
   {
      "class-name": "dog",
      "confidence": 0.00,
      "type": "groundtruth/image-classification",
      "job-name": "identify-animal-species",
      "human-annotated": "yes",
      "creation-date": "2018-10-18T22:18:13.527256"
   }
}
```

```
{  
   "source":"The food was delicious",
   "mood":"1",
   "mood-metadata":
   {
      "class-name": "positive",
      "confidence": 0.8,
      "type": "groundtruth/text-classification",
      "job-name": "label-sentiment",
      "human-annotated": "yes",
      "creation-date": "2020-10-18T22:18:13.527256"
   }
}
```
Multi-label Classification Job Output

The following are example output manifest files from a multi-label image classification job and a multi-label text classification job. They include the labels that Ground Truth assigned to the data object (for example, the image or piece of text) and metadata that describes the labels the worker saw when completing the labeling task.

The label attribute name parameter (for example, image-label-attribute-name) contains an array of all of the labels selected by at least one of the workers who completed this task. This array contains integer keys (for example, [1, 0, 8]) that correspond to the labels found in class-map. In the multi-label image classification example, bicycle, person, and clothing were selected by at least one of the workers who completed the labeling task for the image, exampleimage.jpg.

The confidence-map shows the confidence score that Ground Truth assigned to each label selected by a worker. To learn more about Ground Truth confidence scores, see Confidence Score (p. 616).

The red, italicized text in the examples below depends on labeling job specifications and output data.

The following is an example of a multi-label image classification output manifest file.

```
{
    "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/example_image.jpg",
    "image-label-attribute-name":[1,0,8],
    "image-label-attribute-name-metadata":
    {
        "job-name":"labeling-job/image-label-attribute-name",
        "class-map":
        {
            "1":"bicycle","0":"person","8":"clothing"
        },
        "human-annotated":"yes",
        "creation-date":"2020-02-27T21:36:25.000201",
        "confidence-map":
        {
            "1":0.95,"0":0.77,"8":0.2
        },
        "type":"groundtruth/image-classification-multilabel"
    }
}
```

The following is an example of a multi-label text classification output manifest file. In this example, approving, sad and critical were selected by at least one of the workers who completed the labeling task for the object exampltext.txt found in AWSDOC-EXAMPLE-BUCKET.

```
{
    "source-ref": "AWSDOC-EXAMPLE-BUCKET/text_file.txt",
    "text-label-attribute-name":[1,0,4],
    "text-label-attribute-name-metadata":
    {
        "job-name":"labeling-job/text-label-attribute-name",
        "class-map":
        {
            "1":"approving","0":"sad","4":"critical"
        },
        "human-annotated":"yes",
        "creation-date":"2020-02-20T21:36:25.000201",
        "confidence-map":
        {
            "1":0.95,"0":0.77,"4":0.2
        }
    }
}
```
Bounding Box Job Output

The following is sample output (output manifest file) from a bounding box job. For this task, three bounding boxes are returned. The label value contains information about the size of the image, and the location of the bounding boxes.

The class_id element is the index of the box's class in the list of available classes for the task. The class-map metadata element contains the text of the class.

The metadata has a separate confidence score for each bounding box. The metadata also includes the class-map element that maps the class_id to the text value of the class. For more information, see Object Detection - MXNet (p. 2196).

The red, italicized text in the examples below depends on labeling job specifications and output data.

```json
{
  "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/example_image.png",
  "bounding-box-attribute-name":
  {
    "image_size": [{ "width": 500, "height": 400, "depth": 3 }],
    "annotations":
    [
      { "class_id": 0, "left": 111, "top": 134, "width": 61, "height": 128 },
      { "class_id": 5, "left": 131, "top": 250, "width": 30, "height": 30 },
      { "class_id": 5, "left": 20, "top": 20, "width": 30, "height": 30 }
    ],
    "bounding-box-attribute-name-metadata":
    {
      "objects":
      [
        { "confidence": 0.8 },
        { "confidence": 0.9 },
        { "confidence": 0.9 }
      ],
      "class-map":
      {
        "0": "dog",
        "5": "bone"
      },
      "type": "groundtruth/object-detection",
      "human-annotated": "yes",
      "creation-date": "2018-10-18T22:18:13.527256",
      "job-name": "identify-dogs-and-toys"
    }
  }
}
```

The output of a bounding box adjustment job looks like the following JSON. Note that the original JSON is kept intact and two new jobs are listed, each with "adjust-" prepended to the original attribute's name.

```json
{
  "source-ref": "S3 bucket location",
  "bounding-box-attribute-name":
  {
    "image_size": [{ "width": 500, "height": 400, "depth": 3 }],
    "annotations":
    [
      { "class_id": 0, "left": 111, "top": 134, "width": 61, "height": 128 },
      { "class_id": 5, "left": 131, "top": 250, "width": 30, "height": 30 },
      { "class_id": 5, "left": 20, "top": 20, "width": 30, "height": 30 }
    ],
    "bounding-box-attribute-name-metadata":
    {
      "objects":
      [
        { "confidence": 0.8 },
        { "confidence": 0.9 },
        { "confidence": 0.9 }
      ],
      "class-map":
      {
        "0": "dog",
        "5": "bone"
      },
      "type": "groundtruth/object-detection",
      "human-annotated": "yes",
      "creation-date": "2018-10-18T22:18:13.527256",
      "job-name": "identify-dogs-and-toys"
    }
  }
}
```
In this output, the job's type doesn't change, but an adjustment-status field is added. This field has the value of adjusted or unadjusted. If multiple workers have reviewed the object and at least one adjusted the label, the status is adjusted.
Named Entity Recognition

The following is an example output manifest file from a named entity recognition (NER) labeling task. For this task, seven entities are returned.

In the output manifest, the JSON object, annotations, includes a list of the labels (label categories) that you provided.

Worker responses are in a list named entities. Each entity in this list is a JSON object that contains a label value that matches one in the labels list, an integer startOffset value for labeled span's starting Unicode offset, and an integer endOffset value for the ending Unicode offset.

The metadata has a separate confidence score for each entity. If a single worker labeled each data object, the confidence value for each entity will be zero.

The red, italicized text in the examples below depends on labeling job inputs and worker responses.

```json
{
  "source": "Amazon SageMaker is a cloud machine-learning platform that was launched in November 2017. SageMaker enables developers to create, train, and deploy machine-learning (ML) models in the cloud. SageMaker also enables developers to deploy ML models on embedded systems and edge-devices",
  "ner-labeling-job-attribute-name": {
    "annotations": {
      "labels": [
        {
          "label": "Date",
          "shortDisplayName": "dt"
        },
        {
          "label": "Verb",
          "shortDisplayName": "vb"
        },
        {
          "label": "Thing",
          "shortDisplayName": "tng"
        },
        {
          "label": "People",
          "shortDisplayName": "ppl"
        }
      ],
      "entities": [
        {
          "label": "Thing",
          "startOffset": 22,
          "endOffset": 53
        },
        {
          "label": "Thing",
          "startOffset": 269,
          "endOffset": 281
        },
        {
          "label": "Verb",
          "startOffset": 63,
          "endOffset": 71
        },
        {
          "label": "Verb",
          "startOffset": 228,
          "endOffset": 234
        }
      ]
    }
  }
}```
Label Verification Job Output

The output (output manifest file) of a bounding box verification job looks different than the output of a bounding box annotation job. That's because the workers have a different type of task. They're not labeling objects, but evaluating the accuracy of prior labeling, making a judgment, and then providing that judgment and perhaps some comments.

If human workers are verifying or adjusting prior bounding box labels, the output of a verification job would look like the following JSON. The red, italicized text in the examples below depends on labeling job specifications and output data.

```json
{
    "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/image_example.png",
    "bounding-box-attribute-name": {
        "image_size": [
            ["width": 500, "height": 400, "depth": 3]
```
Although the type on the original bounding box output was `groundtruth/object-detection`, the new type is `groundtruth/label-verification`. Also note that the `worker-feedback` array provides worker comments. If the worker doesn't provide comments, the empty fields are excluded during consolidation.

**Semantic Segmentation Job Output**

The following is the output manifest file from a semantic segmentation labeling job. The value of the label for this job is a reference to a PNG file in an Amazon S3 bucket.

In addition to the standard elements, the metadata for the label includes a color map that defines which color is used to label the image, the class name associated with the color, and the confidence score for each color. For more information, see [Semantic Segmentation Algorithm](p. 2215).

The red, italicized text in the examples below depends on labeling job specifications and output data.

```json
{
  "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/example_city_image.png",
  "city-streets-ref": "S3 bucket location"
}
```
Confidence is scored on a per-image basis. Confidence scores are the same across all classes within an image.

The output of a semantic segmentation adjustment job looks similar to the following JSON.

```json
{
   "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/example_city_image.png",
   "city-streets-ref": "S3 bucket location",
   "city-streets-ref-metadata": {
      "internal-color-map": {
         "0": {
            "class-name": "BACKGROUND",
            "confidence": 0.9,
            "hex-color": "#ffffff"
         },
         "1": {
            "class-name": "buildings",
            "confidence": 0.9,
            "hex-color": "#2acf59"
         },
         "2": {
            "class-name": "road",
            "confidence": 0.9,
            "hex-color": "#f28333"
         }
      },
      "type": "groundtruth/semantic-segmentation",
      "human-annotated": "yes",
      "creation-date": "2018-10-18T22:18:13.527256",
      "job-name": "label-city-streets",
      "verify-city-streets-ref": "1",
      "verify-city-streets-ref-metadata": {
         "class-name": "bad",
         "confidence": 0.93,
         "type": "groundtruth/label-verification",
         "job-name": "verify-city-streets",
         "human-annotated": "yes",
         "creation-date": "2018-11-20T22:18:13.527256",
         "worker-feedback": [{
            "comment": "The mask on the leftmost building is assigned the wrong side of the road.",
            "comment": "The curb of the road is not labeled but the instructions say otherwise."
         }]
      }
   }
}
```
Video Frame Object Detection Output

The following is the output manifest file from a video frame object detection labeling job. The red, italicized text in the examples below depends on labeling job specifications and output data.

In addition to the standard elements, the metadata includes a class map that lists each class that has at least one label in the sequence. The metadata also includes job-name which is the name you assigned to the labeling job. For adjustment tasks, if one or more bounding boxes were modified, there is an adjustment-status parameter in the metadata for audit workflows that is set to adjusted.

```
{
  "source-ref": "s3://DOC-EXAMPLE-BUCKET/example-path/input-manifest.json",
  "CarObjectDetection-ref": "s3://AWSDOC-EXAMPLE-BUCKET/output/labeling-job-name/annotations/consolidated-annotation/output/0/SeqLabel.json",
  "CarObjectDetection-ref-metadata": {
    "class-map": {
      "0": "car",
      "1": "bus"
    },
    "job-name": "labeling-job/labeling-job-name",
    "human-annotated": "yes",
    "creation-date": "2021-09-29T05:50:35.566000",
    "type": "groundtruth/video-object-detection"
  }
}
```

Ground Truth creates one output sequence file for each sequence of video frames that was labeled. Each output sequence file contains the following:
• All annotations for all frames in a sequence in the detection-annotations list of JSON objects.
• For each frame that was annotated by a worker, the frame file name (frame), number (frame-no), a list of JSON objects containing annotations (annotations), and if applicable, frame-attributes. The name of this list is defined by the task type you use: polylines, polygons, keypoints, and for bounding boxes, annotations.

Each JSON object contains information about a single annotation and associated label. The following table outlines the parameters you'll see for each video frame type.

<table>
<thead>
<tr>
<th>Task Type</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bounding Box</td>
<td>Box dimensions: height and width</td>
</tr>
<tr>
<td></td>
<td>Box top, left corner pixel location: top and left</td>
</tr>
<tr>
<td>Keypoint</td>
<td>Keypoint vertices: { &quot;x&quot;: int, &quot;y&quot;: int }</td>
</tr>
<tr>
<td>Polygon</td>
<td>A list of polygon vertices: vertices</td>
</tr>
<tr>
<td></td>
<td>Polygon vertices: { &quot;x&quot;: int, &quot;y&quot;: int }</td>
</tr>
<tr>
<td></td>
<td>A polygon is a closed shape and so the first point will also represent the last point.</td>
</tr>
<tr>
<td>Polyline</td>
<td>A list of polyline vertices: vertices</td>
</tr>
<tr>
<td></td>
<td>Polyline vertices: { &quot;x&quot;: int, &quot;y&quot;: int }</td>
</tr>
</tbody>
</table>

In addition to task type specific values, you will see the following in each JSON object:
• Values of any label-category-attributes that were specified for that label.
• The class-id of the box. Use the class-map in the output manifest file to see which label category this ID maps to.

The following is an example of a SeqLabel.json file from a bounding box video frame object detection labeling job. This file will be located under s3://your-output-bucket/output-prefix/annotations/consolidated-annotation/output/annotation-number/.

```json
{
  "detection-annotations": [
    {
      "annotations": [
        {
          "height": 41,
          "width": 53,
          "top": 152,
          "left": 339,
          "class-id": "1",
          "label-category-attributes": {
            "occluded": "no",
            "size": "medium"
          }
        },
        {
          "height": 24,
          "width": 37,
          "top": 148,
          "left": 183,
          "class-id": "0",
          "label-category-attributes": {
```
Video Frame Object Tracking Output

The following is the output manifest file from a video frame object tracking labeling job. The red, italicized text in the examples below depends on labeling job specifications and output data.

In addition to the standard elements, the metadata includes a class map that lists each class that has at least one label in the sequence of frames. The metadata also includes job-name which is the name you assigned to the labeling job. For adjustment tasks, if one or more bounding boxes were modified, there is an adjustment-status parameter in the metadata for audit workflows that is set to adjusted.

```json
{
  "source-ref": "s3://DOC-EXAMPLE-BUCKET/example-path/input-manifest.json",
  "CarObjectTracking-ref": "s3://AWSDOC-EXAMPLE-BUCKET/output labeling-job-name/annotations/consolidated-annotation/output/0/SeqLabel.json",
  "CarObjectTracking-ref-metadata": {
    "class-map": {
      "0": "car",
      "1": "bus"
    },
    "job-name": "labeling-job labeling-job-name",
    "human-annotated": "yes",
    "creation-date": "2021-09-29T05:50:35.566000",
    "type": "groundtruth/video-object-tracking"
  }
}```
Ground Truth creates one output sequence file for each sequence of video frames that was labeled. Each output sequence file contains the following:

- All annotations for all frames in a sequence in the tracking-annotations list of JSON objects.
- For each frame that was annotated by a worker, the frame (frame), number (frame-no), a list of JSON objects containing annotations (annotations), and if applicable, frame attributes (frame-attributes). The name of this list is defined by the task type you use: polylines, polygons, keypoints, and for bounding boxes, annotations.

Each JSON object contains information about a single annotation and associated label. The following table outlines the parameters you'll see for each video frame task type.

<table>
<thead>
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<td>Keypoint</td>
<td>Keypoint vertices: { &quot;x&quot;: int, &quot;y&quot;: int }</td>
</tr>
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<td></td>
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<tr>
<td></td>
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</tr>
</tbody>
</table>

In addition to task type specific values, you will see the following in each JSON object:

- Values of any label-category-attributes that were specified for that label.
- The class-id of the box. Use the class-map in the output manifest file to see which label category this ID maps to.
- An object-id which identifies an instance of a label. This ID will be the same across frames if a worker identified the same instance of an object in multiple frames. For example, if a car appeared in multiple frames, all bounding boxes uses to identify that car would have the same object-id.
- The object-name which is the instance ID of that annotation.

The following is an example of a SeqLabel.json file from a bounding box video frame object tracking labeling job. This file will be located under s3://your-output-bucket/output-prefix/annotations/consolidated-annotation/output/annotation-number/:

```json
[
  "tracking-annotations": [
    {
      "annotations": [
        {
          "height": 36,
          "width": 46,
          "top": 178,
          "left": 315,
          "class-id": "0",
          "label-category-attributes": {
            "occluded": "no"
          },
          "object-id": "480dc450-c0ca-11ea-961f-a9b1c5c97972",
```
3D Point Cloud Semantic Segmentation Output

The following is the output manifest file from a 3D point cloud semantic segmentation labeling job.

In addition to the standard elements, the metadata for the label includes a color map that defines which color is used to label the image, the class name associated with the color, and the confidence score for each color. Additionally, there is an adjustment-status parameter in the metadata for audit workflows that is set to adjusted if the color mask is modified. If you added one or more frameAttributes to your label category configuration file, worker responses for frame attributes are in the JSON object, dataset-object-attributes.

The your-label-attribute-ref parameter contains the location of a compressed file with a .zlib extension. When you uncompess this file, it contains an array. Each index in the array corresponds to the index of an annotated point in the input point cloud. The value of the array at a given index gives the class of the point at the same index in the point cloud, based on the semantic color map found in the color-map parameter of the metadata.

You can use Python code similar to the following to decompress a .zlib file:

```python
import zlib
from array import array
```
```python
# read the label file
compressed_binary_file = open(zlib_file_path/file.zlib, 'rb').read()

# uncompress the label file
binary_content = zlib.decompress(compressed_binary_file)

# load labels to an array
my_int_array_data = array('B', binary_content);
print(my_int_array_data)
```

The code block above will produce an output similar to the following. Each element of the printed array contains the class of a point at the that index in the point cloud. For example, `my_int_array_data[0] = 1` means point[0] in the input point cloud has a class 1. In the following output manifest file example, class 0 corresponds with "Background", 1 with Car, and 2 with Pedestrian.

```python
>> array('B', [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 2, 2, 2, 2, 2, 2, 2])
```

The following is an example of a semantic segmentation 3D point cloud labeling job output manifest file. The red, italicized text in the examples below depends on labeling job specifications and output data.

```json
{
    "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/examplefolder/frame1.bin",
    "source-ref-metadata": {
        "format": "binary/xyz",
        "unix-timestamp": 1566861644.759115,
        "ego-vehicle-pose": {...},
        "prefix": "s3://AWSDOC-EXAMPLE-BUCKET/lidar_singleframe_dataset/prefix",
        "images": [...]}
},
    "lidar-ss-label-attribute-ref": "s3://your-output-bucket/labeling-job-name/annotations/consolidated-annotation/output/dataset-object-id/filename.zlib",
    "lidar-ss-label-attribute-ref-metadata": {
        'color-map': {
            '0': {
                "class-name": "Background",
                "hex-color": "#ffffff",
                "confidence": 0.00
            },
            '1': {
                "class-name": "Car",
                "hex-color": "#2ca02c",
                "confidence": 0.00
            },
            '2': {
                "class-name": "Pedestrian",
                "hex-color": "#1f77b4",
                "confidence": 0.00
            },
            '3': {
                "class-name": "Tree",
                "hex-color": "#ff7f0e",
                "confidence": 0.00
            }
        },
        'type': 'groundtruth/point_cloud_single_frame_semantic_segmentation',
        'human-annotated': 'yes',
        'creation-date': '2019-11-12T01:18:14.271944',
        'job-name': 'labeling-job-name',
        // only present for adjustment audit workflow
        "adjustment-status": "adjusted", // "adjusted" means the label was adjusted
```

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3D Point Cloud Object Detection Output

The following is sample output from a 3D point cloud objected detection job. For this task type, the data about 3D cuboids is returned in the `3d-bounding-box` parameter, in a list named `annotations`. In this list, each 3D cuboid is described using the following information.

- Each class, or label category, that you specify in your input manifest is associated with a `class-id`. Use the `class-map` to identify the class associated with each class ID.
- These classes are used to give each 3D cuboid an `object-name` in the format `<class>:<integer>` where `integer` is a unique number to identify that cuboid in the frame.
- `center-x`, `center-y`, and `center-z` are the coordinates of the center of the cuboid, in the same coordinate system as the 3D point cloud input data used in your labeling job.
- `length`, `width`, and `height` describe the dimensions of the cuboid.
- `yaw` is used to describe the orientation (heading) of the cuboid in radians.

**Note**
yaw is now in the right-handed Cartesian system. Since this feature was added on September 02, 2022 19:02:17 UTC, you can convert the yaw measurement in the output data prior to that using the following (all units are in radians):

\[
\text{old\_yaw\_in\_output} = \pi - \text{yaw}
\]

- In our definition, +x is to the right, +y is to the forward, and +z is up from the ground plane. The rotation order is x - y - z. The roll, pitch and yaw are represented in the right-handed Cartesian system. In 3D space, roll is along the x-axis, pitch is along the y-axis and yaw is along the z-axis. All three are counterclockwise.
- If you included label attributes in your input manifest file for a given class, a `label-category-attributes` parameter is included for all cuboids for which workers selected label attributes.

If one or more cuboids were modified, there is an `adjustment-status` parameter in the metadata for audit workflows that is set to `adjusted`. If you added one or more `frameAttributes` to your label category configuration file, worker responses for frame attributes are in the JSON object, `dataset-object-attributes`.

The red, italicized text in the examples below depends on labeling job specifications and output data. The ellipses (...), denote a continuation of that list, where additional objects with the same format as the proceeding object can appear.

```json
{
    "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/examplefolder/frame1.txt",
    "source-ref-metadata": {
        "format": "text/xyzi",
        "unix-timestamp": 1566861644.759115,
        "prefix": "s3://AWSDOC-EXAMPLE-BUCKET/lidar_singleframe_dataset/prefix",
        "ego-vehicle-pose": {
            "heading": {
                "qx": -0.02111296123795955,
                "qy": -0.006495469416730261,
                "qz": -0.008024565904865688,
                "qw": 0.9997181192298087
            },
            "position": {
                "x": -2.7161461413869947,
```
"y": 116.25822288149078,
"z": 1.8348751887989483
},
"images": [
{
"fx": 847.7962624528487,
"fy": 850.0340893791985,
"cx": 576.2129134707038,
"cy": 317.2423573573745,
"k1": 0,
"k2": 0,
"k3": 0,
"k4": 0,
"p1": 0,
"p2": 0,
"skew": 0,
"unix-timestamp": 1566861644.759115,
"image-path": "images/frame_0_camera_0.jpg",
"position": {
"x": -2.2722515189268138,
"y": 116.86003310568965,
"z": 1.454614668542299
},
"heading": {
"qx": 0.7594754093069037,
"qy": 0.02181790885672969,
"qz": -0.02461725233103356,
"qw": -0.6496916273040025
},
"camera_model": "pinhole"
}
"3d-bounding-box":
{
"annotations": [
{
"label-category-attributes": {
"Occlusion": "Partial",
"Type": "Sedan"
},
"object-name": "Car:1",
"class-id": 0,
"center-x": -2.616382013657516,
"center-y": 125.04149850484193,
"center-z": 0.311272296465834,
"length": 2.993000265181146,
"width": 1.83552680519692056,
"height": 1.3233490884304047,
"roll": 0,
"pitch": 0,
"yaw": 1.6479308313703527
},
"label-category-attributes": {
"Occlusion": "Partial",
"Type": "Sedan"
},
"object-name": "Car:2",
"class-id": 0,
"center-x": -5.188984560617168,
"center-y": 99.7954483288783,
"center-z": 0.2226435567445657,
"length": 4,
"width": 2,
3D Point Cloud Object Tracking Output

The following is an example of an output manifest file from a 3D point cloud object tracking labeling job. The red, italicized text in the examples below depends on labeling job specifications and output data. The ellipses (…) denote a continuation of that list, where additional objects with the same format as the proceeding object can appear.

In addition to the standard elements, the metadata includes a class map that lists each class that has at least one label in the sequence. If one or more cuboids were modified, there is an adjustment-status parameter in the metadata for audit workflows that is set to adjusted.

```json
{
  "source-ref": "s3://AWSDOC-EXAMPLE-BUCKET/myfolder/seq1.json",
  "lidar-label-attribute-ref": "s3://<CustomerOutputLocation>/<labelingJobName>/annotations/consolidated-annotation/output/<datasetObjectId>/SeqLabel.json",
  "lidar-label-attribute-ref-metadata": {
    "objects": [
      {
        "frame-no": 300,
        "confidence": []
      },
      {
        "frame-no": 301,
        "confidence": []
      },
      ...
    ],
    'class-map': {'0': 'Car', '1': 'Person'},
    'type': 'groundtruth/point_cloud_object_tracking',
    'human-annotated': 'yes',
    'creation-date': '2019-11-12T01:18:14.271944',
    'job-name': 'identify-3d-objects',
    'adjustment-status': "adjusted"
  }
}
```

In the above example, the cuboid data for each frame in seq1.json is in SeqLabel.json in the Amazon S3 location, s3://<customerOutputLocation>/<labelingJobName>/annotations/
consolidated-annotation/output/<datasetObjectId>/SeqLabel.json. The following is an example of this label sequence file.

For each frame in the sequence, you see the frame-number, frame-name, if applicable, frame-attributes, and a list of annotations. This list contains 3D cuboids that were drawn for that frame. Each annotation includes the following information:

- An object-name in the format `<class>:<integer>` where class identifies the label category and integer is a unique ID across the dataset.
- When workers draw a cuboid, it is associated with a unique object-id which is associated with all cuboids that identify the same object across multiple frames.
- Each class, or label category, that you specified in your input manifest is associated with a class-id. Use the class-map to identify the class associated with each class ID.
- center-x, center-y, and center-z are the coordinates of the center of the cuboid, in the same coordinate system as the 3D point cloud input data used in your labeling job.
- length, width, and height describe the dimensions of the cuboid.
- yaw is used to describe the orientation (heading) of the cuboid in radians.

**Note**
yaw is now in the right-handed Cartesian system. Since this feature was added on September 02, 2022 19:02:17 UTC, you can convert the yaw measurement in the output data prior to that using the following (all units are in radians):

\[
\text{old}_\text{yaw}\text{in}\text{output} = \pi - \text{yaw}
\]

- In our definition, +x is to the right, +y is to the forward, and +z is up from the ground plane. The rotation order is x - y - z. The roll, pitch and yaw are represented in the right-handed Cartesian system. In 3D space, roll is along the x-axis, pitch is along the y-axis and yaw is along the z-axis. All three are counterclockwise.
- If you included label attributes in your input manifest file for a given class, a label-category-attributes parameter is included for all cuboids for which workers selected label attributes.

```json
{
  "tracking-annotations": [
    {
      "frame-number": 0,
      "frame-name": "0.txt.pcd",
      "frame-attributes": {"name": value, name: value},
      "annotations": [
        {
          "label-category-attributes": {},
          "object-name": "Car:4",
          "class-id": 0,
          "center-x": -2.2906369208300674,
          "center-y": 103.73924823843463,
          "center-z": 0.37634114027023313,
          "length": 4,
          "width": 2,
          "height": 2,
          "roll": 0,
          "pitch": 0,
          "yaw": 1.5827222214406014,
          "object-id": "ae5dc770-a782-11ea-b57d-67c51a0561a1"
        },
        {
          "label-category-attributes": {"Occlusion": "Partial",
          "Type": "Sedan"
        }
      ]
    }
  ]
}
```
<table>
<thead>
<tr>
<th>Frame Number</th>
<th>Frame Name</th>
<th>Annotations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1.txt.pcd</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Annotations for Frame 1: object names and attributes:
- Car:1
  - class-id: 0
  - center-x: -2.6451293634707413
  - center-y: 124.9534455706848
  - center-z: 0.5020834081743839
  - length: 4
  - width: 2
  - height: 2.080488827301309
  - roll: 0
  - pitch: 0
  - yaw: -1.596335581398077
  - object-id: 06efb020-a782-11ea-b57d-67c51a0561a1

- Car:2
  - class-id: 0
  - center-x: -5.205611313118477
  - center-y: 99.91731932137061
  - center-z: 0.22917217081212138
  - length: 3.8747142207671956
  - width: 1.9999999999999918
  - height: 2
  - roll: 0
  - pitch: 0
  - yaw: 1.5672228760316775
  - object-id: 26fad020-a782-11ea-b57d-67c51a0561a1

- Car:4
  - class-id: 0
  - center-x: -2.2906369208300674
  - center-y: 103.73924823843463
  - center-z: 0.37634114027023313
  - length: 4
  - width: 2
  - height: 2
  - roll: 0
  - pitch: 0
  - yaw: 1.58272222214406014
  - object-id: ae5dc770-a782-11ea-b57d-67c51a0561a1

Annotations for Frame 2: object names and attributes:
- Car:1
- Car:2

Annotations for Frame 3: object names and attributes:
- Car:1
- Car:2

Annotations for Frame 4: object names and attributes:
- Car:1
- Car:2
Enhanced Data Labeling

Amazon SageMaker Ground Truth manages sending your data objects to workers to be labeled. Labeling each data object is a task. Workers complete each task until the entire labeling job is complete. Ground Truth divides the total number of tasks into smaller batches that are sent to workers. A new batch is sent to workers when the previous one is finished.

Ground Truth provides two features that help improve the accuracy of your data labels and reduce the total cost of labeling your data:

- **Annotation consolidation** helps to improve the accuracy of your data object labels. It combines the results of multiple workers' annotation tasks into one high-fidelity label.
- **Automated data labeling** uses machine learning to label portions of your data automatically without having to send them to human workers.

**Topics**

- Control the Flow of Data Objects Sent to Workers (p. 637)
- Consolidate Annotations (p. 639)
- Automate Data Labeling (p. 640)
- Chaining Labeling Jobs (p. 646)

**Control the Flow of Data Objects Sent to Workers**

Depending on the type of labeling job you create, Amazon SageMaker Ground Truth sends data objects to workers in batches or in a streaming fashion. You can control the flow of data objects to workers in the following ways:
• For both types of labeling jobs, you can use MaxConcurrentTaskCount to control the total number of data objects available to all workers at a given point in time when the labeling job is running.
• For streaming labeling jobs, you can control the flow of data objects to workers by monitoring and controlling the number of data objects sent to the Amazon SQS associated with your labeling job.

Use the following sections to learn more about these options. To learn more about streaming labeling jobs, see Ground Truth Streaming Labeling Jobs (p. 576).

Topics
• Use MaxConcurrentTaskCount to Control the Flow of Data Objects (p. 638)
• Use Amazon SQS to Control the Flow of Data Objects to Streaming Labeling Jobs (p. 638)

Use MaxConcurrentTaskCount to Control the Flow of Data Objects

MaxConcurrentTaskCount defines the maximum number of data objects that can be labeled by human workers at the same time. If you use the console, this parameter is set to 1,000. If you use CreateLabelingJob, you can set this parameter to any integer between 1 and 1,000, inclusive.

When you start a labeling job using an input manifest file, Ground Truth does the following:

1. For each data object listed in your input manifest file, one or more tasks are created, depending on the value you specify for NumberOfHumanWorkersPerDataObject. For example, if you set the number of workers per data object to 3, 3 tasks will be created for each dataset object. To be marked as successfully labeled, at least one worker must label the object. Alternatively, the tasks can expire or be declined.
2. If you are using the Mechanical Turk workforce, Ground Truth first sends a batch of 10 dataset objects to your workers. It uses this small batch to set up the labeling job and to make sure that the job is correctly configured.
3. Next, Ground Truth sends MaxConcurrentTaskCount number of dataset objects to workers. For example, if you have 2,000 input data objects in your input manifest file and have set the number of workers per data object to 3 and set MaxConcurrentTaskCount to 900, the first 900 data objects in your input manifest are sent to workers, corresponding to 2,700 tasks (900 x 3). This is the first full-sized set of objects sent to workers.
4. What happens next depends on the type of labeling job you create. This step assumes one or more dataset objects in your input manifest file, or sent using an Amazon SNS input data source (in a streaming labeling job) were not include in the set sent to workers in step 3.
   - **Streaming labeling job:** As long as the total number of objects available to workers is equal to MaxConcurrentTaskCount, all remaining dataset objects on your input manifest file and that you send in real time using Amazon SNS are placed on an Amazon SQS queue. When the total number of objects available to workers falls below MaxConcurrentTaskCount minus NumberOfHumanWorkersPerDataObject, a new data object from the queue is used to create NumberOfHumanWorkersPerDataObject-tasks, which are sent to workers in real time.
   - **Non-streaming labeling job:** As workers finish labeling one set of objects, up to MaxConcurrentTaskCount times NumberOfHumanWorkersPerDataObject number of new tasks will be sent to workers. This process is repeated until all data objects in the input manifest file are labeled.

Use Amazon SQS to Control the Flow of Data Objects to Streaming Labeling Jobs

When you create a streaming labeling job, an Amazon SQS queue is automatically created in your account. Data objects are only added to the Amazon SQS queue when the total number of objects sent to workers is above MaxConcurrentTaskCount. Otherwise, objects are sent directly to workers.
You can use this queue to manage the flow of data objects to your labeling job. To learn more, see Manage Labeling Requests with an Amazon SQS Queue (p. 578).

**Consolidate Annotations**

An *annotation* is the result of a single worker's labeling task. *Annotation consolidation* combines the annotations of two or more workers into a single label for your data objects. A label, which is assigned to each object in the dataset, is a probabilistic estimate of what the true label should be. Each object in the dataset typically has multiple annotations, but only one label or set of labels.

You decide how many workers annotate each object in your dataset. Using more workers can increase the accuracy of your labels, but also increases the cost of labeling. To learn more about Ground Truth pricing, see Amazon SageMaker Ground Truth pricing.

If you use the Amazon SageMaker console to create a labeling job, the following are the defaults for the number of workers who can annotate objects:

- Text classification—3 workers
- Image classification—3 workers
- Bounding boxes—5 workers
- Semantic segmentation—3 workers
- Named entity recognition—3 workers

When you use the `CreateLabelingJob` operation, you set the number of workers to annotate each data object with the `NumberOfHumanWorkersPerDataObject` parameter. You can override the default number of workers that annotate a data object using the console or the `CreateLabelingJob` operation.

Ground Truth provides an annotation consolidation function for each of its predefined labeling tasks: bounding box, image classification, name entity recognition, semantic segmentation, and text classification. These are the functions:

- Multi-class annotation consolidation for image and text classification uses a variant of the Expectation Maximization approach to annotations. It estimates parameters for each worker and uses Bayesian inference to estimate the true class based on the class annotations from individual workers.
- Bounding box annotation consolidates bounding boxes from multiple workers. This function finds the most similar boxes from different workers based on the Jaccard index, or intersection over union, of the boxes and averages them.
- Semantic segmentation annotation consolidation treats each pixel in a single image as a multi-class classification. This function treats the pixel annotations from workers as "votes," with more information from surrounding pixels incorporated by applying a smoothing function to the image.
- Named entity recognition clusters text selections by Jaccard similarity and calculates selection boundaries based on the mode, or the median if the mode isn't clear. The label resolves to the most assigned entity label in the cluster, breaking ties by random selection.

You can use other algorithms to consolidate annotations. For information, see Create Your Own Annotation Consolidation Function (p. 639).

**Create Your Own Annotation Consolidation Function**

You can choose to use your own annotation consolidation function to determine the final labels for your labeled objects. There are many possible approaches for writing a function and the approach that you take depends on the nature of the annotations to consolidate. Broadly, consolidation functions look at the annotations from workers, measure the similarity between them, and then use some form of probabilistic judgment to determine what the most probable label should be.
If you want to use other algorithms to create annotation consolidations functions, you can find the worker responses in the `[project-name]/annotations/worker-response` folder of the Amazon S3 bucket where you direct the job output.

**Assess Similarity**

To assess the similarity between labels, you can use one of the following strategies, or you can use one that meets your data labeling needs:

- For label spaces that consist of discrete, mutually exclusive categories, such as multi-class classification, assessing similarity can be straightforward. Discrete labels either match or do not match.
- For label spaces that don't have discrete values, such as bounding box annotations, find a broad measure of similarity. For bounding boxes, one such measure is the Jaccard index. This measures the ratio of the intersection of two boxes with the union of the boxes to assess how similar they are. For example, if there are three annotations, then there can be a function that determines which annotations represent the same object and should be consolidated.

**Assess the Most Probable Label**

With one of the strategies detailed in the previous sections in mind, make some sort of probabilistic judgment on what the consolidated label should be. In the case of discrete, mutually exclusive categories, this can be straightforward. One of the most common ways to do this is to take the results of a majority vote between the annotations. This weights the annotations equally.

Some approaches attempt to estimate the accuracy of different annotators and weight their annotations in proportion to the probability of correctness. An example of this is the Expectation Maximization method, which is used in the default Ground Truth consolidation function for multi-class annotations.

For more information about creating an annotation consolidation function, see Step 3: Processing with AWS Lambda (p. 516).

**Automate Data Labeling**

If you choose, Amazon SageMaker Ground Truth can use active learning to automate the labeling of your input data for certain built-in task types. *Active learning* is a machine learning technique that identifies data that should be labeled by your workers. In Ground Truth, this functionality is called automated data labeling. Automated data labeling helps to reduce the cost and time that it takes to label your dataset compared to using only humans. When you use automated labeling, you incur SageMaker training and inference costs.

We recommend using automated data labeling on large datasets because the neural networks used with active learning require a significant amount of data for every new dataset. Typically, as you provide more data, the potential for high accuracy predictions goes up. Data will only be auto-labeled if the neural network used in the auto-labeling model can achieve an acceptably high level of accuracy. Therefore, with larger datasets, there is more potential to automatically label the data because the neural network can achieve high enough accuracy for auto-labeling. Automated data labeling is most appropriate when you have thousands of data objects. The minimum number of objects allowed for automated data labeling is 1,250, but we strongly suggest providing a minimum of 5,000 objects.

Automated data labeling is available only for the following Ground Truth built-in task types:

- Image Classification (Single Label) (p. 389)
- Image Semantic Segmentation (p. 382)
- Object detection (Bounding Box (p. 376))
- Text Classification (Single Label) (p. 400)
Streaming labeling jobs do not support automated data labeling.

To learn how to create a custom active learning workflow using your own model, see Set up an active learning workflow with your own model (p. 646).

Input data quotas apply for automated data labeling jobs. See Input Data Quotas (p. 580) for information about dataset size, input data size and resolution limits.

Note  
Before you use an the automated-labeling model in production, you need to fine-tune or test it, or both. You might fine-tune the model (or create and tune another supervised model of your choice) on the dataset produced by your labeling job to optimize the model's architecture and hyperparameters. If you decide to use the model for inference without fine-tuning it, we strongly recommend making sure that you evaluate its accuracy on a representative (for example, randomly selected) subset of the dataset labeled with Ground Truth and that it matches your expectations.

How it Works

You enable automated data labeling when you create a labeling job. This is how it works:

1. When Ground Truth starts an automated data labeling job, it selects a random sample of input data objects and sends them to human workers. If more than 10% of these data objects fail, the labeling job will fail. If the labeling job fails, in addition to reviewing any error message Ground Truth returns, check that your input data is displaying correctly in the worker UI, instructions are clear, and that you have given workers enough time to complete tasks.

2. When the labeled data is returned, it is used to create a training set and a validation set. Ground Truth uses these datasets to train and validate the model used for auto-labeling.

3. Ground Truth runs a batch transform job, using the validated model for inference on the validation data. Batch inference produces a confidence score and quality metric for each object in the validation data.

4. The auto labeling component will use these quality metrics and confidence scores to create a confidence score threshold that ensures quality labels.

5. Ground Truth runs a batch transform job on the unlabeled data in the dataset, using the same validated model for inference. This produces a confidence score for each object.

6. The Ground Truth auto labeling component determines if the confidence score produced in step 5 for each object meets the required threshold determined in step 4. If the confidence score meets the threshold, the expected quality of automatically labeling exceeds the requested level of accuracy and that object is considered auto-labeled.

7. Step 6 produces a dataset of unlabeled data with confidence scores. Ground Truth selects data points with low confidence scores from this dataset and sends them to human workers.

8. Ground Truth uses the existing human-labeled data and this additional labeled data from human workers to update the model.

9. The process is repeated until the dataset is fully labeled or until another stopping condition is met. For example, auto-labeling stops if your human annotation budget is reached.

The preceding steps happen in iterations. Select each tab in the following table to see an example of the processes that happen in each iteration for an object detection automated labeling job. The number of data objects used in a given step in these images (for example, 200) is specific to this example. If there are fewer than 5,000 objects to label, the validation set size is 20% of the whole dataset. If there are more than 5,000 objects in your input dataset, the validation set size is 10% of the whole dataset. You can control the number of human labels collected per active learning iteration by changing the value for MaxConcurrentTaskCount when using the API operation CreateLabelingJob. This value is set to 1,000 when you create a labeling job using the console. In the active learning flow illustrated under the Active Learning tab, this value is set to 200.
Model Training

Iterations 1, 2, and 3: Model training

Unlabeled images

Send randomly selected images to annotators

Iteration 3: 20 labeled, 20 valid
Automated Labeling

Iteration 4: Automated Labeling

- 200 human-annotated validation labels
- Compare human-annotated and automated labels
- Trained model
- 200 automated validation labels with confidence scores
- Unlabeled images
- Trained model
**Active Learning**

**Accuracy of Automated Labels**

The definition of *accuracy* depends on the built-in task type that you use with automated labeling. For all task types, these accuracy requirements are pre-determined by Ground Truth and cannot be manually configured.

- For image classification and text classification, Ground Truth uses logic to find a label-prediction confidence level that corresponds to at least 95% label accuracy. This means Ground Truth expects the accuracy of the automated labels to be at least 95% when compared to the labels that human labelers would provide for those examples.
- For bounding boxes, the expected mean *Intersection Over Union (IoU)* of the auto-labeled images is 0.6. To find the mean IoU, Ground Truth calculates the mean IoU of all the predicted and missed boxes on the image for every class, and then averages these values across classes.
- For semantic segmentation, the expected mean IoU of the auto-labeled images is 0.7. To find the mean IoU, Ground Truth takes the mean of the IoU values of all the classes in the image (excluding the background).

At every iteration of Active Learning (steps 3-6 in the list above), the confidence threshold is found using the human-annotated validation set so that the expected accuracy of the auto-labeled objects satisfies certain predefined accuracy requirements.

**Create an Automated Data Labeling Job (Console)**

To create a labeling job that uses automated labeling in the SageMaker console, use the following procedure.

**To create an automated data labeling job (console)**

2. Using Create a Labeling Job (Console) (p. 544) as a guide, complete the *Job overview* and *Task type* sections. Note that auto labeling is not supported for custom task types.
4. In the same section, choose **Enable automated data labeling**.
5. Using Step 4: Configure the Bounding Box Tool (p. 375) as a guide, create worker instructions in the section **Task Type labeling tool**. For example, if you chose **Semantic segmentation** as your labeling job type, this section is called **Semantic segmentation labeling tool**.
6. To preview your worker instructions and dashboard, choose **Preview**.
7. Choose **Create**. This creates and starts your labeling job and the auto labeling process.

You can see your labeling job appear in the **Labeling jobs** section of the SageMaker console. Your output data appears in the Amazon S3 bucket that you specified when creating the labeling job. For more information about the format and file structure of your labeling job output data, see **Output Data** (p. 614).

**Create an Automated Data Labeling Job (API)**

To create an automated data labeling job using the SageMaker API, use the **LabelingJobAlgorithmsConfig** parameter of the **CreateLabelingJob** operation. To learn how to start a labeling job using the **CreateLabelingJob** operation, see **Create a Labeling Job (API)** (p. 547).

Specify the Amazon Resource Name (ARN) of the algorithm that you are using for automated data labeling in the **LabelingJobAlgorithmSpecificationArn** parameter. Choose from one of the four Ground Truth built-in algorithms that are supported with automated labeling:

- Image Classification (Single Label) (p. 389)
- Image Semantic Segmentation (p. 382)
- Object detection (Bounding Box (p. 376))
- Text Classification (Single Label) (p. 400)

When an automated data labeling job finishes, Ground Truth returns the ARN of the model it used for the automated data labeling job. Use this model as the starting model for similar auto-labeling job types by providing the ARN, in string format, in the **InitialActiveLearningModelArn** parameter. To retrieve the model's ARN, use an AWS Command Line Interface (AWS CLI) command similar to the following.

```
# Fetch the mARN of the model trained in the final iteration of the previous labeling job. Ground Truth
pretrained_model_arn = sagemaker_client.describe_labeling_job(LabelingJobName=job_name)
['LabelingJobOutput']['FinalActiveLearningModelArn']
```

To encrypt data on the storage volume attached to the ML compute instance(s) that are used in automated labeling, include an AWS Key Management Service (AWS KMS) key in the **VolumeKmsKeyId** parameter. For information about AWS KMS keys, see **What is AWS Key Management Service?** in the **AWS Key Management Service Developer Guide**.

For an example that uses the **CreateLabelingJob** operation to create an automated data labeling job, see the **object_detection_tutorial** example in the **SageMaker Examples, Ground Truth Labeling Jobs** section of a SageMaker notebook instance. To learn how to create and open a notebook instance, see **Create a Notebook Instance** (p. 296). To learn how to access SageMaker example notebooks, see Example Notebooks (p. 306).

**Amazon EC2 Instances Required for Automated Data Labeling**

The following table lists the Amazon Elastic Compute Cloud (Amazon EC2) instances that you need to run automated data labeling for training and batch inference jobs.
Automated Data Labeling Job Type | Training Instance Type | Inference Instance Type
--- | --- | ---
Image classification | ml.p3.2xlarge* | ml.c5.xlarge
Object detection (bounding box) | ml.p3.2xlarge* | ml.c5.4xlarge
Text classification | ml.c5.2xlarge | ml.m4.xlarge
Semantic segmentation | ml.p3.2xlarge* | ml.p3.2xlarge*  

* In the Asia Pacific (Mumbai) Region (ap-south-1) use ml.p2.8xlarge instead.

Ground Truth manages the instances that you use for automated data labeling jobs. It creates, configures, and terminates the instances as needed to perform your job. These instances don't appear in your Amazon EC2 instance dashboard.

**Set up an active learning workflow with your own model**

You can create an active learning workflow with your own algorithm to run training and inferences in that workflow to auto-label your data. The notebook `bring_your_own_model_for_sagemaker_labeling_workflows_with_active_learning.ipynb` demonstrates this using the SageMaker built-in algorithm, BlazingText. This notebook provides an AWS CloudFormation stack that you can use to execute this workflow using AWS Step Functions. You can find the notebook and supporting files in this GitHub repository.

You can also find this notebook in the SageMaker Examples repository. See Use Example Notebooks to learn how to find an Amazon SageMaker example notebook.

**Chaining Labeling Jobs**

Amazon SageMaker Ground Truth can reuse datasets from prior jobs in two ways: cloning and chaining.

**Cloning** copies the setup of a prior labeling job and allows you to make additional changes before setting it to run.

**Chaining** uses not only the setup of the prior job, but also the results. This allows you to continue an incomplete job and add labels or data objects to a completed job. Chaining is a more complex operation.

For data processing:

- Cloning uses the prior job's *input* manifest, with optional modifications, as the new job's input manifest.
- Chaining uses the prior job's *output* manifest as the new job's input manifest.

Chaining is useful when you need to:

- Continue a labeling job that was manually stopped.
- Continue a labeling job that failed mid-job, after fixing issues.
- Switch to automated data labeling after manually labeling part of a job (or the other way around).
- Add more data objects to a completed job and start the job from there.
- Add another annotation to a completed job. For example, you have a collection of phrases labeled for topic, then want to run the set again, categorizing them by the topic's implied audience.
In Amazon SageMaker Ground Truth you can configure a chained labeling job with either the console or the API.

**Key Term: Label Attribute Name**

The *label attribute name* (LabelAttributeName in the API) is a string used as the key for the key-value pair formed with the label that a worker assigns to the data object.

The following rules apply for the label attribute name:

- It can't end with `-metadata`.
- The names `source` and `source-ref` are reserved and can't be used.
- For semantic segmentation labeling jobs, it must end with `-ref`. For all other labeling jobs, it *can't* end with `-ref`. If you use the console to create the job, Amazon SageMaker Ground Truth automatically appends `-ref` to all label attribute names except for semantic segmentation jobs.
- For a chained labeling job, if you're using the same label attribute name from the originating job and you configure the chained job to use auto-labeling, then if it had been in auto-labeling mode at any point, Ground Truth uses the model from the originating job.

In an output manifest, the label attribute name appears similar to the following.

```json
"source-ref": "<S3 URI>",
"<label attribute name>": {
  "annotations": [{
    "class_id": 0,
    "width": 99,
    "top": 87,
    "height": 62,
    "left": 175
  }],
  "image_size": [{
    "width": 344,
    "depth": 3,
    "height": 234
  }]}
,"<label attribute name>-metadata": {
  "job-name": "<job name>",
  "class-map": {
    "0": "<label attribute name>"
  },
  "human-annotated": "yes",
  "objects": [{
    "confidence": 0.09
  }],
  "creation-date": "<timestamp>",
  "type": "groundtruth/object-detection"
}
```

If you're creating a job in the console and don't explicitly set the label attribute name value, Ground Truth uses the job name as the label attribute name for the job.

**Start a Chained Job (Console)**

Choose a stopped, failed, or completed labeling job from the list of your existing jobs. This enables the **Actions** menu.

From the **Actions** menu, choose **Chain**.
Job Overview Panel

In the Job overview panel, a new Job name is set based on the title of the job from which you are chaining this one. You can change it.

You may also specify a label attribute name different from the labeling job name.

If you're chaining from a completed job, the label attribute name uses the name of the new job you're configuring. To change the name, select the check box.

If you're chaining from a stopped or failed job, the label attribute name uses the name of the job from which you're chaining. It's easy to see and edit the value because the name check box is checked.

Attribute label naming considerations

- The default uses the label attribute name Ground Truth has selected. All data objects without data connected to that label attribute name are labeled.
- Using a label attribute name not present in the manifest causes the job to process all the objects in the dataset.

The input dataset location in this case is automatically selected as the output manifest of the chained job. The input field is not available, so you cannot change it.

Adding data objects to a labeling job

You cannot specify an alternate manifest file. Manually edit the output manifest from the previous job to add new items before starting a chained job. The Amazon S3 URI helps you locate where you are storing the manifest in your Amazon S3 bucket. Download the manifest file from there, edit it locally on your computer, and then upload the new version to replace it. Make sure you are not introducing errors during editing. We recommend you use JSON linter to check your JSON. Many popular text editors and IDEs have linter plugins available.

Start a Chained Job (API)

The procedure is almost the same as setting up a new labeling job with CreateLabelingJob, except for two primary differences:

- Manifest location: Rather than use your original manifest from the prior job, the value for the ManifestS3Uri in the DataSource should point to the Amazon S3 URI of the output manifest from the prior labeling job.
- Label attribute name: Setting the correct LabelAttributeName value is important here. This is the key portion of a key-value pair where labeling data is the value. Sample use cases include:
  - Adding new or more specific labels to a completed job — Set a new label attribute name.
  - Labeling the unlabeled items from a prior job — Use the label attribute name from the prior job.

Use a Partially Labeled Dataset

You can get some chaining benefits if you use an augmented manifest that has already been partially labeled. Check the Label attribute name check box and set the name so that it matches the name in your manifest.

If you're using the API, the instructions are the same as those for starting a chained job. However, be sure to upload your manifest to an Amazon S3 bucket and use it instead of using the output manifest from a prior job.

The Label attribute name value in the manifest has to conform to the naming considerations discussed earlier.
Ground Truth Security and Permissions

Use the topics on this page to learn about Ground Truth security features and how to configure AWS Identity and Access Management (IAM) permissions to allow an IAM user or role to create a labeling job. Additionally, learn how to create an execution role. An execution role is the role that you specify when you create a labeling job. This role is used to start your labeling job.

If you are a new user and want to get started quickly, or if you do not require granular permissions, see Use IAM Managed Policies with Ground Truth (p. 650).

For more information about IAM users and roles, see Identities (Users, Groups, and Roles) in the IAM User Guide.

To learn more about using IAM with SageMaker, see Identity and Access Management for Amazon SageMaker (p. 3500).

Topics

- CORS Permission Requirement (p. 649)
- Assign IAM Permissions to Use Ground Truth (p. 650)
- Using Amazon SageMaker Ground Truth in an Amazon Virtual Private Cloud (p. 661)
- Output Data and Storage Volume Encryption (p. 672)
- Workforce Authentication and Restrictions (p. 673)

CORS Permission Requirement

Earlier in 2020, widely used browsers like Chrome and Firefox changed their default behavior for rotating images based on image metadata, referred to as EXIF data. Previously, browsers would always display images in exactly the manner in which they are stored on disk, which is typically unrotated. After the change, images now rotate according to a piece of image metadata called orientation value. This has important implications for the entire machine learning (ML) community. For example, if applications that annotate images do not consider the EXIF orientation, they may display images in unexpected orientations, resulting in incorrect labels.

Starting with Chrome 89, AWS can no longer automatically prevent the rotation of images because the web standards group W3C has decided that the ability to control rotation of images violates the web’s Same-origin Policy. Therefore, to ensure human workers annotate your input images in a predictable orientation when you submit requests to create a labeling job, you must add a CORS header policy to the Amazon S3 buckets that contain your input images.

Important
If you do not add a CORS configuration to the Amazon S3 buckets that contain your input data, labeling tasks for those input data objects will fail.

If you create a job through the Ground Truth console, CORS is enabled by default. If all of your input data is not located in the same Amazon S3 bucket as your input manifest file, you must add a CORS configuration to all Amazon S3 buckets that contain input data using the following instructions.

If you are using the CreateLabelingJob API to create a Ground Truth labeling job, you can add a CORS policy to an Amazon S3 bucket that contains input data in the S3 console. To set the required CORS headers on the Amazon S3 bucket that contain your input images in the Amazon S3 console, follow the directions detailed in How do I add cross-domain resource sharing with CORS?. Use the following CORS configuration code for the buckets that host your images. If you use the Amazon S3 console to add the policy to your bucket, you must use the JSON format.

Important
If you create a 3D point cloud or video frame labeling job, you must add additional rules to your CORS configuration. To learn more, see 3D Point Cloud Labeling Job Permission Requirements (p. 471) and Video Frame Job Permission Requirements (p. 423) respectively.
Assign IAM Permissions to Use Ground Truth

Use the topics in this section to learn how to use AWS Identity and Access Management (IAM) managed and custom policies to manage access to Ground Truth and associated resources.

You can use the sections on this page to learn the following:

• How to create IAM policies that grant an IAM user or role permission to create a labeling job. Administrators can use IAM policies to restrict access to Amazon SageMaker and other AWS services that are specific to Ground Truth.
• How to create a SageMaker execution role. An execution role is the role that you specify when you create a labeling job. The role is used to start and manage your labeling job.

The following is an overview of the topics you’ll find on this page:

• If you are getting started using Ground Truth, or you do not require granular permissions for your use case, it is recommended that you use the IAM managed policies described in Use IAM Managed Policies with Ground Truth (p. 650).
• Learn about the permissions required to use the Ground Truth console in Grant IAM Permission to Use the Amazon SageMaker Ground Truth Console (p. 651). This section includes policy examples that grant an IAM entity permission to create and modify private work teams, subscribe to vendor work teams, and create custom labeling workflows.
• When you create a labeling job, you must provide an execution role. Use Create a SageMaker Execution Role for a Ground Truth Labeling Job (p. 655) to learn about the permissions required for this role.

Use IAM Managed Policies with Ground Truth

SageMaker and Ground Truth provide AWS managed policies that you can use to create a labeling job. If you are getting started using Ground Truth and you do not require granular permissions for your use case, it is recommended that you use the following policies:

• AmazonSageMakerFullAccess – Use this policy to give an IAM user or role permission to create a labeling job. This is a broad policy that grants an IAM entity permission to use SageMaker features, as well as features of necessary AWS services through the console and API. This policy gives the IAM entity permission to create a labeling job and to create and manage workforces using Amazon Cognito. To learn more, see AmazonSageMakerFullAccess Policy.
• **AmazonSageMakerGroundTruthExecution** – To create an execution role, you can attach the policy AmazonSageMakerGroundTruthExecution to an IAM role. An execution role is the role that you specify when you create a labeling job and it is used to start your labeling job. This policy allows you to create both streaming and non-streaming labeling jobs, and to create a labeling job using any task type. Note the following limits of this managed policy.

- **Amazon S3 permissions**: This policy grants an execution role permission to access Amazon S3 buckets with the following strings in the name: GroundTruth, Groundtruth, groundtruth, SageMaker, Sagemaker, and sagemaker or a bucket with an object tag that includes SageMaker in the name (case insensitive). Make sure your input and output bucket names include these strings, or add additional permissions to your execution role to grant it permission to access your Amazon S3 buckets. You must give this role permission to perform the following actions on your Amazon S3 buckets: AbortMultipartUpload, GetObject, and PutObject.

- **Custom Workflows**: When you create a custom labeling workflow, this execution role is restricted to invoking AWS Lambda functions with one of the following strings as part of the function name: GtRecipe, SageMaker, Sagemaker, sagemaker, or LabelingFunction. This applies to both your pre-annotation and post-annotation Lambda functions. If you choose to use names without those strings, you must explicitly provide lambda:InvokeFunction permission to the execution role used to create the labeling job.

To learn how to attach an AWS managed policy to an IAM user or role (identity), refer to Adding and removing IAM identity permissions in the IAM User Guide.

### Grant IAM Permission to Use the Amazon SageMaker Ground Truth Console

To use the Ground Truth area of the SageMaker console, you need to grant permission to an IAM entity to access SageMaker and other AWS services that Ground Truth interacts with. Required permissions to access other AWS services depends on your use-case:

- **Amazon S3 permissions** are required for all use cases. These permissions must grant access to the Amazon S3 buckets that contain input and output data.
- **AWS Marketplace permissions** are required to use a vendor workforce.
- **Amazon Cognito permission** are required for private work team setup.
- **AWS KMS permissions** are required to view available AWS KMS keys that can be used for output data encryption.
- **IAM permissions** are required to either list pre-existing execution roles, or to create a new one. Additionally, you must use add a PassRole permission to allow SageMaker to use the execution role chosen to start the labeling job.

The following sections list policies you may want to grant to an IAM role to use one or more functions of Ground Truth.

### Topics

- Ground Truth Console Permissions (p. 651)
- Custom Labeling Workflow Permissions (p. 654)
- Private Workforce Permissions (p. 655)
- Vendor Workforce Permissions (p. 655)

### Ground Truth Console Permissions

To grant permission to an IAM user or role to use the Ground Truth area of the SageMaker console to create a labeling job, attach the following policy to the user or role. The following policy will give an IAM role permission to create a labeling job using a built-in task type task type. If you want to create
a custom labeling workflow, add the policy in Custom Labeling Workflow Permissions (p. 654) to the following policy. Each Statement included in the following policy is described below this code block.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "SageMakerApis",
      "Effect": "Allow",
      "Action": [
        "sagemaker:*"
      ],
      "Resource": "*"
    },
    {
      "Sid": "KmsKeysForCreateForms",
      "Effect": "Allow",
      "Action": [
        "kms:DescribeKey",
        "kms:ListAliases"
      ],
      "Resource": "*"
    },
    {
      "Sid": "AccessAwsMarketplaceSubscriptions",
      "Effect": "Allow",
      "Action": [
        "aws-marketplace:ViewSubscriptions"
      ],
      "Resource": "*"
    },
    {
      "Sid": "SecretsManager",
      "Effect": "Allow",
      "Action": [
        "secretsmanager:CreateSecret",
        "secretsmanager:DescribeSecret",
        "secretsmanager:ListSecrets"
      ],
      "Resource": "*"
    },
    {
      "Sid": "ListAndCreateExecutionRoles",
      "Effect": "Allow",
      "Action": [
        "iam:ListRoles",
        "iam:CreateRole",
        "iam:CreatePolicy",
        "iam:AttachRolePolicy"
      ],
      "Resource": "*"
    },
    {
      "Sid": "PassRoleForExecutionRoles",
      "Effect": "Allow",
      "Action": [
        "iam:PassRole"
      ],
      "Resource": "*"
    },
    {
      "Sid": "SecretsManager",
      "Effect": "Allow",
      "Action": [
        "secretsmanager:GetSecretValue"
      ],
      "Resource": "*"
    },
    {
      "Sid": "AccessKmsKeys",
      "Effect": "Allow",
      "Action": [
        "kms:Encrypt",
        "kms:Decrypt",
        "kms:ReEncryptTo",
        "kms:ReEncryptFrom",
        "kms:GenerateDataKey",
        "kms:GenerateDataKeyoi",
        "kms:ReEncrypt",
        "kms:CancelPendingKeyDeletion",
        "kms:ListKeyHistory",
        "kms:DescribeKey",
        "kms:ListAliases"
      ],
      "Resource": "*"
    }
  ]
}
```
This policy includes the following statements. You can scope down any of these statements by adding specific resources to the Resource list for that statement.

**SageMakerApi**

This statement includes `sagemaker:*`, which allows the user to perform all SageMaker API actions. You can reduce the scope of this policy by restricting users from performing actions that are not used to create and monitoring a labeling job.

**KmsKeysForCreateForms**

You only need to include this statement if you want to grant a user permission to list and select AWS KMS keys in the Ground Truth console to use for output data encryption. The policy above grants a user permission to list and select any key in the account in AWS KMS. To restrict the keys that a user can list and select, specify those key ARNs in Resource.

**SecretsManager**

This statement gives the user permission to describe, list, and create resources in AWS Secrets Manager required to create the labeling job.

**ListAndCreateExecutionRoles**

This statement gives a user permission to list (ListRoles) and create (CreateRole) IAM roles in your account. It also grants the user permission to create (CreatePolicy) policies and attach
(AttachRolePolicy) policies to IAM entities. These are required to list, select, and if required, create an 
execution role in the console.

If you have already created an execution role, and want to narrow the scope of this statement so that 
users can only select that role in the console, specify the ARNs of the IAM roles you want the user to 
have permission to view in Resource and remove the actions CreateRole, CreatePolicy, and 
AttachRolePolicy.

AccessAwsMarketplaceSubscriptions

These permissions are required to view and choose vendor work teams that you are already subscribed 
to when creating a labeling job. To give the user permission to subscribe to vendor work teams, add the 
statement in Vendor Workforce Permissions (p. 655) to the policy above

PassRoleForExecutionRoles

This is required to give the labeling job creator permission to preview the worker UI and verify that input 
data, labels, and instructions display correctly. This statement gives an IAM entity permissions to pass 
the IAM execution role used to create the labeling job to SageMaker to render and preview the worker UI. 
To narrow the scope of this policy, add the role ARN of the execution role used to create the labeling job 
under Resource.

GroundTruthConsole

• groundtruthlabeling – This allows a user to perform actions required to use certain features 
of the Ground Truth console. These include permissions to describe the labeling job status 
(DescribeConsoleJob), list all dataset objects in the input manifest file (ListDatasetObjects), 
filter the dataset if dataset sampling is selected (RunFilterOrSampleDatasetJob), and to generate 
input manifest files if automated data labeling is used (RunGenerateManifestByCrawlingJob). 
These actions are only available when using the Ground Truth console and cannot be called directly 
using an API.
• lambda:InvokeFunction and lambda:ListFunctions – these actions give users permission to list 
and invoke Lambda functions that are used to run a custom labeling workflow.
• s3:* – All Amazon S3 permissions included in this statement are used to view Amazon S3 buckets 
for automated data setup (ListAllMyBuckets), access input data in Amazon S3 (ListBucket, 
GetObject), check for and create a CORS policy in Amazon S3 if needed (GetBucketCors and 
PutBucketCors), and write labeling job output files to S3 (PutObject).
• cognito-idp – These permissions are used to create, view and manage a private workforce using 
Amazon Cognito. To learn more about these actions, refer to the Amazon Cognito API References.

Custom Labeling Workflow Permissions

Add the following statement to a policy similar to the one in Ground Truth Console 
Permissions (p. 651) to give an IAM user permission to select pre-existing pre-annotation and post-
annotation Lambda functions while creating a custom labeling workflow.

```
{
  "Sid": "GroundTruthConsoleCustomWorkflow",
  "Effect": "Allow",
  "Action": [
    "lambda:InvokeFunction",
    "lambda:ListFunctions"
  ],
  "Resource": "*"
}
```

To learn how to give an IAM entity permission to create and test pre-annotation and post-annotation 
Lambda functions, see Required Permissions To Use Lambda With Ground Truth.
Private Workforce Permissions

When added to a permissions policy, the following permission grants access to create and manage a private workforce and work team using Amazon Cognito. These permissions are not required to use an OIDC IdP workforce.

```
{
    "Effect": "Allow",
    "Action": [
        "cognito-idp:AdminAddUserToGroup",
        "cognito-idp:AdminCreateUser",
        "cognito-idp:AdminDeleteUser",
        "cognito-idp:AdminDisableUser",
        "cognito-idp:AdminEnableUser",
        "cognito-idp:AdminRemoveUserFromGroup",
        "cognito-idp:CreateGroup",
        "cognito-idp:CreateUserPool",
        "cognito-idp:CreateUserPoolClient",
        "cognito-idp:CreateUserPoolDomain",
        "cognito-idp:DescribeUserPool",
        "cognito-idp:DescribeUserPoolClient",
        "cognito-idp:DescribeUserPoolDomain",
        "cognito-idp:ListGroups",
        "cognito-idp:ListIdentityProviders",
        "cognito-idp:ListUsers",
        "cognito-idp:ListUsersInGroup",
        "cognito-idp:ListUserPoolClients",
        "cognito-idp:ListUserPools",
        "cognito-idp:UpdateUserPool",
        "cognito-idp:UpdateUserPoolClient"
    ],
    "Resource": "*"
}
```

To learn more about creating private workforce using Amazon Cognito, see Create and Manage Amazon Cognito Workforce (p. 700).

Vendor Workforce Permissions

You can add the following statement to the policy in Grant IAM Permission to Use the Amazon SageMaker Ground Truth Console (p. 651) to grant an IAM entity permission to subscribe to a vendor workforce.

```
{
    "Sid": "AccessAwsMarketplaceSubscriptions",
    "Effect": "Allow",
    "Action": [
        "aws-marketplace:Subscribe",
        "aws-marketplace:Unsubscribe",
        "aws-marketplace:ViewSubscriptions"
    ],
    "Resource": "*"
}
```

Create a SageMaker Execution Role for a Ground Truth Labeling Job

When you configure your labeling job, you need to provide an execution role, which is a role that SageMaker has permission to assume to start and run your labeling job.

This role must give Ground Truth permission to access the following:

- Amazon S3 to retrieve your input data and write output data to an Amazon S3 bucket. You can either grant permission for an IAM role to access an entire bucket by providing the bucket ARN, or you can
grant access to the role to access specific resources in a bucket. For example, the ARN for a bucket may look similar to arn:aws:s3:::awsexamplebucket1 and the ARN of a resource in an Amazon S3 bucket may look similar to arn:aws:s3:::awsexamplebucket1/prefix/file-name.png. To apply an action to all resources in an Amazon S3 bucket, you can use the wild card: *. For example, arn:aws:s3:::awsexamplebucket1/prefix/*. For more information, see Amazon S3 Resources in the Amazon Simple Storage Service User Guide.

- CloudWatch to log worker metrics and labeling job statuses.
- AWS KMS for data encryption. (Optional)
- AWS Lambda for processing input and output data when you create a custom workflow.

Additionally, if you create a streaming labeling job, this role must have permission to access:

- Amazon SQS to create an interact with an SQS queue used to manage labeling requests.
- Amazon SNS to subscribe to and retrieve messages from your Amazon SNS input topic and to send messages to your Amazon SNS output topic.

All of these permissions can be granted with the AmazonSageMakerGroundTruthExecution managed policy except:

- Data and storage volume encryption of your Amazon S3 buckets. To learn how to configure these permissions, see Encrypt Output Data and Storage Volume with AWS KMS (p. 660).
- Permission to select and invoke Lambda functions that do not include GtRecipe, SageMaker, Sagemaker, sagemaker, or LabelingFunction in the function name.
- Amazon S3 buckets that do not include either GroundTruth, Groundtruth, groundtruth, SageMaker, Sagemaker, and sagemaker in the prefix or bucket name or an object tag that includes SageMaker in the name (case insensitive).

If you require more granular permissions than the ones provided in AmazonSageMakerGroundTruthExecution, use the following policy examples to create an execution role that fits your specific use case.

Topics
- Built-In Task Types (Non-streaming) Execution Role Requirements (p. 656)
- Built-In Task Types (Streaming) Execution Role Requirements (p. 657)
- Execution Role Requirements for Custom Task Types (p. 659)
- Automated Data Labeling Permission Requirements (p. 659)

Built-In Task Types (Non-streaming) Execution Role Requirements

The following policy grants permission to create a labeling job for a built-in task type. This execution policy does not include permissions for AWS KMS data encryption or decryption. Replace each red, italicized ARN with your own Amazon S3 ARNs.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "S3ViewBuckets",
      "Effect": "Allow",
      "Action": [
        "s3:ListBucket",
        "s3:GetBucketLocation"
      ]
    }
  ]
}
```
Built-In Task Types (Streaming) Execution Role Requirements

If you create a streaming labeling job, you must add a policy similar to the following to the execution role you use to create the labeling job. To narrow the scope of the policy, replace the * in Resource with specific AWS resources that you want to grant the IAM role permission to access and use.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "s3:AbortMultipartUpload",
        "s3:GetObject",
        "s3:PutObject"
      ],
      "Resource": [
        "arn:aws:s3:::<input-bucket-name>/*",
        "arn:aws:s3:::<output-bucket-name>/*"
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "s3:GetObject"
      ],
      "Resource": "*",
      "Condition": {
        "StringEqualsIgnoreCase": {
          "s3:ExistingObjectTag/SageMaker": "true"
        }
      }
    }
  ]
}
```


Execution Role Requirements for Custom Task Types

If you want to create a custom labeling workflow, add the following statement to an execution role policy like the ones found in ??? (p. 656) or Built-In Task Types (Streaming) Execution Role Requirements (p. 657).

This policy gives the execution role permission to Invoke your pre-annotation and post-annotation Lambda functions.

```
    "Sid": "LambdaFunctions",
    "Effect": "Allow",
    "Action": [
      "lambda:InvokeFunction"
    ],
    "Resource": [
      "arn:aws:lambda:<region>:<account-id>:function:<post-annotation-lambda-name>"
    ]
}
```

Automated Data Labeling Permission Requirements

If you want to create a labeling job with automated data labeling enabled, you must 1) add one policy to the IAM policy attached to the execution role and 2) update the trust policy of the execution role.

The following statement allows the IAM execution role to be passed to SageMaker so that it can be used to run the training and inference jobs used for active learning and automated data labeling respectively. Add this statement to an execution role policy like the ones found in ??? (p. 656) or Built-In Task Types (Streaming) Execution Role Requirements (p. 657). Replace `arn:aws:iam::<account-number>:role/<role-name>` with the execution role ARN. You can find your IAM role ARN in the IAM console under Roles.

```
    "Effect": "Allow",
    "Action": [
      "iam:PassRole"
    ],
    "Resource": "arn:aws:iam::<account-number>:role/<execution-role-name>",
    "Condition": {
      "StringEquals": {
        "iam:PassedToService": [
          "sagemaker.amazonaws.com"
        ]
      }
    }
}
```
The following statement allows SageMaker to assume the execution role to create and manage the SageMaker training and inference jobs. This policy must be added to the trust relationship of the execution role. To learn how to add or modify an IAM role trust policy, see Modifying a role in the IAM User Guide.

```
{
  "Version": "2012-10-17",
  "Statement": {
    "Effect": "Allow",
    "Principal": {
      "Service": "sagemaker.amazonaws.com"
    },
    "Action": "sts:AssumeRole"
  }
}
```

## Encrypt Output Data and Storage Volume with AWS KMS

You can use AWS Key Management Service (AWS KMS) to encrypt output data from a labeling job by specifying a customer managed key when you create the labeling job. If you use the API operation CreateLabelingJob to create a labeling job that uses automated data labeling, you can also use a customer managed key to encrypt the storage volume attached to the ML compute instances to run the training and inference jobs.

This section describes the IAM policies you must attach to your customer managed key to enable output data encryption and the policies you must attach to your customer managed key and execution role to use storage volume encryption. To learn more about these options, see Output Data and Storage Volume Encryption (p. 672).

### Encrypt Output Data using KMS

If you specify an AWS KMS customer managed key to encrypt output data, you must add an IAM policy similar to the following to that key. This policy gives the IAM execution role that you use to create your labeling job permission to use this key to perform all of the actions listed in "Action". To learn more about these actions, see AWS KMS permissions in the AWS Key Management Service Developer Guide.

To use this policy, replace the IAM service-role ARN in "Principal" with the ARN of the execution role you use to create the labeling job. When you create a labeling job in the console, this is the role you specify for IAM Role under the Job overview section. When you create a labeling job using CreateLabelingJob, this is ARN you specify for RoleArn.

```
{
  "Sid": "AllowUseOfKmsKey",
  "Effect": "Allow",
  "Principal": {
    "AWS": "arn:aws:iam::111122223333:role/service-role/example-role"
  },
  "Action": [
    "kms:Encrypt",
    "kms:Decrypt",
    "kms:ReEncrypt*",
    "kms:GenerateDataKey*",
    "kms:DescribeKey"
  ],
  "Resource": "*"
}
```
Encrypt Automated Data Labeling ML Compute Instance Storage Volume

If you specify a `VolumeKmsKeyId` to encrypt the storage volume attached to the ML compute instance used for automated data labeling training and inference, you must do the following:

- Attach permissions described in Encrypt Output Data using KMS (p. 660) to the customer managed key.
- Attach a policy similar to the following to the IAM execution role you use to create your labeling job. This is the IAM role you specify for `RoleArn` in `CreateLabelingJob`. To learn more about the "kms:CreateGrant" action that this policy permits, see `CreateGrant` in the AWS Key Management Service API Reference.

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["kms:CreateGrant"],
      "Resource": "*"
    }
  ]
}
```

To learn more about Ground Truth storage volume encryption, see Use Your KMS Key to Encrypt Automated Data Labeling Storage Volume (API Only) (p. 673).

Using Amazon SageMaker Ground Truth in an Amazon Virtual Private Cloud

Amazon Virtual Private Cloud (Amazon VPC) is a service with which you can launch AWS resources in a logically isolated virtual network that you define. You can create and run a Ground Truth labeling job inside of an Amazon VPC instead of connecting over the internet. When you launch a labeling job in an Amazon VPC, communication between your VPC and Ground Truth is conducted entirely and securely within the AWS network.

This guide shows how you can use Ground Truth in an Amazon VPC in the following ways:

1. Run an Amazon SageMaker Ground Truth Labeling Job in an Amazon Virtual Private Cloud (p. 661)
2. Use Amazon VPC Mode from a Private Worker Portal (p. 667)

Run an Amazon SageMaker Ground Truth Labeling Job in an Amazon Virtual Private Cloud

Amazon SageMaker Ground Truth supports the following functionalities.

- You can use Amazon S3 bucket policies to control access to buckets from specific Amazon VPC endpoints, or specific VPCs. If you launch a labeling job and your input data is located in an Amazon S3 bucket with access restricted to users in your VPC, you can add a bucket policy to also grant a Ground Truth endpoint permission to access the bucket. To learn more, see Allow Ground Truth to Access VPC Restricted Amazon S3 Buckets (p. 662).
- You can launch an automated data labeling job in your VPC. You use a VPC configuration to specify VPC subnets and security groups. SageMaker uses this configuration to launch the training and
inference jobs used for automated data labeling in your VPC. To learn more, see Create an Automated Data Labeling Job in a VPC (p. 666).

You may want to use these options in any of the following ways.

- You can use both of these methods to launch a labeling job using a VPC-protected Amazon S3 bucket with automated data labeling enabled.
- You can launch a labeling job using any built-in task type using a VPC-protected bucket.
- You can launch a custom labeling workflow using a VPC-protected bucket. Ground Truth interacts with your pre-annotation and post-annotation Lambda functions using an AWS PrivateLink endpoint.

We recommend that you review Prerequisites to Run a Ground Truth Labeling Job in a VPC (p. 662) before you create a labeling job in an Amazon VPC.

Prerequisites to Run a Ground Truth Labeling Job in a VPC

Review the following prerequisites before you create a Ground Truth labeling job in an Amazon VPC.

- If you are a new user of Ground Truth, review Getting started to learn how to create a labeling job.
- If your input data is located in a VPC-protected Amazon S3 bucket, your workers must access the worker portal from your VPC.

  **Note**
  When you launch a labeling job in your VPC, you must use a private work team. To learn more about creating a private work team, see Use a Private Workforce.

- If you want to launch an automated data labeling job in your VPC, review the following prerequisites.
  - Use the instructions in Create an Amazon S3 VPC Endpoint. Training and inference containers used in the automated data labeling workflow use this endpoint to communicate with your buckets in Amazon S3.
  - Review Automate Data Labeling to learn more about this feature. Note that automated data labeling is supported for the following built-in task types: Image Classification (Single Label), Image Semantic Segmentation, Bounding Box, and Text Classification (Single Label). Streaming labeling jobs do not support automated data labeling.

  - Review the Ground Truth Security and Permissions section and ensure that you have met the following conditions.
    - The user creating the labeling job has all necessary permissions
    - You have created an IAM execution role with required permissions. If you do not require fine-tuned permissions for your use case, we recommend you use the IAM managed policies described in Grant General Permissions To Get Started Using Ground Truth.
    - Allow your VPC to have access to the sagemaker-labeling-data-region and sm-bxcb-region-saved-task-states S3 buckets. These are system owned regionalized S3 buckets that are accessed from worker portal when worker is working on a task. We use these buckets to interact with system managed data.

Allow Ground Truth to Access VPC Restricted Amazon S3 Buckets

The following sections provide details about the permissions Ground Truth requires to launch labeling jobs using Amazon S3 buckets that have access restricted to your VPC and VPC endpoints. To learn how to restrict access to an Amazon S3 bucket to a VPC, see Controlling access from VPC endpoints with bucket policies in the Amazon Simple Storage Service User Guide guide. To learn how to add a policy to an S3 bucket, see Adding a bucket policy using the Amazon S3 console.
Note
Modifying policies on existing buckets can cause IN_PROGRESS Ground Truth jobs to fail. We recommend you start new jobs using a new bucket. If you want to continue using the same bucket, you can do one of the following.

- Wait for an IN_PROGRESS job to finish.
- Terminate the job using the console or the AWS CLI.

You can restrict Amazon S3 bucket access to users in your VPC using an AWS PrivateLink endpoint. For example, the following S3 bucket policy allows access to a specific bucket, `<bucket-name>`, from `<vpc>` and the endpoint `<vpc-endpoint>` only. When you modify this policy, you must replace all *red-italicized text* with your resources and specifications.

**Note**
The following policy *denies* all entities *other than* users within a VPC to perform the actions listed in *Action*. If you do not include actions in this list, they are still accessible to any entity that has access to this bucket and permission to perform those actions. For example, if an IAM user has permission to perform GetBucketLocation on your Amazon S3 bucket, the policy below does not restrict the user from performing this action outside of your VPC.

```
{
   "Version": "2012-10-17",
   "Id": "Policy1415115909152",
   "Statement": [
      {
         "Sid": "Access-to-specific-VPCE-only",
         "Principal": "*",
         "Action": ["s3:GetObject", "s3:PutObject"],
         "Effect": "Deny",
         "Resource": ["arn:aws:s3:::<bucket-name>", "arn:aws:s3:::<bucket-name>/*"],
         "Condition": {
            "StringNotEquals": {
               "aws:sourceVpce": ["<vpc-endpoint>", "<vpc>"
            ]
            }
         }
      }
   ]
}
```

Ground Truth must be able to perform the following Amazon S3 actions on the S3 buckets you use to configure the labeling job.

```
"s3:AbortMultipartUpload",
"s3:GetObject",
"s3:PutObject",
"s3:ListBucket",
"s3:GetBucketLocation"
```

You can do this by adding a Ground Truth endpoint to the bucket policy like the one previously mentioned. The following table includes Ground Truth service endpoints for each AWS Region. Add an endpoint in the same AWS Region you use to run your labeling job to your bucket policy.
For example, the following policy restricts GetObject and PutObject actions on:

- An Amazon S3 bucket to users in a VPC (<vpc>)
- A VPC endpoint (<vpc-endpoint>)
- A Ground Truth service endpoint (<ground-truth-endpoint>)

```
{
   "Version": "2012-10-17",
   "Id": "1",
   "Statement": [
      {
         "Sid": "DenyAccessFromNonGTandCustomerVPC",
         "Effect": "Deny",
         "Principal": "*",
         "Action": [
            "s3:GetObject",
            "s3:PutObject"
         ],
         "Resource": [
            "arn:aws:s3:::<bucket-name>",
            "arn:aws:s3:::<bucket-name>/*"
         ],
         "Condition": {
            "ForAllValues:StringNotEquals": {
               "aws:sourceVpce": [
                  "<vpc-endpoint>",
                  "<ground-truth-endpoint>"
               ],
               "aws:SourceVpc": "<vpc>"
            }
         }
      }
   ]
}
```
If you want an IAM user to have permission to launch a labeling job using the Ground Truth console, you must also add the IAM user's ARN to the bucket policy using the `aws:PrincipalArn` condition. This user must also have permission to perform the following Amazon S3 actions on the bucket you use to launch the labeling job.

```
"s3:GetObject",
"s3:PutObject",
"s3:ListBucket",
"s3:GetBucketCors",
"s3:PutBucketCors",
"s3:ListAllMyBuckets",
```

The following code is an example of a bucket policy that restricts permission to perform the actions listed in `Action` on the S3 bucket `<bucket-name>` to the following.

- `<role-name>`
- The VPC endpoints listed in `aws:sourceVpce`
- Users within the VPC named `<vpc>`

```json
{
  "Version": "2012-10-17",
  "Id": "1",
  "Statement": [
    {
      "Sid": "DenyAccessFromNonGTandCustomerVPC",
      "Effect": "Deny",
      "Principal": "*",
      "Action": [
        "s3:GetObject",
        "s3:PutObject"
      ],
      "Resource": [
        "arn:aws:s3::<bucket-name>/**",
        "arn:aws:s3::<bucket-name>"
      ],
      "Condition": {
        "ForAllValues:StringNotEquals": {
          "aws:sourceVpc": ["<vpc-endpoint>", "<ground-truth-endpoint>"],
          "aws:PrincipalArn": "arn:aws:iam::<aws-account-id>:role/<role-name>",
          "aws:SourceVpc": "<vpc>"
        }
      }
    }
  ]
}
```

**Note**

The Amazon VPC interface endpoints and the protected Amazon S3 buckets you use for input and output data must be located in the same AWS Region that you use to create the labeling job.

After you have granted Ground Truth permission to access your Amazon S3 buckets, you can use one of the topics in Create a Labeling Job to launch a labeling job. Specify the VPC-restricted Amazon S3 buckets for your input and output data buckets.
Create an Automated Data Labeling Job in a VPC

To create an automated data labeling job using an Amazon VPC, you provide a VPC configuration using the Ground Truth console or CreateLabelingJob API operation. SageMaker uses the subnets and security groups you provide to launch the training and inferences jobs used for automated labeling.

**Important**
Before you launch an automated data labeling job with a VPC configuration, make sure you have created an Amazon S3 VPC endpoint using the VPC you want to use for the labeling job. To learn how, see [Create an Amazon S3 VPC Endpoint](#). Additionally, if you create an automated data labeling job using a VPC-restricted Amazon S3 bucket, you must follow the instructions in [Allow Ground Truth to Access VPC Restricted Amazon S3 Buckets](#) to give Ground Truth permission to access the bucket.

Use the following procedures to learn how to add a VPC configuration to your labeling job request.

**Add a VPC configuration to an automated data labeling job (console):**

1. Follow the instructions in [Create a Labeling Job (Console)](#) and complete each step in the procedure, up to step 15.
2. In the Workers section, select the checkbox next to Enable automated data labeling.
3. Maximize the VPC configuration section of the console by selecting the arrow.
4. Specify the [Virtual private cloud (VPC)](#) that you want to use for your automated data labeling job.
5. Choose the dropdown list under Subnets and select one or more subnets.
6. Choose the dropdown list under Security groups and select one or more groups.
7. Complete all remaining steps of the procedure in [Create a Labeling Job (Console)](#).

**Add a VPC configuration to an automated data labeling job (API):**

To configure a labeling job using the Ground Truth API operation, CreateLabelingJob, follow the instructions in [Create an Automated Data Labeling Job (API)](#) to configure your request. In addition to the parameters described in this documentation, you must include a VpcConfig parameter in LabelingJobResourceConfig to specify one or more subnets and security groups using the following schema.

```json
"LabelingJobAlgorithmsConfig": {
   "InitialActiveLearningModelArn": "string",
   "LabelingJobAlgorithmSpecificationArn": "string",
   "LabelingJobResourceConfig": {
      "VolumeKmsKeyId": "string",
      "VpcConfig": {
         "SecurityGroupIds": [ "string" ],
         "Subnets": [ "string" ]
      }
   }
}
```

The following is an example of an AWS Python SDK (Boto3) request to create an automated data labeling job in the US East (N. Virginia) Region using a private workforce. Replace all red-italicized text with your labeling job resources and specifications. To learn more about the CreateLabelingJob operation, see the [Create a Labeling Job (API)](#) tutorial and [CreateLabelingJob](#) API documentation.

```python
import boto3
client = boto3.client(service_name='sagemaker')

response = client.create_labeling_job(
   LabelingJobName="example-labeling-job",
   LabelAttributeName="label",
)`
Use Amazon VPC Mode from a Private Worker Portal

To restrict worker portal access to labelers working inside of your Amazon VPC, you can add a VPC configuration when you create a Ground Truth private workforce. You can also add a VPC configuration to an existing private workforce. Ground Truth automatically creates VPC interface endpoints in your VPC and sets up AWS PrivateLink between your VPC endpoint and the Ground Truth services. The worker portal URL associated with the workforce can be accessed from your VPC. The worker portal URL can also
be accessed from public internet until you set the restriction on the public internet. When you delete the workforce or remove the VPC configuration from your workforce, Ground Truth automatically deletes the VPC endpoints associated with the workforce.

**Note**
There can be only one VPC supported for a workforce.

**Point Cloud** and **video** tasks do not support loading through a VPC.

The guide demonstrates how to complete the necessary steps to add and delete an Amazon VPC configuration to your workforce, and satisfy the prerequisites.

**Prerequisites**

To run a Ground Truth labeling job in Amazon VPC, review the following prerequisites.

- You have an Amazon VPC configured that you can use. If you have not configured a VPC, follow these instructions for [creating a VPC](#).
- Depending on how a Worker Task Template is written, labeling data stored in an Amazon S3 bucket may be accessed directly from Amazon S3 during labeling tasks. In these cases, the VPC network must be configured to allow traffic from the device used by the human labeler to the S3 bucket containing labeling data.
- Follow [View and update DNS attributes for your VPC](#) to enable DNS hostnames and DNS resolution for your VPC.

**Note**
There are two ways to configure your VPC for your workforce. You can do this through the console or the AWS SageMaker CLI.

**Using the SageMaker console to manage a VPC config**

You can use the SageMaker console to add or remove a VPC configuration. You can also delete an existing workforce.

**Adding a VPC configuration to your workforce**

**Create a private workforce**

- Create a private workforce using Amazon Cognito
- Create a private workforce using OpenID Connect (OIDC) Identity Provider(IdP).

After you have created your private workforce, add a VPC configuration to it.

1. Navigate to Amazon SageMaker in your console.
2. Select **Labeling workforces** in the left panel.
3. Select **Private** to access your private workforce. After your Workforce status is **Active**, select Add next to VPC.
4. When you are prompted to configure your VPC, provide the following:
   a. Your VPC
   b. **Subnets**
      i. Ensure that your VPC has an existing subnet
   c. **Security groups**
      i. **Note**
         You cannot select more than 5 security groups.
   d. After filling in this information, choose Confirm.
5. After you choose Confirm, you are redirected back to the Private page under Labeling workforces. You should see a green banner at the top that reads Your private workforce update with VPC configuration was successfully initialized. The workforce status is Updating. Next to the Delete workforce button is the Refresh button, which can be used to retrieve the latest Workforce status. After the workforce status has changed to Active, the VPC endpoint ID is updated as well.

Removing a VPC configuration from your workforce

Use the following information to remove a VPC configuration from your workforce using the console.

1. Navigate to Amazon SageMaker in your console.
2. Select Labeling workforces in the left panel.
3. Find and select your workforce.
4. Under Private workforce summary, find VPC and choose Remove next to it.
5. Select Remove.

Deleting a workforce through the console

If you delete a workforce, you should not have any teams associated with it. You can delete a workforce only if the workforce status is Active or Failed.

Use the following information to delete a workforce using the console.

1. Navigate to Amazon SageMaker in your console.
2. Select Labeling workforces in the left panel.
3. Find and select your workforce.
5. Choose Delete.

Using the SageMaker AWS API to manage a VPC config

Download the following files to use a new VpcConfig parameter into to the SageMaker workforce CLI:

- sagemaker-2017-07-24.normal.json
- sagemaker-2017-07-24.paginators.json
- sagemaker-2017-07-24.waiters-2.json

After downloading the files, run the following commands in your CLI:

```
aws configure add-model --service-model file://./sagemaker-2017-07-24.normal.json --service-name sagemaker


```

You can now test your API changes using AWS CLI. You can either create a new workforce with a VPC configuration or update an existing workforce to add a VPC configuration. You can also remove a VPC configuration from an existing workforce.
Create a workforce with a VPC configuration

If the account already has a workforce, then you must delete it first. You can also update the workforce with VPC configuration.

```bash
aws sagemaker create-workforce --cognito-config '{"ClientId": "app-client-id","UserPool": "Pool_ID",}' --workforce-vpc-config "{"VpcId": "vpc-id", "SecurityGroupIds": ["sg-0123456789abcdef0"], "Subnets": ["subnet-0123456789abcdef0"]}" --workforce-name workforce-name

{ "WorkforceArn": "arn:aws:sagemaker:us-west-2:xxxxxxxxx:workforce/workforce-name"
}

Describe the workforce and make sure the status is Initializing.

```bash
aws sagemaker describe-workforce --workforce-name workforce-name

}
```

Navigate to the Amazon VPC console. Select Endpoints from the left panel. There should be two VPC endpoints created in your account.

Adding a VPC configuration your workforce

Update a non-VPC private workforce with a VPC configuration using the following command.

```bash
aws sagemaker update-workforce --workforce-name workforce-name
--workforce-vpc-config "{"VpcId": "vpc-id", "SecurityGroupIds": ["sg-0123456789abcdef0"], "Subnets": ["subnet-0123456789abcdef0"]}"

Describe the workforce and make sure the status is Updating.

```bash
aws sagemaker describe-workforce --workforce-name workforce-name

}
```
aws sagemaker describe-workforce --workforce-name workforce-name
{
  "Workforce": {
    "WorkforceName": "workforce-name",
    "LastUpdatedDate": 1622151252.451,
    "SourceIpConfig": {
      "Cidrs": []
    },
    "SubDomain": "subdomain.us-west-2.sagemaker.aws.com",
    "CognitoConfig": {
      "UserPool": "Pool_ID",
      "ClientId": "app-client-id"
    },
    "CreateDate": 1622151252.451,
    "WorkforceVpcConfig": {
      "VpcId": "vpc-id",
      "SecurityGroupIds": [
        "sg-0123456789abcdef0"
      ],
      "Subnets": [
        "subnet-0123456789abcdef0"
      ],
      "Status": "Updating"
    }
  }
}

Navigate to your Amazon VPC console. Select Endpoints from the left panel. There should be two VPC endpoints created in your account.

Removing a VPC configuration from your workforce

Update a VPC private workforce with an empty VPC configuration to remove VPC resources.

aws sagemaker update-workforce --workforce-name workforce-name\ --workforce-vpc-config "{}"

Describe the workforce and make sure the status is Updating.

aws sagemaker describe-workforce --workforce-name workforce-name
{
  "Workforce": {
    "WorkforceName": "workforce-name",
    "LastUpdatedDate": 1622151252.451,
    "SourceIpConfig": {
      "Cidrs": []
    },
    "SubDomain": "subdomain.us-west-2.sagemaker.aws.com",
    "CognitoConfig": {
      "UserPool": "Pool_ID",
      "ClientId": "app-client-id"
    },
    "CreateDate": 1622151252.451,
    "Status": "Updating"
  }
}
Navigate to your Amazon VPC console. Select **Endpoints** from the left panel. The two VPC endpoints should be deleted.

**Restrict public access to the worker portal while maintaining access through a VPC**

The workers in a VPC or non-VPC worker portal are be able to see the labeling job tasks assigned to them. The assignment comes from assigning workers in a work team through OIDC groups. It is the customer’s responsibility to restrict the access to their public worker portal by setting the `sourceIpConfig` in their workforce.

**Note**
You can restrict access to the worker portal only through the SageMaker API. This cannot be done through the console.

Use the following command to restrict public access to the worker portal.

```bash
aws sagemaker update-workforce --region us-west-2 \
--workforce-name workforce-demo --source-ip-config '{"Cidrs": ["0.0.0.0/0"]}'
```

After the `sourceIpConfig` is set on the workforce, the workers can access the worker portal in VPC but not through public internet.

**Note**
You can not set the `sourceIP` restriction for worker portal in VPC.

**Output Data and Storage Volume Encryption**

With Amazon SageMaker Ground Truth, you can label highly sensitive data, stay in control of your data, and employ security best practices. While your labeling job is running, Ground Truth encrypts data in transit and at rest. Additionally, you can use AWS Key Management Service (AWS KMS) with Ground Truth to do the following:

- Use a **customer managed key** to encrypt your output data.
- Use AWS KMS customer managed key with your automated data labeling job to encrypt the storage volume attached to the compute instance used for model training and inference.

Use the topics on this page to learn more about these Ground Truth security features.

**Use Your KMS Key to Encrypt Output Data**

Optionally, you can provide an AWS KMS customer managed key when you create a labeling job, which Ground Truth uses to encrypt your output data.

If you don’t provide a customer managed key, Amazon SageMaker uses the default AWS managed key for Amazon S3 for your role's account to encrypt your output data.

If you provide a customer managed key, you must add the required permissions to the key described in *Encrypt Output Data and Storage Volume with AWS KMS* (p. 660). When you use the API operation `CreateLabelingJob`, you can specify your customer managed key ID using the parameter `KmsKeyId`. See the following procedure to learn how to add a customer managed key when you create a labeling job using the console.

**To add an AWS KMS key to encrypt output data (console):**

1. Complete the first 7 steps in *Create a Labeling Job (Console)* (p. 544).
2. In step 8, select the arrow next to **Additional configuration** to expand this section.
3. For **Encryption key**, select the AWS KMS key that you want to use to encrypt output data.
4. Complete the rest of steps in **Create a Labeling Job (Console)** (p. 544) to create a labeling job.

**Use Your KMS Key to Encrypt Automated Data Labeling Storage Volume (API Only)**

When you create a labeling job with automated data labeling using the CreateLabelingJob API operation, you have the option to encrypt the storage volume attached to the ML compute instances that run the training and inference jobs. To add encryption to your storage volume, use the parameter `VolumeKmsKeyId` to input an AWS KMS customer managed key. For more information about this parameter, see **LabelingJobResourceConfig**.

If you specify a key ID or ARN for `VolumeKmsKeyId`, your SageMaker execution role must include permissions to call `kms:CreateGrant`. To learn how to add this permission to an execution role, see **Create a SageMaker Execution Role for a Ground Truth Labeling Job** (p. 655).

**Note**

If you specify an AWS KMS customer managed key when you create a labeling job in the console, that key is *only* used to encrypt your output data. It is not used to encrypt the storage volume attached to the ML compute instances used for automated data labeling.

**Workforce Authentication and Restrictions**

Ground Truth enables you to use your own private workforce to work on labeling jobs. A *private workforce* is an abstract concept which refers to a set of people who work for you. Each labeling job is created using a work team, composed of workers in your workforce. Ground Truth supports private workforce creation using Amazon Cognito.

A Ground Truth workforce maps to a Amazon Cognito user pool. A Ground Truth work team maps to a Amazon Cognito user group. Amazon Cognito manages the worker authentication. Amazon Cognito supports Open ID connection (OIDC) and customers can set up Amazon Cognito federation with their own identity provider (IdP).

Ground Truth only allows one workforce per account per AWS Region. Each workforce has a dedicated Ground Truth work portal login URL.

You can also restrict workers to a Classless Inter-Domain Routing (CIDR) block/IP address range. This means annotators must be on a specific network to access the annotation site. You can add up to ten CIDR blocks for one workforce. To learn more, see **Manage Private Workforce Using the Amazon SageMaker API** (p. 716).

To learn how you can create a private workforce, see **Create a Private Workforce (Amazon Cognito)** (p. 700).

**Restrict Access to Workforce Types**

Amazon SageMaker Ground Truth work teams fall into one of three *workforce types*: public (with Amazon Mechanical Turk), private, and vendor. To restrict IAM user access to a specific work team using one of these types or the work team ARN, use the `sagemaker:WorkteamType` and/or the `sagemaker:WorkteamArn` condition keys. For the `sagemaker:WorkteamType` condition key, use string condition operators. For the `sagemaker:WorkteamArn` condition key, use Amazon Resource Name (ARN) condition operators. If the user attempts to create a labeling job with a restricted work team, SageMaker returns an access denied error.

The policies below demonstrate different ways to use the `sagemaker:WorkteamType` and `sagemaker:WorkteamArn` condition keys with appropriate condition operators and valid condition values.
The following example uses the sagemaker:WorkteamType condition key with the StringEquals condition operator to restrict access to a public work team. It accepts condition values in the following format: workforcetype-crowd, where workforcetype can equal public, private, or vendor.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "RestrictWorkteamType",
            "Effect": "Deny",
            "Action": "sagemaker:CreateLabelingJob",
            "Resource": "*",
            "Condition": {
                "StringEquals": {
                    "sagemaker:WorkteamType": "public-crowd"
                }
            }
        }
    ]
}
```

The following policies show how to restrict access to a public work team using the sagemaker:WorkteamArn condition key. The first shows how to use it with a valid IAM regex-variant of the work team ARN and the ArnLike condition operator. The second shows how to use it with the ArnEquals condition operator and the work team ARN.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "RestrictWorkteamType",
            "Effect": "Deny",
            "Action": "sagemaker:CreateLabelingJob",
            "Resource": "*",
            "Condition": {
                "ArnLike": {
                    "sagemaker:WorkteamArn": "arn:aws:sagemaker:*:*:workteam/public-crowd/*"
                }
            }
        }
    ]
}
```

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "RestrictWorkteamType",
            "Effect": "Deny",
            "Action": "sagemaker:CreateLabelingJob",
            "Resource": "*",
            "Condition": {
                "ArnEquals": {
                }
            }
        }
    ]
}
```
Monitor Labeling Job Status

To monitor the status of your labeling jobs, you can set up an Amazon CloudWatch Events (CloudWatch Events) rule for Amazon SageMaker Ground Truth (Ground Truth) to send an event to CloudWatch Events when a labeling job status changes to Completed, Failed, or Stopped or when a worker accepts, declines, submits, or returns a task.

Once you create a rule, you can add a target to it. CloudWatch Events uses this target to invoke another AWS service to process the event. For example, you can create a target using a Amazon Simple Notification Service (Amazon SNS) topic to send a notification to your email when a labeling job status changes.

Prerequisites:

To create a CloudWatch Events rule, you will need an AWS Identity and Access Management (IAM) role with an events.amazonaws.com trust policy attached. The following is an example of an events.amazonaws.com trust policy.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "",
      "Effect": "Allow",
      "Principal": {
        "Service": ["events.amazonaws.com"
      ],
      "Action": "sts:AssumeRole"
    }
  ]
}
```

Topics

- Send Events to CloudWatch Events (p. 675)
- Set Up a Target to Process Events (p. 676)
- Labeling Job Expiration (p. 677)
- Declining Tasks (p. 677)

Send Events to CloudWatch Events

To configure a CloudWatch Events rule to get status updates, or events, for your Ground Truth labeling jobs, use the AWS Command Line Interface (AWS CLI) put-rule command. You can filter events that are sent to your rule by status change. For example, you can create a rule that notifies you only if a labeling job status changes to Completed. When using the put-rule command, specify the following to receive labeling job statuses:

- "source": ["aws.sagemaker"]
- "detail-type": ["SageMaker Ground Truth Labeling Job State Change"]

To configure a CloudWatch Events rule to watch for all status changes, use the following command and replace the placeholder text. For example, replace "GLabelingJobStateChanges" with a unique CloudWatch Events rule name and "arn:aws:iam::111122223333:role/MyRoleForThisRule"
with the Amazon Resource Number (ARN) of an IAM role with an events.amazonaws.com trust policy attached.

```bash
aws events put-rule --name "GTLabelingJobStateChanges"  
--event-pattern "{"source": ["aws.sagemaker"], "detail-type": ["SageMaker Ground Truth Labeling Job State Change"]}"  
--role-arn "arn:aws:iam::111122223333:role/MyRoleForThisRule"  
--region "region"
```

To filter by job status, use the "detail":{"LabelingJobStatus":["Status"]}" syntax. Valid values for Status are Completed, Failed, and Stopped.

The following example creates a CloudWatch Events rule that notifies you when a labeling job in us-west-2 (Oregon) changes to Completed.

```bash
aws events put-rule --name "LabelingJobCompleted"  
--event-pattern "{"source": ["aws.sagemaker"], "detail-type": ["SageMaker Ground Truth Labeling Job State Change"], "detail":{"LabelingJobStatus": ["Completed"]}"  
--role-arn "arn:aws:iam::111122223333:role/MyRoleForThisRule"  
--region us-west-2
```

The following example creates a CloudWatch Events rule that notifies you when a labeling job in us-east-1 (Virginia) changes to Completed or Failed.

```bash
aws events put-rule --name "LabelingJobCompletedOrFailed"  
--event-pattern "{"source": ["aws.sagemaker"], "detail-type": ["SageMaker Ground Truth Labeling Job State Change"], "detail":{"LabelingJobStatus": ["Completed", "Failed"]}"  
--role-arn "arn:aws:iam::111122223333:role/MyRoleForThisRule"  
--region us-east-1
```

To learn more about the put-rule request, see Event Patterns in CloudWatch Events in the Amazon CloudWatch Events User Guide.

### Set Up a Target to Process Events

After you have created a rule, events similar to the following are sent to CloudWatch Events. In this example, the labeling job test-labeling-job's status changed to Completed.

```json
{
  "version": "0",
  "id": "111e1111-11d1-111f-b111-1111b11dcb11",
  "detail-type": "SageMaker Ground Truth Labeling Job State Change",
  "source": "aws.sagemaker",
  "account": "111122223333",
  "time": "2018-10-06T12:26:13Z",
  "region": "us-east-1",
  "resources": [
  ],
  "detail": {
    "LabelingJobStatus": "Completed"
  }
}
```

To process events, you need to set up a target. For example, if you want to receive an email when your labeling job status changes, use a procedure in Setting Up Amazon SNS Notifications in the Amazon CloudWatch User Guide to set up an Amazon SNS topic and subscribe your email to it. Once you have create a topic, you can use it to create a target.
To add a target to your CloudWatch Events rule

1. Open the CloudWatch console: https://console.aws.amazon.com/cloudwatch/home
2. In the navigation pane, choose Rules.
3. Choose the rule that you want to add a target to.
4. Choose Actions, and then choose Edit.
5. Under Targets, choose Add Target and choose the AWS service you want to act when a labeling job status change event is detected.
6. Configure your target. For instructions, see the topic for configuring a target in the AWS documentation for that service.
7. Choose Configure details.
8. For Name, enter a name and, optionally, provide details about the purpose of the rule in Description.
9. Make sure that the check box next to State is selected so that your rule is listed as Enabled.
10. Choose Update rule.

Labeling Job Expiration

If your labeling job is not completed after 30 days, it will expire. If your labeling job expires, you can chain the job to create a new labeling job that will only send unlabeled data to workers. For more information, and to learn how to create a labeling job using chaining, see Chaining Labeling Jobs (p. 646).

Declining Tasks

Workers are able to decline tasks.

Workers decline a task if the instructions are not clear, input data is not displaying correctly, or if they encounter some other issue with the task. If the number of workers per dataset object (NumberOfHumanWorkersPerDataObject) decline the task, the data object is marked as expired and will not be sent to additional workers.

Use Amazon SageMaker Ground Truth Plus to Label Data

Amazon SageMaker Ground Truth Plus is a turnkey data labeling service that uses an expert workforce to deliver high-quality annotations quickly and reduces costs by up to 40%. Using Ground Truth Plus, data scientists and business managers, such as data operations managers and program managers, can create high-quality training datasets without having to build labeling applications and manage labeling workforces on their own. You can get started with Amazon SageMaker Ground Truth Plus by uploading data along with the labeling requirements in Amazon S3.

Why use Ground Truth Plus?

To train a machine learning (ML) model, data scientists need large, high-quality, labeled datasets. As ML adoption grows, labeling needs increase. This forces data scientists to spend weeks on building data labeling workflows and managing a data labeling workforce. Unfortunately, this slows down innovation and increases cost. To ensure data scientists can spend their time building, training, and deploying ML models, data scientists typically task other in-house teams consisting of data operations managers and program managers to produce high-quality training datasets. However, these teams typically don't have access to skills required to deliver high-quality training datasets, which affects ML results. As a result, you
look for a data labeling partner that can help them create high-quality training datasets at scale without consuming their in-house resources.

When you upload the data, Ground Truth Plus sets up the data labeling workflows and operates them on your behalf. From there, an expert workforce trained on a variety of machine learning (ML) tasks performs data labeling. Ground Truth Plus currently offers two types of expert workforce: an Amazon employed workforce and a curated list of third-party vendors. Ground Truth Plus provides you with the flexibility to choose the labeling workforce. AWS experts select the best labeling workforce based on your project requirements. For example, if you need people proficient in labeling audio files, specify that in the guidelines provided to Ground Truth Plus, and the service automatically selects labelers with those skills.

**Note**

Ground Truth Plus does not support PHI, PCI or FedRAMP certified data, and you should not provide this data to Ground Truth Plus.

**How does it work?**

There are five main components to the Ground Truth Plus workflow.

- Requesting a pilot
- Sharing the data to be labeled
- Creating a project team
- Accessing the project portal to monitor progress of training datasets and review labeled data
- Receiving the labeled data

**How do I use Ground Truth Plus?**

If you are a first-time user of Ground Truth Plus, we recommend that you follow the procedures outlined in the [Getting Started with Amazon SageMaker Ground Truth Plus](#). (p. 678) section.

**Getting Started with Amazon SageMaker Ground Truth Plus.**

The guide demonstrates how to complete the necessary steps to start an Amazon SageMaker Ground Truth Plus project, review labels, and satisfy Ground Truth Plus prerequisites.

To get started using Ground Truth Plus, review Set Up Amazon SageMaker Ground Truth Plus Prerequisites (p. 678) and Core Components of Amazon SageMaker Ground Truth Plus (p. 679).

**Set Up Amazon SageMaker Ground Truth Plus Prerequisites**

Use the following information to sign up for an AWS account. If you already have an AWS account, skip this step.
When you sign up for Amazon Web Services (AWS), your AWS account is automatically signed up for all AWS services, including SageMaker. You are charged only for the services that you use.

**To create an AWS account**

2. Follow the online instructions.

Part of the sign-up procedure involves receiving a phone call and entering a verification code on the phone keypad.

When you sign up for an AWS account, an **AWS account root user** is created. The root user has access to all AWS services and resources in the account. As a security best practice, assign administrative access to an administrative user, and use only the root user to perform tasks that require root user access.

Write down your AWS account ID because you need it for the next task.

AWS sends you a confirmation email after the sign up process is complete. At any time, you can view your current account activity and manage your account by going to [https://aws.amazon.com/](https://aws.amazon.com/) and choosing My Account.

**Core Components of Amazon SageMaker Ground Truth Plus**

The following terms are key to understanding the capabilities of Ground Truth Plus:

- **Project**: Each qualified engagement with an AWS expert results in a Ground Truth Plus project. A project can be in the pilot or production stage.
- **Batch**: A batch is a collection of similar recurring data objects such as images, video frames and text to be labeled. A project can have multiple batches.
- **Metrics**: Metrics are data about your Ground Truth Plus project for a specific date or over a date range.
- **Data type**: Ground Truth Plus currently supports five task types for data labeling. These include text, image, video, audio, and 3D point cloud.
- **Data objects**: Individual items that are to be labeled.

**Request a Pilot**

To get started with Amazon SageMaker Ground Truth Plus, go to the SageMaker console and complete the intake form.
Once you submit the intake form in the AWS console, the status of your pilot changes to submitted on your Ground Truth Plus console. An AWS expert from the Ground Truth Plus team will reach out to discuss your data labeling project requirements and pricing.

**Share Data with Amazon SageMaker Ground Truth Plus**

After the initial consultation call with the AWS expert, you can share your data in a secure Amazon S3 bucket to start the pilot.

**To share data from your Amazon S3 bucket:**

1. Once your project is approved, ask your AWS expert for your Ground Truth Plus account ID.
   
   Write down your Ground Truth Plus account ID since you will need it in the next step.

2. Create an Amazon S3 bucket for storing your input and output data. To create a bucket, follow the instructions in Create a Bucket in the Amazon Simple Storage Service Console User Guide.

3. We recommend using the following naming convention while storing your data in an Amazon S3 bucket.
   
   a. The *project-name* should contain fewer than 63 characters.
b. The `project-name` can include hyphens, but no spaces and underscores.

c. Batches can be named as `batch1`, `batch2`, `batch3`, and so on.

d. Store your input data in the Amazon S3 bucket under the following prefix (directory):

   ```
s3://your-bucket-name/ground-truth-plus/input/project-name/batch-name/..
   ```

e. Ground Truth Plus currently accepts videos in .mp4 format.

f. Video frames can be in .jpg, .jpeg, or .png format. The frames can be in a folder, sorted with UTF-8 ordering.

4. In the **Buckets** list, choose the name of the bucket you created.

5. Choose **Permissions**.

6. In the **Bucket policy** section, choose **Edit**.

7. Copy the **policy** shown below and enter `your-ground-truth-plus-account-id` and `your-bucket-name`:

   ```json
   {
   "Version": "2012-10-17",
   "Statement": [
   {
   "Effect": "Allow",
   "Principal": {
   "AWS": ["your-ground-truth-plus-account-id"]
   // Ex: ["999999999999"]
   },
   "Action": [
   "s3:GetObject",
   "s3:GetBucketLocation",
   "s3:ListBucket",
   "s3:PutObject"
   ],
   "Resource": [
   "arn:aws:s3:::your-bucket-name",
   "arn:aws:s3:::your-bucket-name/*"
   //Ex: "arn:aws:s3:::input-data-to-label/*"
   ]
   }
   ]
   }
   ```

8. Choose **Save changes**.

**Note**

If you have additional requirements for accessing your data in an Amazon S3 bucket, please contact your AWS expert.

---

## Create a Project Team

A project team provides access to the members from your organization or team to track projects, view metrics, and review annotations. You can create a Ground Truth Plus project team once you have shared your data in an Amazon S3 bucket.

To add team members using Amazon Cognito, you have two options:

1. Create a new Amazon Cognito user group
a. Enter an **Amazon Cognito user group name**. This name cannot be changed.

b. Enter the email addresses of up to 50 team members in the **Email addresses** field. The addresses must be separated by a comma.

c. Choose **Create project team**.

d. Your team members receive an email inviting them to join the Ground Truth Plus project team as shown in the following image.

2. Import team members from existing Amazon Cognito user groups.

   a. Choose a user pool that you have created. User pools require a domain and an existing user group. If you get an error that the domain is missing, set it in the **Domain name** options on the **App integration** page of the Amazon Cognito console for your group.

   b. Choose an app client. We recommend using a client generated by Amazon SageMaker.

   c. Choose a user group from your pool to import its members.

   d. Choose **Create project team**.

You can view and manage the list of team members through the AWS console.

**To add team members after creating the project team:**

1. Choose **Invite new members** in the **Members** section.
2. Enter the email addresses of up to 50 team members in the **Email addresses** field. The addresses must be separated by a comma.

3. Choose **Invite new members**

**To delete existing team members:**

1. Choose the team member to be deleted in the **Members** section.
2. Choose **Delete**.

Once you have added members to your project team, you can open the project portal to access your projects.

### Open the Project Portal

Once you have successfully submitted the intake form and created a project team, you can access the Ground Truth Plus project by clicking the **Open project portal** button on the AWS console.

Each project consists of one or more batches. A **batch** is a collection of recurring similar data objects (text, image, video frame, and point cloud) to be labeled. The project portal provides you with transparency into the data labeling process. You can stay updated about the project, review the progress of the datasets across multiple projects, and track and analyze project metrics. The project portal also allows you to review a subset of the labeled data and provide feedback.

You can use the Ground Truth Plus project portal to track the following details about your project.

**Project name**: Each project is identified using a unique name.

**Status**: A Ground Truth Plus project has one of the following status types:

1. **Consultation**: An AWS expert collects all the project requirements.
2. **Workflow design and setup progress**: An AWS expert is setting up your project.
3. **Pilot in-progress**: Object labeling for the project in the pilot stage is currently in progress.
4. **Pilot complete**: Object labeling is complete and the labeled data is stored in your Amazon S3 bucket.
5. **Pricing complete**: An AWS expert shares the pricing for the production project with you.
6. **Contract executed**: The contract is complete.
7. **Production in-progress**: Labeling for the project in the production stage is in progress.
8. **Production complete**: Object labeling is complete and the labeled data is stored in your Amazon S3 bucket.
9. **Paused**: Project is currently paused at your request.

**Task type**: Ground Truth Plus lets you label five types of tasks that include text, image, video, audio, and point cloud.
Batches: Total number of batches within a project.

Project creation date: Starting date of a project.

Total objects: Total number of objects to be labeled across all batches.

Objects completed: Number of labeled objects.

Remaining objects: Number of objects left to be labeled.

Failed objects: Number of objects that cannot be labeled due to an issue with the input data.

Review Metrics

Metrics are data about your Ground Truth Plus project for a specific date or over a date range.

You can review metrics for all batches or choose a batch of your choice as shown in the following image.

You can review the following metrics about the batch:

Total objects: Total number of objects in a batch or across all batches.

Objects completed by day: Total numbers of objects labeled on a specific date or over a date range.

Labels completed by day: Total numbers of labels completed on a specific date or over a date range. An object can have more than one label.

Review Batches

Every Amazon SageMaker Ground Truth Plus project consists of one or more batches. Each batch is made up of data objects to be labeled. You can view all the batches for your project using the project portal as shown in the following image.
You can use the Ground Truth Plus project portal to track the following details about every batch:

**Batch name**: Each batch is identified with a unique batch name.

**Status**: A Ground Truth Plus batch has one of the following status types:

1. **Waiting for data**: The AWS expert is awaiting data from you.
2. **Data received**: We have received your unlabeled input data.
3. **In-progress**: Data labeling is in-progress.
4. **Ready for review**: Data labeling is completed. A subset of labeled objects from the batch are ready for you to review. This is an optional step.
5. **Review submission in-progress**: Review feedback is currently being processed.
6. **Review complete**: You have successfully reviewed the batch. Next, you have to accept or reject it. This action can not be undone.
7. **Accepted**: You have accepted the labeled data and will receive it in your Amazon S3 bucket shortly.
8. **Rejected**: Labeled data needs to be reworked.
9. **Data delivered**: Object labeling is complete and the labeled data is stored in your Amazon S3 bucket.
10. **Paused**: Batch is paused at your request.

**Task type**: Ground Truth Plus lets you label five types of tasks that include text, image, video, audio, and point cloud.

**Batch creation date**: Date when the batch was created.

**Total objects**: Total number of objects to be labeled across a batch.

**Completed objects**: Number of labeled objects.

**Remaining objects**: Number of objects left to be labeled

**Failed objects**: Number of objects that cannot be labeled due to an issue with the input data.

**Objects to review**: Number of objects that are ready for your review.

**Objects with feedback**: Number of objects that have gotten feedback from the team members.

Ground Truth Plus lets you review a sample set of your labeled data (determined during the initial consultation call) through the review UI shown in the following image.
Hello,

Instructions  Shortcuts  Help

Instructions

Please review the following sample set of the batch selected and provide your feedback.

Feedback
Provide feedback for each object. The Feedback section is in the lower right panel.

Navigation
Use the arrow controls in the lower left panel to navigate through the images.

Submit
Choose Submit to submit feedback for all data objects.

Image controls
Use the image controls in the bottom tray to zoom, pan, control brightness and, contrast.

Save
Choose Save to save your progress. It's also autosaved every 15 minutes.

Close
To exit the review UI, choose the Close button on the upper right corner.

Verify the label attributes and frame attributes on each frame. You can't create new objects or modify existing objects in this task.
The portal allows your project team members and you to review a small sample set of the labeled objects for each batch. You can provide feedback for each labeled object within that subset through this UI. The review UI allows you to navigate across the subset of labeled objects and provide feedback for those labeled objects.

You can perform the following actions using the review UI.

- Use the arrow controls on the bottom left to navigate through the data objects.
- You can provide feedback for each object. The Feedback section is in the right panel. Choose Submit to submit feedback for all images.
- Use the image controls in the bottom tray to zoom, pan, and control contrast.
- If you plan on returning to finish up your review, choose Stop and resume later on the top right.
- Choose Save to save your progress. It is also autosaved every 15 minutes.
- To exit the review UI, choose Close on the upper right corner of the review UI.
- You can verify the Label attributes and Frame attributes on each frame using the panel on the right. You cannot create new objects or modify existing objects in this task.

**Accept or Reject Batches**

After you have reviewed a batch, you must choose to accept or reject it.

If you accept a batch, the output from that labeling job is placed in the Amazon S3 bucket that you specify. Once the data is delivered to your S3 bucket, the status of your batch changes from Accepted to Data delivered.

If you reject a batch, you can provide feedback and explain your reasons for rejecting the batch.

Ground Truth Plus allows you to provide feedback at the data object level as well as the batch level. You can provide feedback for data objects through the review UI. You can use the project portal to provide feedback for each batch. When you reject a batch, an AWS expert contacts you to determine the rework process and the next steps for the batch.

**Note**

Accepting or rejecting a batch is a one-time action and cannot be undone. It is necessary to either accept or reject every batch of the project.

**Use Amazon SageMaker Ground Truth Synthetic Data to Generate and Label Data**

Amazon SageMaker Ground Truth synthetic data is a turnkey data generation and labeling service that makes it quicker and more cost effective for machine learning (ML) scientists to acquire images that are used to train computer vision (CV) models. To train a CV model, ML scientists need large, high-quality, labeled datasets. With Ground Truth synthetic data, ML scientists can generate and label thousands of images within days. Ground Truth synthetic data uses computer-generated 3D models to create virtual environments representing real-world scenarios, generates synthetic images captured from these environments, and automatically annotates each image with labels. You can use the labeled synthetic images with AWS's CV model training services such as Amazon SageMaker and Amazon Lookout for Vision.

**Why use Ground Truth Synthetic Data?**
Collecting and labeling data in dynamic environments with variations in object size, shape, color, position, background, and lighting is often a time-consuming and expensive process. To effectively train a model to operate in a dynamic environment, ML scientists must collect a large set of real-world images to represent all possible scenarios, a process that can take months. For scenarios that don’t occur frequently, such as rare product defects and faulty product placement, it can take years to capture a sufficient number of images to train a CV model. To acquire images with product defects, ML scientists may intentionally damage products in order to acquire defective images. Ground Truth synthetic data makes it faster and more cost effective for ML scientists to quickly acquire labeled images that represent real-world scenarios, a core requirement for training CV models. Ground Truth synthetic data can use Ground Truth synthetic data to generate thousands of synthetic images from 3D virtual environments representing real world scenarios in hours instead of months. Ground Truth provides a synthetic image fidelity and diversity report and a manifest file along with the labeled synthetic data. The synthetic image fidelity and diversity report provides statistics and plots that help you better understand the generated synthetic images. The manifest file contains information about the images and image labels that you can use to train and test a model.

Note
Ground Truth synthetic data does not support PHI, PCI, or FedRAMP certified data, and you should not provide this data to Ground Truth synthetic data.

How do I use Ground Truth Synthetic Data?

If you are a first-time user of Ground Truth synthetic data, we recommend that you follow the procedures outlined in the Getting Started with Amazon SageMaker Ground Truth Synthetic Data (p. 688) section.

Getting Started with Amazon SageMaker Ground Truth Synthetic Data

The guide demonstrates how to complete the necessary steps to satisfy the prerequisites, start a Ground Truth synthetic data project, and review labels.

To get started using synthetic data, review Set Up Amazon SageMaker Ground Truth Synthetic Data Prerequisites (p. 688) and Core Components of Amazon SageMaker Ground Truth Synthetic Data (p. 689).

Set Up Amazon SageMaker Ground Truth Synthetic Data Prerequisites

To use Ground Truth synthetic data, you need an AWS account. If you already have an AWS account, skip this step.

When you sign up for Amazon Web Services (AWS), your AWS account is automatically signed up for all AWS services, including SageMaker. You are charged only for the services that you use.

To create an AWS account

2. Follow the online instructions.

Part of the sign-up procedure involves receiving a phone call and entering a verification code on the phone keypad.

When you sign up for an AWS account, an AWS account root user is created. The root user has access to all AWS services and resources in the account. As a security best practice, assign administrative
access to an administrative user, and use only the root user to perform tasks that require root user access.

Write down your AWS account ID because you need it for the next task.

AWS sends you a confirmation email after the sign-up process is complete. At any time, you can view your current account activity and manage your account by going to https://aws.amazon.com/ and choosing My Account.

Core Components of Amazon SageMaker Ground Truth Synthetic Data

The following terms are key to understanding the capabilities of Ground Truth synthetic data:

- **Project:** Each qualified engagement with an AWS expert results in a Ground Truth synthetic data project.
- **Batch:** A batch is a collection of similar labeled images. A project can have multiple batches. A batch can be in the test or production stage. A project can have multiple batches.
- **Synthetic Image Fidelity and Diversity Report:** Ground Truth synthetic data provides a metrics report that helps you compare the generated synthetic images with your typical dataset.

Request a Project

To get started with Amazon SageMaker Ground Truth synthetic data, go to the SageMaker console and complete the intake form.

Once you submit the intake form in the AWS console, an AWS expert from the Ground Truth synthetic data team reaches out to discuss your data labeling project requirements and pricing.

Share Data from Your Amazon S3 Bucket

After an AWS expert reaches out to discuss your project, you may be required to fill out an intake form with questions specific to your synthetic data requirements. The intake form, along with assets shared with Ground Truth synthetic data, allows the Ground Truth synthetic data team to evaluate your project and the estimated work required to complete your project.

Create an Amazon S3 bucket to share your project assets with Ground Truth synthetic data and store your project’s output data.

**To create an Amazon S3 bucket and share it with us:**

1. Follow the instructions in Create a Bucket in the Amazon Simple Storage Service Console User Guide.
2. We recommend using the following naming convention while storing your data in an Amazon S3 bucket.
   a. The *bucket-name* should contain fewer than 63 characters.
   b. The *bucket-name* can include hyphens, but no spaces and underscores.
3. In the Buckets list, choose the name of the bucket you created.
4. Choose Permissions.
5. In the Bucket policy section, choose Edit.
6. Confirm that ACLs disabled is selected.

**Note**

Under Object Ownership should have ACLs disabled as shown in the image below.
7. Choose **Save changes**.

**Note**

If you have additional requirements for accessing your data in an Amazon S3 bucket, please contact your AWS expert.

To share your project assets with the Ground Truth synthetic data team for project evaluation, work estimation, and synthetic data generation, follow the steps in the **Send Project Data to Ground Truth Synthetic Data** (p. 690) section below.

After receiving your intake form and project assets, we return a statement of work (SOW) within 5 business days. The SOW outlines your engagement with Ground Truth synthetic data generation and labeling. After you approve the SOW, the Ground Truth synthetic data team produces a test batch consisting of 50 synthetic images. An AWS expert meets with you to review the test batch, approve or reject images, and complete the final production. The timeline for this is based on the responses in your intake form.

**Send Project Data to Ground Truth Synthetic Data**

After an AWS expert has been assigned to your project, you can send project data to the Ground Truth synthetic data team to assist in project evaluation, work estimation, and synthetic data generation.

**To send project data to Ground Truth synthetic data:**

1. Under the **Project data transfers** table in the project portal, choose **Send project data**.
2. Enter the name of your S3 bucket from which you would like to send project data as the Amazon S3 source location of the project data transfer.
3. Select an IAM role for the project data transfer. If you select **Automatic**, Ground Truth synthetic data creates an IAM role in your account with the required permissions to run the project data transfer and call other services on your behalf (recommended). If you select an existing IAM role in your account, Ground Truth synthetic data uses that IAM role to run the project data transfer and call other services on your behalf.
4. Choose **Create** to create and start the project data transfer.

After creating a project data transfer, you can view the status of the transfer in the **Project data transfers** table on the project details page in the project portal. When the project data transfer status is **Completed**, the project data is available to the Ground Truth synthetic data team.
Project Portal

Each project consists of one or more batches. A batch is a collection of similar generated and labeled images. The project portal provides you access to the projects you have contracted with Ground Truth synthetic data. You can view the status of your projects and access completed batches along with the synthetic image fidelity and diversity report. You also review your batches to accept or reject them through the project portal.

You can use the Ground Truth synthetic data project portal to track the following details about your project:

**Project name**: Each project is identified using a unique name.

**Status**: A Ground Truth synthetic data project has one of the following status types:

1. **Request submitted**: You have successfully submitted the project request form. Next, an AWS expert schedules a call with you to discuss the details for your project.
2. **Review in progress**: We are reviewing your project. An AWS expert has been assigned to your project.
3. **Production in progress**: We are currently working on generating labeled data for your project.
4. **Data ready for review**: At least one batch is ready for your review.
5. **Project complete**: We have completed the generation of the required labeled images. The images are stored in your Amazon S3 bucket.

**Batches**: Total number of batches within a project.

**Project start date**: Starting date of a project.

**Total images**: Number of images you requested.

**Completed images**: Number of labeled images generated across all accepted production batches.

**Delete a Project**

You can delete a project using the console if the project status is **Request submitted** or **Project complete**. To delete a project with any other status, contact your AWS expert. Deleting a Ground Truth synthetic data project does not delete your data from the Amazon S3 buckets and can be subject to charge.

You can delete a project based on its status as follows:
• **Request submitted**: Deleting a requested project deletes all the project and customer information from the Ground Truth synthetic data database.

• **Review in progress / Production in progress / Data ready for review**: You can request your AWS expert to delete a project having one of these statuses. Deleting a project deletes all the project and personal information from Ground Truth synthetic data database and S3 buckets.

• **Project complete**: Once a project is marked as **Project complete**, we delete all customer information from the Ground Truth synthetic data database and S3 buckets. You can view the project and batches as long as you want, or delete them using the console.

**Note**
Deleting a project does not delete the images from your S3 bucket. To learn more about deleting images from your S3 bucket, refer to Deleting Amazon S3 objects.

**Review Batches**

Every Amazon SageMaker Ground Truth synthetic data project consists of one or more batches. Each batch is made up of labeled synthetic images. Batches are of two types, **Test Batch** and **Production Batch**. A test batch provides a small preview of how the synthetic images look using your 3D assets and environment. Images in the test batch are not counted towards the total number of synthetic images you contract. After you approve the test batch for a specific configuration of images, Ground Truth synthetic data starts generating images for your production batch. Images in a production batch are counted towards the total required images.

For every batch, Ground Truth synthetic data provides a **Synthetic Image Fidelity and Diversity Report**. This report provides image and object level statistics and plots that help you make sense of the generated synthetic images. The statistics are used to describe the diversity and the fidelity of the synthetic images and compare them with real images. Examples of the statistics and plots provided are the distributions of object classes, object sizes, image brightness, image contrast, as well as the plots evaluating the indistinguishability between synthetic and real images. The raw data for all the computed dataset statistics is also provided as CSV files to help you accelerate model debugging and enable further analyses.
You can view all the batches for your project using the project portal.

You can use the Ground Truth synthetic data project portal to track the following details about every batch:

- **Batch name**: Each batch is identified with a unique batch name.
- **Status**: A Ground Truth synthetic data batch has one of the following status types:
  1. **In progress**: We are currently generating labeled images for this batch. It will soon be ready for your review.
  2. **Ready for review**: A batch of labeled synthetic images is now ready for your review. Follow the steps in the Transfer Batch Data to Your Amazon S3 bucket (p. 693) section to view the images and review the batch.
  3. **Accepted**: You have accepted this batch.
  4. **Rejected**: You have rejected this batch and it needs to be reworked. When you reject a batch, an AWS expert contacts you to discuss this further.

- **Batch type**: A batch can either be a test batch or a production batch.
- **Creation date**: Date when the batch was created.
- **Images**: Total number of images in the batch.

**Transfer Batch Data to Your Amazon S3 bucket**

When the batch status is **Ready for review**, you must transfer the batch data to your S3 bucket to view the images and review the batch.

**To transfer batch data to your S3 bucket:**

1. On the batch details page in the project portal, choose **Get batch data**.
2. Under **S3 destination location**, enter the name of the S3 bucket where you would like to receive your batch data.
3. Select an IAM role for the project data transfer. If you select **Automatic**, Ground Truth synthetic data creates an IAM role in your account with the required permissions to run the project data transfer and call other services on your behalf (recommended). If you select an existing IAM role in your account, Ground Truth synthetic data uses that IAM role to run the project data transfer and call other services on your behalf.
4. Choose **Create** to create and start the batch data transfer.
After creating a batch data transfer, you can view the status of the transfer in the **Batch data transfers** table on the batch details page in the project portal. When the batch data transfer status is **Completed**, the batch data is available in your S3 bucket, the batch images are viewable on the batch details page in the project portal, and you can proceed to review the batch.

### Accept or Reject Batches

After you have reviewed a batch, you can choose to accept or reject it from the project portal as shown below.

Accepting a batch informs your AWS expert to continue or complete the project, based on the number of remaining images you contracted.

When you reject a batch, an AWS expert contacts you to determine the rework process and the next steps for the batch.

Accepting or rejecting a batch is a one-time action and can only be undone by contacting your AWS expert. It is necessary to either accept or reject every batch of the project.

### Create and Manage Workforces

A *workforce* is the group of workers that you have selected to label your dataset. You can choose either the Amazon Mechanical Turk workforce, a vendor-managed workforce, or you can create your own private workforce to label or review your dataset. Whichever workforce type you choose, Amazon SageMaker takes care of sending tasks to workers.

When you use a private workforce, you also create *work teams*, a group of workers from your workforce that are assigned to specific *jobs*—Amazon SageMaker Ground Truth labeling jobs or Amazon Augmented AI human review tasks. You can have multiple work teams and can assign one or more work teams to each job.

You can use Amazon Cognito or your own private OpenID Connect (OIDC) Identity Provider (IdP) to manage your private workforce and work teams. For more information about the permissions required to manage your workforce this way, see Permissions Required to Use the Amazon SageMaker Ground Truth Console (p. 3510).

**Topics**

- Using the Amazon Mechanical Turk Workforce (p. 695)
Using the Amazon Mechanical Turk Workforce

The Amazon Mechanical Turk (Mechanical Turk) workforce provides the most workers for your Amazon SageMaker Ground Truth labeling job and Amazon Augmented AI human review task. The Amazon Mechanical Turk workforce is a world-wide resource. Workers are available 24 hours a day, 7 days a week. You typically get the fastest turnaround for your human review tasks and labeling jobs when you use the Amazon Mechanical Turk workforce.

Any Amazon Mechanical Turk workforce billing is handled as part of your Ground Truth or Amazon Augmented AI billing. You do not need to create a separate Mechanical Turk account to use the Amazon Mechanical Turk workforce.

**Important**

You should not share confidential information, personal information, or protected health information with this workforce. You should not use the Amazon Mechanical Turk workforce when you use Amazon A2I in conjunction with AWS HIPAA-eligible services, such as Amazon Textract and Amazon Rekognition, for workloads containing protected health information.

You can choose Mechanical Turk as your workforce when you create a Ground Truth labeling job or Amazon A2I human review workflow (flow definition). You can create a labeling job and a human review workflow using the SageMaker console and API.

When you use an API operation to create a labeling job or human review workflow, you use the following ARN for the Amazon Mechanical Turk workforce for your WorkteamArn. Replace `region` with the AWS Region you are using to create the labeling job or human loops. For example, if you create a labeling job in US West (Oregon), replace `region` with `us-west-2`.

```
arn:aws:sagemaker:region:394669845002:workteam/public-crowd/default
```

Ground Truth and Amazon A2I require that your input data is free of personally identifiable information (PII) when you use Mechanical Turk. If you use the Mechanical Turk workforce and do not specify that your input data is free of PII, your Ground Truth labeling jobs and Augmented AI tasks will fail. You specify that your input data is free of PII when you create a Ground Truth labeling job and when you create a Amazon A2I human loop using a built-in integration or the StartHumanLoop operation.

Use the following sections to learn how to use Mechanical Turk with these services.

**Topics**

- Use Mechanical Turk with Ground Truth (p. 695)
- Use Mechanical Turk with Amazon A2I (p. 697)
- When is Mechanical Turk Not Supported? (p. 698)

**Use Mechanical Turk with Ground Truth**

You can use Mechanical Turk with Ground Truth when you create a labeling job using the console, or the CreateLabelingJob operation.

When you create a labeling job, we recommend you adjust the number of workers that annotate each data object based on the complexity of the job and the quality that you need. Amazon SageMaker Ground Truth uses annotation consolidation to improve the quality of the labels. More workers can make
a difference in the quality of the labels for more complex labeling jobs, but might not make a difference for simpler jobs. For more information, see Consolidate Annotations (p. 639). Note that annotation consolidation is not supported for Amazon A2I human review workflows.

To use Mechanical Turk when you create a labeling job (console):

1. Use the following to create a labeling job using the Ground Truth area of the SageMaker console: Create a Labeling Job (Console) (p. 544).
2. When you are selecting Worker types in the Workers section, select Amazon Mechanical Turk.
3. Specify the total amount of time workers have to complete a task using Task timeout.
4. Specify the total amount of time a task remains available to workers in Task expiration. This is how long workers have to pick up a task before it fails.
5. Select the Price per task using the dropdown list. This is the amount of money a worker receives for completing a single task.
6. (Optional) If applicable, select The dataset does not contain adult content. SageMaker may restrict the Mechanical Turk workers that can view your task if it contains adult content.
7. You must read and confirm the following statement by selecting the check box to use the Mechanical Turk workforce. If your input data contains confidential information, personal information, or protected health information, you must select another workforce.

   You understand and agree that the Mechanical Turk workforce consists of independent contractors located worldwide and that you should not share confidential information, personal information, or protected health information with this workforce.
8. (Optional) Select the check box next to Enable automated data labeling if you want to enable automated data labeling. To learn more about this feature, see Automate Data Labeling (p. 640).
9. You can specify the Number of workers per dataset object under Additional configuration. For example, if you enter 3 in this field, each data object will be labeled by 3 workers.

When you create your labeling job by selecting Create, your labeling tasks are sent to Mechanical Turk workers.

To use Mechanical Turk when you create a labeling job (API):

1. Use the following to create a labeling job using the CreateLabelingJob operation: Create a Labeling Job (API) (p. 547).
2. Use the following for the WorkteamArn. Replace region with the AWS Region you are using to create the labeling job.

   arn:aws:sagemaker:region:394669845002:workteam/public-crowd/default
3. Use TaskTimeLimitInSeconds to specify the total amount of time workers have to complete a task.
4. Use TaskAvailabilityLifetimeInSeconds to specify the total amount of time a task remains available to workers. This is how long workers have to pick up a task before it fails.
5. Use NumberOfHumanWorkersPerDataObject to specify the number of workers per dataset object.
6. Use PublicWorkforceTaskPrice to set the price per task. This is the amount of money a worker receives for completing a single task.
7. Use DataAttributes to specify that your input data is free of confidential information, personal information, or protected health information.

   Ground Truth requires that your input data is free of personally identifiable information (PII) if you use the Mechanical Turk workforce. If you use Mechanical Turk and do not specify that your input data...
data is free of PII using the `FreeOfPersonallyIdentifiableInformation` flag, your labeling job will fail.

Use the `FreeOfAdultContent` flag to declare that your input data is free of adult content. SageMaker may restrict the Mechanical Turk workers that can view your task if it contains adult content.

You can see examples of how to use this API in the following notebooks, found on GitHub: [Ground Truth Jupyter Notebook Examples](https://github.com/aws-samples/amazon-sagemaker-ground-truth). You can access these notebooks under the SageMaker Example Notebooks (p. 306) in a notebook instance.

**Use Mechanical Turk with Amazon A2I**

You can specify that you want to use Mechanical Turk with Amazon A2I when you create a human review workflow, also referred to as a flow definition, in the console, or with the `CreateFlowDefinition` API operation. When you use this human review workflow to configure human loops, you must specify that your input data is free of PII.

**To use Mechanical Turk when you create a human review workflow (console):**

1. Use the following to create a human review workflow in the Augmented AI section of the SageMaker console: [Create a Human Review Workflow (Console)](https://docs.aws.amazon.com/sagemaker/latest/dg/how-to-human-review-workflow-console.html) (p. 3420).
2. When you are selecting **Worker types** in the **Workers** section, select Amazon Mechanical Turk.
3. Select the **Price per task** using the dropdown list. This is the amount of money a worker receives for completing a single task.
4. (Optional) You can specify the **Number of workers per dataset object** under **Additional configuration**. For example, if you enter 3 in this field, each data object will be labeled by 3 workers.
5. (Optional) Specify the total amount of time workers have to complete a task using **Task timeout**.
6. (Optional) Specify the total amount of time a task remains available to workers in **Task expiration**. This is how long workers have to pick up a task before it fails.
7. Once you have created your human review workflow, you can use it to configure a human loop by providing its Amazon Resource Name (ARN) in the parameter `FlowDefinitionArn`. You configure a human loop using one of the API operations of a built-in task type, or the Amazon A2I runtime API operation, `StartHumanLoop`. To learn more, see [Create and Start a Human Loop](https://docs.aws.amazon.com/sagemaker/latest/dg/how-to-human-review-workflow-api.html) (p. 3438).

When you configure your human loop, you must specify that your input data is free of personally identifiable information (PII) using the `FreeOfPersonallyIdentifiableInformation` content classifier in `DataAttributes`. If you use Mechanical Turk and do not specify that your input data is free of PII, your human review tasks will fail.

Use the `FreeOfAdultContent` flag to declare that your input data is free of adult content. SageMaker may restrict the Mechanical Turk workers that can view your task if it contains adult content.

**To use Mechanical Turk when you create a human review workflow (API):**

1. Use the following to create a human review workflow using the `CreateFlowDefinition` operation: [Create a Human Review Workflow (API)](https://docs.aws.amazon.com/sagemaker/latest/dg/how-to-human-review-workflow-api.html) (p. 3422).
2. Use the following for the `WorkteamArn`. Replace `region` with the AWS Region you are using to create the labeling job.

   `arn:aws:sagemaker:region:394669845002:workteam/public-crowd/default`

3. Use `TaskTimeLimitInSeconds` to specify the total amount of time workers have to complete a task.
4. Use `TaskAvailabilityLifetimeInSeconds` to specify the total amount of time a task remains available to workers. This is how long workers have to pick up a task before it fails.

5. Use `TaskCount` to specify the number of workers per dataset object. For example, if you specify 3 for this parameter, each data object will be labeled by 3 workers.

6. Use `PublicWorkforceTaskPrice` to set the price per task. This is the amount of money a worker receives for completing a single task.

7. Once you have created your human review workflow, you can use it to configure a human loop by providing its Amazon Resource Name (ARN) in the parameter `FlowDefinitionArn`. You configure a human loop using one of the API operations of a built-in task type, or the Amazon A2I runtime API operation, `StartHumanLoop`. To learn more, see Create and Start a Human Loop (p. 3438).

When you configure your human loop, you must specify that your input data is free of personally identifiable information (PII) using the `FreeOfPersonallyIdentifiableInformation` classifier in `DataAttributes`. If you use Mechanical Turk and do not specify that your input data is free of PII, your human review tasks will fail.

Use the `FreeOfAdultContent` flag to declare that your input data is free of adult content. SageMaker may restrict the Mechanical Turk workers that can view your task if it contains adult content.

You can see examples of how to use this API in the following notebooks, found on GitHub: Amazon A2I Jupyter Notebook Examples.

**When is Mechanical Turk Not Supported?**

This workforce is not supported under the following scenarios. In each scenario, you must use a private or vendor workforce.

- This workforce is not supported for Ground Truth video frame labeling jobs and 3D point cloud labeling jobs.
- You cannot use this workforce if your input data contains personally identifiable information (PII).
- Mechanical Turk is not available in some of the AWS special regions. If applicable, refer to the documentation for your special region for more information.

**Managing Vendor Workforces**

You can use a vendor-managed workforce to label your data using Amazon SageMaker Ground Truth (Ground Truth) and Amazon Augmented AI (Amazon A2I). Vendors have extensive experience in providing data labeling services for the purpose of machine learning. Vendor workforces for these two services must be created and managed separately through the Amazon SageMaker console.

Vendors make their services available via the AWS Marketplace. You can find details of the vendor's services on their detail page, such as the number of workers and the hours that they work. You can use these details to make estimates of how much the labeling job will cost and the amount of time that you can expect the job to take. Once you have chosen a vendor you subscribe to their services using the AWS Marketplace.

A subscription is an agreement between you and the vendor. The agreement spells out the details of the agreement, such as price, schedule, or refund policy. You work directly with the vendor if there are any issues with your labeling job.

You can subscribe to any number of vendors to meet your data annotation needs. When you create a labeling job or human review workflow you can specify that the job be routed to a specific vendor.
Important
Before you send sensitive data to a vendor, check the vendor's security and compliance practices on their detail page and review the end user license agreement (EULA) that is part of your subscription agreement. You are responsible for ensuring that the vendor meets your compliance requirements for personal or confidential information. Do not share protected health information with this workforce.

You must use the console to subscribe to a vendor workforce. Once you have a subscription, you can use the `ListSubscribedWorkteams` operation to list your subscribed vendors.

**To subscribe to a vendor workforce**

2. Choose the appropriate page in the SageMaker console.
   - For Ground Truth labeling jobs, choose Labeling workforces, choose Vendor, and then choose Find data labeling services.
   - For Amazon A2I human review workflows, choose Human review workforces, choose Vendor, and then choose Find human review services.
3. The console opens the AWS Marketplace with:
   - data labeling services category selected for Ground Truth
   - human review services category selected for Amazon A2I

   Here you see a list of the vendor services available for this service.
4. Choose a vendor. The AWS Marketplace shows detailed information about the data labeling or human review service. Use this information to determine if the vendor meets your requirements for your task.
5. If the vendor meets your requirements, choose Continue to subscribe.
6. Review the details of the subscription. If you agree to the terms, choose Subscribe to complete your subscription to the service.

**Use a Private Workforce**

A private workforce is a group of workers that you choose. These can be employees of your company or a group of subject matter experts from your industry. For example, if the task is to label medical images, you could create a private workforce of people knowledgeable about the images in question.

Each AWS account has access to a single private workforce per region, and the owner has the ability to create multiple private work teams within that workforce. A single private work team is used to complete a labeling job or human review task, or a job. You can assign each work team to a separate job or use a single team for multiple jobs. A single worker can be in more than one work team.

Your private workforce can either be created and managed using Amazon Cognito or your own private OpenID Connect (OIDC) Identity Provider (IdP).

If you are a new user of Amazon SageMaker Ground Truth or Amazon Augmented AI and do not require your workers to be managed with your own IdP, it is recommended that you use Amazon Cognito to create and manage your private workforce.

After you create a workforce, in addition to creating and managing work teams, you can do the following:

- Track worker performance
- Create and manage Amazon SNS topics to notify workers when labeling tasks are available
Use a Private Workforce

- Manage Private Workforce Access to Tasks Using IP Addresses

**Note**
Your private workforce is shared between Ground Truth and Amazon A2I. To create and manage private work teams used by Augmented AI, use the Ground Truth section of the SageMaker console.

**Topics**
- Create and Manage Amazon Cognito Workforce (p. 700)
- Create and Manage OIDC IdP Workforce (p. 707)
- Manage Private Workforce Using the Amazon SageMaker API (p. 716)
- Track Worker Performance (p. 717)
- Create and manage Amazon SNS topics for your work teams (p. 719)

**Create and Manage Amazon Cognito Workforce**

Create and manage your private workforce using Amazon Cognito when you want to create your workforce using the Amazon SageMaker console or you don’t want the overhead of managing worker credentials and authentication. When you create a private workforce with Amazon Cognito, it provides authentication, authorization, and user management for your private workers.

**Topics**
- Create a Private Workforce (Amazon Cognito) (p. 700)
- Manage a Private Workforce (Amazon Cognito) (p. 703)

**Create a Private Workforce (Amazon Cognito)**

When you use Amazon Cognito, you can create a private workforce in one of the following ways:

- Create a new workforce while you are creating your labeling job. To learn how, see Create an Amazon Cognito Workforce When Creating a Labeling Job (p. 701).
- Create a new workforce before you create your labeling job. To learn how, see Create an Amazon Cognito Workforce Using the Labeling Workforces Page (p. 701).
- Import an existing workforce after creating a user pool in the Amazon Cognito console. To learn how, see Create a Private Workforce (Amazon Cognito Console) (p. 702).

Once you create a private workforce, that workforce and all work teams and workers associated with it are available to use for all Ground Truth labeling job tasks and Amazon Augmented AI human review workflows tasks.

If you are new to Amazon SageMaker and want to test Ground Truth or Amazon A2I, we suggest that you create a private work team consisting of people from your organization using the console. Use this work team when creating labeling or human review workflows (flow definitions) to test your worker UI and job workflow.

**Topics**
- Create a Private Workforce (Amazon SageMaker Console) (p. 700)
- Create a Private Workforce (Amazon Cognito Console) (p. 702)

**Create a Private Workforce (Amazon SageMaker Console)**

You can create a private workforce in the Amazon SageMaker console in one of two ways:
When creating a labeling job in the **Labeling jobs** page of the Amazon SageMaker Ground Truth section.

- Using the **Labeling workforces** page of the Amazon SageMaker Ground Truth section. If you are creating a private workforce for an Amazon A2I human review workflow, use this method.

Both of these methods also create a default work team containing all of the members of the workforce. This private workforce is available to use for both Ground Truth and Amazon Augmented AI jobs.

When you create a private workforce using the console, SageMaker uses Amazon Cognito as an identity provider for your workforce. If you want to use your own OpenID Connect (OIDC) Identity Provider (IdP) to create and manage your private workforce, you must create a workforce using the SageMaker API operation **CreateWorkforce**. To learn more, see [Create a Private Workforce (OIDC IdP)](p. 707).

### Create an Amazon Cognito Workforce When Creating a Labeling Job

If you haven't created a private workforce when you create your labeling job and you choose to use private workers, you are prompted to create a work team. This will create a private workforce using Amazon Cognito.

#### To create a workforce while creating a labeling job (console)

2. In the navigation pane, choose **Labeling jobs** and fill in all required fields. For instructions on how to start a labeling job, see [Getting started](p. 371). Choose Next.
3. Choose **Private** for the workforce type.
4. In the **Workers** section, enter:
   a. The **Team name**.
   b. Email addresses for up to 100 workforce members. Email addresses are case sensitive. Your workers must log in using the same case used when the address was initially entered. You can add additional workforce members after the job has been created.
   c. The name of your organization. SageMaker uses this to customize the email sent to the workers.
   d. A contact email address for workers to report issues related to the task.

When you create the labeling job, an email is sent to each worker inviting them to join the workforce. After creating the workforce, you can add, delete, and disable workers using the SageMaker console or the Amazon Cognito console.

### Create an Amazon Cognito Workforce Using the Labeling Workforces Page

To create and manage your private workforce using Amazon Cognito, you can use the **Labeling workforces** page. When following the instructions below, you have the option to create a private workforce by entering worker emails importing a pre-existing workforce from an Amazon Cognito user pool. To import a workforce, see [Create a Private Workforce (Amazon Cognito Console)](p. 702).

#### To create a private workforce using worker emails

2. In the navigation pane, choose **Labeling workforces**.
3. Choose **Private**, then choose **Create private team**.
4. Choose **Invite new workers by email**.
5. Paste or type a list of up to 50 email addresses, separated by commas, into the email addresses box.
6. Enter an organization name and contact email.

7. Optionally, choose an SNS topic to which to subscribe the team so workers are notified by email when new Ground Truth labeling jobs become available. Amazon SNS notifications are supported by Ground Truth and are not supported by Augmented AI. If you subscribe workers to receive SNS notifications, they only receive notifications about Ground Truth labeling jobs. They do not receive notifications about Augmented AI tasks.

8. Click the Create private team button.

After you import your private workforce, refresh the page. On the Private workforce summary page, you can see information about the Amazon Cognito user pool for your workforce, a list of work teams for your workforce, and a list of all of the members of your private workforce.

**Note**

If you delete all of your private work teams, you have to repeat this process to use a private workforce in that region.

Create a Private Workforce (Amazon Cognito Console)

Amazon Cognito is used to define and manage your private workforce and your work teams. It is a service that you can use to create identities for your workers and authenticate these identities with identity providers. A private workforce corresponds to a single Amazon Cognito user pool. Private work teams correspond to Amazon Cognito user groups within that user pool.

Example identity providers supported by Amazon Cognito:

- Social sign-in providers such as Facebook and Google
- OpenID Connect (OIDC) providers
- Security Assertion Markup Language (SAML) providers such as Active Directory
- The Amazon Cognito built-in identity provider

For more information, see What Is Amazon Cognito?

To create a private workforce using Amazon Cognito, you must have an existing Amazon Cognito user pool containing at least one user group. See Tutorial: Creating a User Pool to learn how to create a user pool. See Adding Groups to a User Pool to learn how to add a user group to a pool.

Once your user pool has been created, follow the steps below to create a private workforce by importing that user pool into Amazon SageMaker.

**To create a private workforce by importing a Amazon Cognito user pool**

2. In the navigation pane, choose Labeling workforces.
3. Choose Private.
4. Choose Create private team. This creates a private workforce and a work team.
5. Choose Import workers from existing Amazon Cognito user groups.
6. Choose a user pool that you have created. User pools require a domain and an existing user group. If you get an error that the domain is missing, set it in the Domain name options on the App integration page of the Amazon Cognito console for your group.
7. Choose an app client. We recommend using a client generated by SageMaker.
8. Choose a user group from your pool to import its members.
9. Optionally choose an Amazon Simple Notification Service (Amazon SNS) topic to which to subscribe the team so that workers are notified by email when new labeling jobs become available. Amazon
SNS notifications are supported by Ground Truth and are not supported by Augmented AI. If you subscribe workers to receive SNS notifications, they only receive notifications about Ground Truth labeling jobs. They do not receive notifications about Augmented AI tasks.

10. Choose Create private team.

Important
After you create a workforce using an Amazon Cognito user pool, it should not be deleted without first deleting all work teams associated with that pool in the SageMaker console.

After you import your private workforce, refresh the page to see the Private workforce summary page. On this page, you can see information about the Amazon Cognito user pool for your workforce, a list of work teams for your workforce, and a list of all of the members of your private workforce. This workforce is now available to use in both Amazon Augmented AI and Amazon SageMaker Ground Truth for human review tasks and data labeling jobs respectively.

Manage a Private Workforce (Amazon Cognito)

After you have created a private workforce using Amazon Cognito, you can create and manage work teams using the Amazon SageMaker console and API operations.

You can do the following using either the SageMaker console or Amazon Cognito console.

- Add and delete work teams.
- Add workers to your workforce and one or more work teams.
- Disable or remove workers from your workforce and one or more work teams. If you add workers to a workforce using the Amazon Cognito console, you must use the same console to remove the worker from the workforce.

You can restrict access to tasks to workers at specific IP addresses using the SageMaker API. For more information, see Manage Private Workforce Using the Amazon SageMaker API (p. 716).

Topics
- Manage a Workforce (Amazon SageMaker Console) (p. 703)
- Manage a Private Workforce (Amazon Cognito Console) (p. 705)

Manage a Workforce (Amazon SageMaker Console)

You can use the Amazon SageMaker console to create and manage the work teams and individual workers that make up a private workforce.

Use a work team to assign members of your private workforce to a labeling or human review job. When you create your workforce using the SageMaker console, there is a work team called Everyone-in-private-workforce that enables you to assign your entire workforce to a job. Because an imported Amazon Cognito user pool may contain members that you don’t want to include in your work teams, a similar work team is not created for Amazon Cognito user pools.

You have two choices to create a new work team:

- You can create a work team in the SageMaker console and add members from your workforce to the team.
- You can create a user group by using the Amazon Cognito console and then create a work team by importing the user group. You can import more than one user group into each work team. You manage the members of the work team by updating the user group in the Amazon Cognito console. See Manage a Private Workforce (Amazon Cognito Console) (p. 705) for more information.
Create a Work Team Using the SageMaker Console

You can create a new Amazon Cognito user group or import an existing user group using the SageMaker console, on the Labeling workforces page. For more information on creating a user group in the Amazon Cognito console, see Manage a Private Workforce (Amazon Cognito Console) (p. 705).

To create a work team using the SageMaker console

2. Choose Labeling workforces from the left menu.
3. Under Private, choose Create private team.
4. Under Team details, enter a Team name. The name must be unique in your account in an AWS Region.
5. Under Add workers, choose a method to add workers to the team using a user group.
   - If you chose Create a team by adding workers to a new Amazon Cognito user group, select the workers to add to the team.
   - If you chose Create a team by importing existing Amazon Cognito user groups, choose the user groups that are part of the new team.
6. If you select an SNS topic, all workers added to the team are subscribed to the Amazon SNS topic and notified when new work items are available to the team. Select from a list of your existing Ground Truth related Amazon SNS topics or select Create new topic to open a topic-creation dialog.

Amazon SNS notifications are supported by Ground Truth and are not supported by Augmented AI. If you subscribe workers to receive SNS notifications, they only receive notifications about Ground Truth labeling jobs. They do not receive notifications about Augmented AI tasks.

Workers in a workteam subscribed to a topic receive notifications when a new Ground Truth labeling job for that team becomes available and when one is about to expire.

Read Create and manage Amazon SNS topics for your work teams (p. 719) for more information about using Amazon SNS topic.

Subscriptions

After you have created a work team, you can see more information about the team and change or set the Amazon SNS topic to which its members are subscribed by visiting the Amazon Cognito console. If you added any team members before you subscribed the team to a topic, you need to manually subscribe those members to that topic. Read Create and manage Amazon SNS topics for your work teams for more information on creating and managing the Amazon SNS topic.

Add or Remove Workers

A work team is a group of workers within your workforce to whom you can assign jobs. A worker can be added to more than one work team. Once a worker has been added to a work team, that worker can be disabled or removed.

Add Workers to the Workforce

Adding a worker to the workforce enables you to add that worker to any work team within that workforce.

To add workers using the private workforce summary page

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Choose Labeling workforces to navigate to your private workforce summary page.
3. Choose Private.
4. Choose **Invite new workers.**
5. Paste or type a list of email addresses, separated by commas, into the email addresses box. You can have up to 50 email addresses in this list.

**Add a Worker to a Work Team**

A worker must be added to the workforce before being added to a work team. To add a worker to a work team, first navigate to the **Private workforce summary** page using the steps above.

**To add a worker to a work team from the private workforce summary page**

1. In the **Private teams** section, choose the team to which you want to add the workers.
2. Choose the **Workers** tab.
3. Choose **Add workers to team** and choose the boxes next to the workers that you want to add.
4. Click **Add workers to team.**

**Disable and Remove a Worker from the Workforce**

Disabling a worker stops the worker from receiving a job. This action does not remove the worker from the workforce, or from any work team with which the worker is associated. To disable or remove a worker from a work team, first navigate to the private workforce summary page using the steps above.

**To deactivate a worker using the private workforce summary page**

1. In the **Workers** section, choose the worker that you would like to disable.
2. Choose **Disable.**

If desired, you can subsequently **Enable** a worker after they have been disabled.

You can remove workers from your private workforce directly in the SageMaker console if that worker was added in this console. If you added the worker (user) in the Amazon Cognito console, see **Manage a Private Workforce (Amazon Cognito Console)** (p. 705) to learn how to remove the worker in the Amazon Cognito console.

**To remove a worker using the private workforce summary page**

1. In the **Workers** section, choose the worker that you would like to delete.
2. If the worker has not been disabled, choose **Disable.**
3. Select the worker and choose **Delete.**

**Manage a Private Workforce (Amazon Cognito Console)**

A private workforce corresponds to a single **Amazon Cognito user pool.** Private work teams correspond to **Amazon Cognito user groups** within that user pool. Workers correspond to **Amazon Cognito users** within those groups.

After your workforce has been created, you can add work teams and individual workers through the Amazon Cognito console. You can also delete workers from your private workforce or remove them from individual teams in the Amazon Cognito console.

**Important**

You can't delete work teams from the Amazon Cognito console. Deleting a Amazon Cognito user group that is associated with an Amazon SageMaker work team will result in an error. To remove work teams, use the SageMaker console.
Create Work Teams (Amazon Cognito Console)

You can create a new work team to complete a job by adding a Amazon Cognito user group to the user pool associated with your private workforce. To add a Amazon Cognito user group to an existing worker pool, see Adding groups to a User Pool.

To create a work team using an existing Amazon Cognito user group

2. In the navigation pane, choose Workforces.
3. For Private teams, choose Create private team.
4. Under Team details, give the team a name. The name must be unique in your account in an AWS Region.
5. For Add workers, choose Import existing Amazon Cognito user groups, and choose one or more user groups that are part of the new team.
6. If you choose an SNS topic, all workers added to the team are subscribed to the Amazon Simple Notification Service (Amazon SNS) topic and notified when new work items are available to the team. Choose from a list of your existing SNS topics related to SageMaker Ground Truth or Amazon Augmented AI or choose Create new topic to create one.

   Note
   Amazon SNS notifications are supported by Ground Truth and are not supported by Augmented AI. If you subscribe workers to receive SNS notifications, they only receive notifications about Ground Truth labeling jobs. They do not receive notifications about Augmented AI tasks.

Subscriptions

After you have created a work team, you can see more information about the team and change or set the SNS topic to which its members are subscribed using the Amazon Cognito console. If you added any team members before you subscribed the team to a topic, you need to manually subscribe those members to that topic. For more information, see Create and manage Amazon SNS topics for your work teams (p. 719).

Add and Remove Workers (Amazon Cognito Console)

When using the Amazon Cognito console to add workers to a work team, you must add a user to the user pool associated with the workforce before adding that user to a user group. Users can be added to a user pool in various ways. For more information, see Signing Up and Confirming User Accounts.

Add a Worker to a Work Team

After a user has been added to a pool, the user can be associated with user groups inside of that pool. After a user has been added to a user group, that user becomes a worker on any work team created using that user group.

To add a user to a user group

1. Open the Amazon Cognito console: https://console.aws.amazon.com/cognito/.
2. Choose Manage User Pools.
3. Choose the user pool associated with your SageMaker workforce.
4. Under General Settings, choose Users and Groups and do one of the following:
   • Choose Groups, choose the group that you want to add the user to, and choose Add users. Choose the users that you want to add by choosing the plus-icon to the right of the user’s name.
   • Choose Users, choose the user that you want to add to the user group, and choose Add to group. From the dropdown menu, choose the group and choose Add to group.
Disable and Remove a Worker From a Work Team

Disabling a worker stops the worker from receiving jobs. This action doesn't remove the worker from the workforce, or from any work team the worker is associated with. To remove a user from a work team in Amazon Cognito, you remove the user from the user group associated with that team.

To deactivate a worker (Amazon Cognito console)

1. Open the Amazon Cognito console: https://console.aws.amazon.com/cognito/.
2. Choose Manage User Pools.
3. Choose the user pool associated with your SageMaker workforce.
4. Under General Settings, choose Users and Groups.
5. Choose the user that you want to disable.
6. Choose Disable User.

You can enable a disabled user by choosing Enable User.

To remove a user from a user group (Amazon Cognito console)

1. Open the Amazon Cognito console: https://console.aws.amazon.com/cognito/.
2. Choose Manage User Pools.
3. Choose the user pool associated with your SageMaker workforce.
4. Under General Settings, choose Users and Groups.
5. For User tab, choose the X icon to the right of the group from which you want to remove the user.

Create and Manage OIDC IdP Workforce

Create a private workforce using an OpenID Connect (OIDC) Identity Provider (IdP) when you want to manage and authenticate your workers using your own OIDC IdP. Individual worker credentials and other data will be kept private. Ground Truth and Amazon A2I will only have visibility into worker information you provide through the claims that you send to these services. To create a workforce using an OIDC IdP, your IdP must support groups because Ground Truth and Amazon A2I map one or more groups in your IdP to a work team. To learn more, see Send Required and Optional Claims to Ground Truth and Amazon A2I (p. 708).

If you are a new user of Ground Truth or Amazon A2I, you can test your worker UI and job workflow by creating a private work team and adding yourself as a worker. Use this work team when you create a labeling job or human review workflow. First, create a private OIDC IdP workforce using the instructions in Create a Private Workforce (OIDC IdP) (p. 707). Next, refer to Manage a Private Workforce (OIDC IdP) (p. 713) to learn how to create a work team.

Topics

- Create a Private Workforce (OIDC IdP) (p. 707)
- Manage a Private Workforce (OIDC IdP) (p. 713)

Create a Private Workforce (OIDC IdP)

Create a private workforce using an OpenID Connect (OIDC) Identity Provider (IdP) when you want to authenticate and manage workers using your own identity provider. Use this page to learn how to configure your IdP to communicate with Amazon SageMaker Ground Truth (Ground Truth) or Amazon Augmented AI (Amazon A2I) and to learn how to create a workforce using your own IdP.

To create a workforce using an OIDC IdP, your IdP must support groups because Ground Truth and Amazon A2I use one or more groups that you specify to create work teams. You use work teams to
specify workers for your labeling jobs and human review tasks. Because groups are not a standard claim, your IdP may have a different naming convention for a group of users (workers). Therefore, you must identify one or more user groups to which a worker belongs using the custom claim `sagemaker:groups` that is sent to Ground Truth or Amazon A2I from your IdP. To learn more, see Send Required and Optional Claims to Ground Truth and Amazon A2I (p. 708).

You create an OIDC IdP workforce using the SageMaker API operation `CreateWorkforce`. Once you create a private workforce, that workforce and all work teams and workers associated with it are available to use for all Ground Truth labeling job tasks and Amazon A2I human review workflows tasks. To learn more, see Create an OIDC IdP Workforce (p. 710).

Send Required and Optional Claims to Ground Truth and Amazon A2I

When you use your own IdP, Ground Truth and Amazon A2I use your Issuer, ClientId, and ClientSecret to authenticate workers by obtaining an authentication CODE from your AuthorizationEndpoint.

Ground Truth and Amazon A2I will use this CODE to obtain a custom claim from either your IdP’s TokenEndpoint or UserInfoEndpoint. You can either configure TokenEndpoint to return a JSON web token (JWT) or UserInfoEndpoint to return a JSON object. The JWT or JSON object must contain required and optional claims that you specify. A claim is a key-value pair that contains information about a worker or metadata about the OIDC service. The following table lists the claims that must be included, and that can optionally be included in the JWT or JSON object that your IdP returns.

**Note**

Some of the parameters in the following table can be specified using a : or a -. For example, you can specify the groups a worker belongs to using `sagemaker:groups` or `sagemaker-groups` in your claim.

<table>
<thead>
<tr>
<th>Name</th>
<th>Required</th>
<th>Accepted Format and Values</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>sagemaker:groups</code> or <code>sagemaker-groups</code></td>
<td>Yes</td>
<td>Data type: If a worker belongs to a single group, identify the group using a string. If a worker belongs to multiple groups, use a list of up to 10 strings.</td>
<td>Assigns a worker to one or more groups. Groups are used to map the worker into work teams.</td>
<td>Example of worker that belongs to a single group: &quot;work_team1&quot; Example of a worker that belongs to more than one groups: [&quot;work_team1&quot;, &quot;work_team2&quot;]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Allowable characters:</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Regex: \p{L}\p{M}\p{S}\p{N}\p{P}+</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Quotas: 10 groups per worker 63 characters per group name</td>
<td></td>
<td></td>
</tr>
<tr>
<td><code>sagemaker:sub</code> or <code>sagemaker-sub</code></td>
<td>Yes</td>
<td>Data type: String</td>
<td>This is mandatory to track a worker identity inside the</td>
<td>&quot;111011101-123456789-3687056437-1111&quot;</td>
</tr>
<tr>
<td>Name</td>
<td>Required</td>
<td>Accepted Format and Values</td>
<td>Description</td>
<td>Example</td>
</tr>
<tr>
<td>---------------------------</td>
<td>----------</td>
<td>-----------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>------------------------------------------------------------------------</td>
</tr>
<tr>
<td>sagemaker:client_id</td>
<td>Yes</td>
<td>Data type: String</td>
<td>A client ID. All tokens must be issued for this client ID.</td>
<td>&quot;00b600bb-1f00-05d0-bd00-00be00fbd0e0&quot;</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Allowable characters:</td>
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<td></td>
<td>Regex: [\w+-]+</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Quotes: 128 characters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>sagemaker:name</td>
<td>Yes</td>
<td>Data type: String</td>
<td>The worker name to be displayed in the worker portal.</td>
<td>&quot;Jane Doe&quot;</td>
</tr>
<tr>
<td>or sagemaker-name</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>email</td>
<td>No</td>
<td>Data type: String</td>
<td>The worker email. Ground Truth uses this email to notify workers that they have been invited to work on labeling tasks. Ground Truth will also use this email to notify your workers when labeling tasks become available if you set up an Amazon SNS topic for a work team that this worker is on.</td>
<td>&quot;<a href="mailto:example-email@domain.com">example-email@domain.com</a>&quot;</td>
</tr>
<tr>
<td>email_verified</td>
<td>No</td>
<td>Data type: Bool</td>
<td>Indicates if the user email was verified or not.</td>
<td>True</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Accepted Values: True, False</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The following an example of the JSON object syntax your UserInfoEndpoint can return.

```json
{
  "sub":"122",
  "exp":10000,
  "sagemaker-groups":["group1","group2"]
}```
Ground Truth or Amazon A2I compares the groups listed in sagemaker:groups or sagemaker-groups to verify that your worker belongs to the work team specified in the labeling job or human review task. After the work team has been verified, labeling or human review tasks are sent to that worker.

**Create an OIDC IdP Workforce**

You can create a workforce using the SageMaker API operation CreateWorkforce and associated language-specific SDKs. Specify a WorkforceName and information about your OIDC IDP in the parameter OidcConfig. It is recommended that you configure your OIDC with a place-holder redirect URI, and then update the URI with the worker portal URL after you create the workforce. To learn more, see Configure your OIDC IdP (p. 710).

The following shows an example of the request. See CreateWorkforce to learn more about each parameter in this request.

```json
CreateWorkforceRequest: {
    #required fields
    WorkforceName: "example-oidc-workforce",
    OidcConfig: {
        ClientId: "clientId",
        ClientSecret: "secret",
        Issuer: "https://example-oidc-idp.com/adfs",
        TokenEndpoint: "https://example-oidc-idp.com/adfs/oauth2/token",
        UserInfoEndpoint: "https://example-oidc-idp.com/adfs/oauth2/userInfo",
        JwksUri: "https://example-oidc-idp.com/adfs/discovery/keys"
    },
    SourceIpConfig: {
        Cidrs: ["string", "string"]
    }
}
```

**Configure your OIDC IdP**

How you configure your OIDC IdP depends on the IdP you use, and your business requirements.

When you configure your IdP, you must to specify a callback or redirect URI. After Ground Truth or Amazon A2I authenticates a worker, this URI will redirect the worker to the worker portal where the workers can access labeling or human review tasks. To create a worker portal URL, you need to create a workforce with your OIDC IdP details using the CreateWorkforce API operation. Specifically, you must configure your OIDC IdP with required custom sagemaker claims (see the next section for more details). Therefore, it is recommended that you configure your OIDC with a place-holder redirect URI, and then update the URI after you create the workforce. See Create an OIDC IdP Workforce (p. 710) to learn how to create a workforce using this API.

You can view your worker portal URL in the SageMaker Ground Truth console, or using the SageMaker API operation, DescribeWorkforce. The worker portal URL is in the SubDomain parameter in the response.

**Important**

Make sure you add the workforce subdomain to your OIDC IdP allow list. When you add the subdomain to your allow list, it must end with /oauth2/idpresponse.

**To view your worker portal URL after creating a private workforce (Console):**

2. In the navigation pane, choose **Labeling workforces**.
3. Select the **Private** tab.
4. In **Private workforce summary** you will see **Labeling portal sign-in URL**. This is your worker portal URL.

**To view your worker portal URL after creating a private workforce (API):**

When you create a private workforce using **CreateWorkforce**, you specify a **WorkforceName**. Use this name to call **DescribeWorkforce**. The following table includes examples of requests using the AWS CLI and AWS SDK for Python (Boto3).

**SDK for Python (Boto3)**

```python
response = client.describe_workforce(WorkforceName='string')
print(f'The workforce subdomain is: {response['SubDomain']}'
```

**AWS CLI**

```
$ C:\> describe-workforce --workforce-name 'string'
```

**Validate Your OIDC IdP Workforce Authentication Response**

After you have created your OIDC IdP workforce, you can use the following procedure to validate its authentication workflow using cURL. This procedure assumes you have access to a terminal, and that you have cURL installed.

**To validate your OIDC IdP authorization response:**

1. Get an authorization code using a URI configured as follows:

   `{AUTHORIZE ENDPOINT}?client_id={CLIENT ID}&redirect_uri={REDIRECT URI}&scope={SCOPE}&response_type=code`  

   a. Replace `{AUTHORIZE ENDPOINT}` with the authorize endpoint for your OIDC IdP.
   b. Replace `{CLIENT ID}` with the Client ID from your OAuth client.
   c. Replace `{REDIRECT URI}` with the worker portal URL. If it is not already present, you must add `/oauth2/idpresponse` to the end of the URL.
   d. If you have a custom scope, use it to replace `{SCOPE}`. If you do not have a custom scope, replace `{SCOPE}` with `openid`.

   The following is an example of a URI after the modifications above are made:

   ```text
   ```

2. Copy and paste the modified URI from step 1 into your browser and press Enter on your keyboard.
3. Authenticate using your IdP.
4. Copy the authentication code query parameter in the URI. This parameter beings with `code=`. The following is an example of what the response might look like. In this example, copy `code=MCNYDB...` and everything thereafter.
5. Open a terminal and enter the following command after making required modifications listed below:

```
curl --request POST \
--url '{TOKEN ENDPOINT}' \
--header 'content-type: application/x-www-form-urlencoded' \
--data grant_type=authorization_code \
--data 'client_id={CLIENT ID}' \
--data client_secret={CLIENT SECRET} \
--data code={CODE} \
--data 'redirect_uri={REDIRECT URI}'
```

- Replace `{TOKEN ENDPOINT}` with the token endpoint for your OIDC IdP.
- Replace `{CLIENT ID}` with the Client ID from your OAuth client.
- Replace `{CLIENT SECRET}` with the Client Secret from your OAuth client.
- Replace `{CODE}` with the authentication code query parameter you copied in step 4.
- Replace `{REDIRECT URI}` with the worker portal URL.

The following is an example of the cURL request after making the modifications described above:

```
curl --request POST \
--url 'https://example.com/token' \
--header 'content-type: application/x-www-form-urlencoded' \
--data grant_type=authorization_code \
--data 'client_id=f490a907-9bf1-4471-97aa-6bfd159f81ac' \
--data client_secret=client-secret \
--data code=MCNYDB... \
--data 'redirect_uri=https://example.labeling.sagemaker.aws/oauth2/idpresponse'
```

6. This step depends on the type of access_token your IdP returns, a plain text access token or a JWT access token.

- If your IdP does not support JWT access tokens, `access_token` may be plain text (for example, a UUID). The response you see may look similar to the following. In this case, move to step 7.

```
{
    "access_token":"179c144b-fccb-4d96-a28f-eea060f39c13",
    "token_type":"Bearer",
    "expires_in":3600,
    "refresh_token":"ef43e52e-9b4f-410c-8d4c-d5c5ee57631a",
    "scope":"openid"
}
```

- If your IdP supports JWT access tokens, step 5 should generate an access token in JWT format. For example, the response may look similar to the following:

```
{
    "access_token":"eyJh...JV_adQssw5c",
    "refresh_token":"i6mapTIAVSp2oJkgUnCACKKfZxt_H5MBLiqcybBBd04",
    "refresh_token_expires_in":6327,
    "scope":"openid",
    "id_token":"eyJ0eXAiOiJK9...-rDaQzUHl6cQQWNiDpW01_lxJqQEvQ"
}
```
Copy the JWT and decode it. You can use python script or a third party website to decode it. For example, you can go to the website https://jwt.io/ and paste the JWT into the Encoded box to decode it.

Make sure the decoded response contains the following:

- The **Required** SageMaker claims in the table found in Send Required and Optional Claims to Ground Truth and Amazon A2I (p. 708). If it does not, you must reconfigure your OICD IdP to contain these claims.
- The **Issuer** you specified when you set up the IdP workforce.

7. In a terminal and enter the following command after making required modifications listed below:

```
curl -X POST -H 'Authorization: Bearer {ACCESS_TOKEN}' -d '' -k -v {USERINFO ENDPOINT}
```

   a. Replace `{USERINFO ENDPOINT}` with the user info endpoint for your OICD IdP.
   b. Replace `{ACCESS_TOKEN}` with the access token in the response you received in step 7. This is the entry for the "access_token" parameter.

The following is an example of the cURL request after making the modifications described above:

```
curl -X POST -H 'Authorization: Bearer eyJ0eX...' -d '' -k -v https://example.com/userinfo
```

8. The response to the final step in the procedure above may look similar to the following code block.

If the access_token returned in step 6 was plain text, you must verify that this response contains required information. In this case, the response must contain the **Required** SageMaker claims in the table found in Send Required and Optional Claims to Ground Truth and Amazon A2I (p. 708). For example, `sagemaker-groups`, `sagemaker-name`.

```
{
    "sub" : "122",
    "exp" : "10000",
    "sagemaker-groups" : ["group1","group2"],
    "sagemaker-name" : "name",
    "sagemaker-sub" : "122",
    "sagemaker-client_id" : "123456"
}
```

**Next Steps**

Once you've created a private workforce using your IdP and verified your IdP authentication response, you can create work teams using your IdP groups. To learn more, see Manage a Private Workforce (OIDC IdP) (p. 713).

You can restrict worker access to tasks to specific IP addresses, and update or delete your workforce using the SageMaker API. To learn more, see Manage Private Workforce Using the Amazon SageMaker API (p. 716).

**Manage a Private Workforce (OIDC IdP)**

Once you've created a private workforce using your OpenID Connect (OIDC) Identity Provider (IdP), you can manage your workers using your IdP. For example, you can add, remove, and group workers directly through your IdP.
To add workers to an Amazon SageMaker Ground Truth (Ground Truth) labeling job or Amazon Augmented AI (Amazon A2I) human review task, you create work teams using 1-10 IdP groups and assign that work team to the job or task. You assign a work team to a job or task by specifying that work team when you create a labeling job (Ground Truth) or a human review workflow (Amazon A2I).

You can only assign one team to each labeling job or human review workflow. You can use the same team to create multiple labeling jobs or human review tasks. You can also create multiple work teams to work on different labeling jobs or human review tasks.

**Prerequisites**

To create and manage private work teams using your OIDC IdP groups, first you must create a workforce using the SageMaker API operation `CreateWorkforce`. To learn more, see Create a Private Workforce (OIDC IdP) (p. 707).

**Add work teams**

You can use the SageMaker console to create a private work team using your OIDC IdP workforce on the Labeling workforces page under Ground Truth. If you are creating a Ground Truth labeling job, you can also create a private work team while creating a labeling job.

**Note**

You create and manage work teams for Amazon A2I in the Ground Truth area of the SageMaker console.

You can also use the SageMaker API and associated language-specific SDKs to create a private work team.

Use the following procedures to learn how to create a private work team using the SageMaker console and API.

**To create a private work team on the Labeling workforces page (console)**

2. Select Labeling workforces.
3. Select Private.
4. In the Private teams section, select Create private team.
5. In the Team details section, enter a Team name.
6. In the Add workers section, enter the name of a single user group. All workers associated with this group in your IdP are added to this work team.
7. To add more than one user group, select Add new user group and enter the names of the user groups you want to add to this work team. Enter one user group per line.
8. (Optional) For Ground Truth labeling jobs, if you provide an email for workers in your JWT, Ground Truth notifies workers when a new labeling task is available if you select an SNS topic.
9. Select Create private team.

**To create a private work team while creating a Ground Truth labeling job (console)**

2. Select Labeling jobs.
3. Use the instructions in Create a Labeling Job (Console) (p. 544) to create a labeling job. Stop when you get to the Workers section on the second page.
4. Select Private for your worker type.
5. Enter a **Team name**.
6. In the **Add workers** section, enter the name of a single user group under **User groups**. All workers associated with this group in your IdP are added to this work team.

   **Important**
   The group names you specify for **User groups** must match the group names specified in your OIDC IdP.

7. To add more than one user group, select **Add new user group** and enter the names of the user groups you want to add to this work team. Enter one user group per line.
8. Complete all remaining steps to create your labeling job.

The private team that you create is used for this labeling job, and is listed in the **Labeling workforces** section of the SageMaker console.

**To create a private work team using the SageMaker API**

You can create a private work team using the SageMaker API operation **CreateWorkteam**.

When you use this operation, list all user groups that you want included in the work team in the **OidcMemberDefinition** parameter **Groups**.

   **Important**
   The group names you specify for **Groups** must match the group names specified in your OIDC IdP.

For example, if your user group names are group1, group2, and group3 in your OIDC IdP, configure **OidcMemberDefinition** as follows:

```
"OidcMemberDefinition": {
   "Groups": ["group1", "group2", "group3"]
}
```

Additionally, you must give the work team a name using the **WorkteamName** parameter.

**Add or remove IdP groups from work teams**

After you've created a work team, you can use the SageMaker API to manage that work team. Use the **UpdateWorkteam** operation to update the IdP user groups included in that work team.

- Use the **WorkteamName** parameter to identify the work team that you want to update.
- When you use this operation, list all user groups that you want included in the work team in the **OidcMemberDefinition** parameter **Groups**. If a user group is associated with a work team and you do not include it in this list, that user group is no longer associated with this work team.

**Delete a work team**

You can delete a work team using the SageMaker console and SageMaker API.

**To delete a private work team in the SageMaker console**

2. Select **Labeling workforces**.
3. Select **Private**.
4. In the **Private teams** section, select the work team that you want to delete.
5. **Select Delete.**

To delete a private work team (API)

You can delete a private work team using the SageMaker API operation `DeleteWorkteam`.

Manage Individual Workers

When you create a workforce using your own OIDC IdP, you cannot use Ground Truth or Amazon A2I to manage individual workers.

- To add a worker to a work team, add that worker to a group associated with that work team.
- To remove a worker from a work team, remove that worker from all user groups associated with that work team.

Update, Delete, and Describe Your Workforce

You can update, delete, and describe your OIDC IdP workforce using the SageMaker API. The following is a list of API operations that you can use to manage your workforce. For additional details, including how you can locate your workforce name, see Manage Private Workforce Using the Amazon SageMaker API (p. 716).

- **UpdateWorkforce** – You may want to update a workforce created using your own OIDC IdP to specify a different authorization endpoint, token endpoint, or issuer. You can update any parameter found in `OidcConfig` using this operation.

You can only update your OIDC IdP configuration when there are no work teams associated with your workforce. To learn how to delete work teams, see Delete a work team (p. 715).

- **DeleteWorkforce** – Use this operation to delete your private workforce. If you have any work teams associated with your workforce, you must delete those work teams before you delete your work force. For more information, see Delete a work team (p. 715).

- **DescribeWorkforce** – Use this operation to list private workforce information, including workforce name, Amazon Resource Name (ARN), and, if applicable, allowed IP address ranges (CIDRs).

Manage Private Workforce Using the Amazon SageMaker API

You can use Amazon SageMaker API operations to manage, update, and delete your private workforce. For each API operation linked on this page, you can find a list of supported language-specific SDKs and their documentation in the See Also section of the API documentation.

Find Your Workforce Name

Some of the SageMaker workforce-related API operations require your workforce name as input. You can see your Amazon Cognito or OIDC IdP private and vendor workforce names in an AWS Region using the `ListWorkforces` API operation in that AWS Region.

If you created your workforce using your own OIDC IdP, you can find your workforce name in the Ground Truth area of the SageMaker console.

To find your workforce name in the SageMaker console

2. Select Labeling workforces.
3. Select Private.

4. In the Private workforce summary section, locate your workforce ARN. Your workforce name is located at the end of this ARN. For example, if the ARN is arn:aws:sagemaker:us-east-2:111122223333:workforce/example-workforce, the workforce name is example-workforce.

Restrict Worker Access to Tasks to Allowable IP Addresses

By default, a workforce isn't restricted to specific IP addresses. You can use the UpdateWorkforce operation to require that workers use a specific range of IP addresses (CIDRs) to access tasks. If you specify one or more CIDRs, workers who attempt to access tasks using any IP address outside the specified ranges are denied and will get a HTTP 204 No Content error message on the worker portal. You can specify up to 10 CIDR values using UpdateWorkforce.

After you have restricted your workforce to one or more CIDRs, the output of UpdateWorkforce lists all allowable CIDRs. You can also use the DescribeWorkforce operation to view all allowable CIDRs for a workforce.

Update OIDC Identity Provider Workforce Configuration

You may want to update a workforce created using your own OIDC IdP to specify a different authorization endpoint, token endpoint, or issuer. You can update any parameter found in OidcConfig using the UpdateWorkforce operation.

Important
You can only update your OIDC IdP configuration when there are no work teams associated with your workforce. You can delete a private work team using the DeleteWorkteam operation.

Delete a Private Workforce

You can only have one private workforce in each AWS Region. You may want to delete your private workforce in an AWS Region when:

- You want to create a workforce using a new Amazon Cognito user pool.
- You have already created a private workforce using Amazon Cognito and you want to create a workforce using your own OpenID Connect (OIDC) Identity Provider (IdP).

To delete a private workforce, use the DeleteWorkforce API operation. If you have any work teams associated with your workforce, you must delete those work teams before you delete your workforce. You can delete a private work team using the DeleteWorkteam operation.

Track Worker Performance

Amazon SageMaker Ground Truth logs worker events to Amazon CloudWatch, such as when a worker starts or submits a task. Use Amazon CloudWatch metrics to measure and track throughput across a team or for individual workers.

Important
Worker event tracking is not available for Amazon Augmented AI human review workflows.

Enable Tracking

During the set-up process for a new work team, the permissions for Amazon CloudWatch logging of worker events are created. Since this feature was added in August 2019, work teams created prior to that may not have the correct permissions. If all of your work teams were created before August 2019, create
a new work team. It does not need any members and may be deleted after creation, but by creating it, you establish the permissions and apply them to all of your work teams, regardless of when they were created.

Examine Logs

After tracking is enabled, the activity of your workers is logged. Open the Amazon CloudWatch console and choose Logs in the navigation pane. You should see a log group named `aws/sagemaker/groundtruth/WorkerActivity`.

Each completed task is represented by a log entry, which contains information about the worker, their team, the job, when the task was accepted, and when it was submitted.

Example Log entry

```json
{
  "worker_id": "cd449a289e129409",
  "cognito_user_pool_id": "us-east-2_IpicJXXX",
  "cognito_sub_id": "d6947aeb-0650-447a-ab5d-894db61017fd",
  "task_accepted_time": "Wed Aug 14 16:00:59 UTC 2019",
  "task_submitted_time": "Wed Aug 14 16:01:04 UTC 2019",
  "task_returned_time": "",
  "task_declined_time": "",
  "workteam_arn": "arn:aws:sagemaker:us-east-2:############:workteam/private-crowd/Sample-labeling-team",
  "labeling_job_arn": "arn:aws:sagemaker:us-east-2:############:labeling-job/metrics-demo",
  "work_requester_account_id": "############",
  "job_reference_code": "############",
  "job_type": "Private",
  "event_type": "TasksSubmitted",
  "event_timestamp": "1565798464"
}
```

A useful data point in each event is the `cognito_sub_id`. You can match that to an individual worker.

2. Under the Ground Truth section, choose Workforces.
3. Choose Private.
4. Choose the name of a team in the Private teams section.
5. In the Team summary section, choose the user group identified under Amazon Cognito user group. That will take you to the group in the Amazon Cognito console.
6. The Group page lists the users in the group. Choose any user's link in the Username column to see more information about the user, including a unique sub ID.

To get information about all of the team's members, use the ListUsers action (examples) in the Amazon Cognito API.

Use Log Metrics

If you don't want to write your own scripts to process and visualize the raw log information, Amazon CloudWatch metrics provide insights into worker activity for you.

To view metrics

2. In the navigation pane, choose Metrics.
3. Choose the AWS/SageMaker/Workteam name space, then explore the available metrics (p. 3663). For example, selecting the Workteam and Workforce metrics lets you calculate the average time per submitted task for a specific labeling job.

For more information, see Using Amazon CloudWatch Metrics.

Create and manage Amazon SNS topics for your work teams

Use the procedures in this topic when you want to:

- Create a topic to which you want an existing work team to subscribe.
- Create a topic before you've created a work team.
- Create or modify the work team with an API call, and specify a topic Amazon Resource Name (ARN).

If you create a work team using the console, the console provides an option to create a new topic for the team so that you don't have to perform these steps.

**Important**
The Amazon SNS feature is not supported by Amazon A2I. If you subscribe your work team to an Amazon SNS topic, workers will only receive notifications about Ground Truth labeling jobs. Workers will not receive notifications about new Amazon A2I human review tasks.

Create the Amazon SNS topic

The steps for creating Amazon SNS topics for work team notifications are similar to the steps in Getting Started in the Amazon SNS Developer Guide, with one significant addition—you must add an access policy so that Amazon SageMaker can publish messages to the topic on your behalf.

**To add the policy when you create the topic**

2. In Create topic, enter the name of your topic and then choose Next steps.
4. In the JSON editor, find the Resource property, which displays the topic's ARN.
5. Copy the Resource ARN value.
6. Before the final closing brace (}), add the following policy.

```json
, {
  "Sid": "AwsSagemaker_SnsAccessPolicy",
  "Effect": "Allow",
  "Principal": {
    "Service": "sagemaker.amazonaws.com"
  },
  "Action": "sns:Publish",
  "Resource": "arn:partition:sns:region:111122223333:MyTopic", # ARN of the topic you copied in the previous step
  "Condition": {
    " ArnLike": {
      "aws:SourceArn": "arn:partition:sagemaker:region:111122223333:workteam/*" # Workteam ARN
    },
    "StringEquals": {
      "aws:SourceAccount": "111122223333" # SNS topic account
    }
  }
}
```
7. Create the topic.

After you create the topic, it appears in your Topics summary screen. For more information about creating topics, see Creating a Topic in the Amazon SNS Developer Guide.

Manage worker subscriptions

If you subscribe a work team to a topic after you’ve already created the work team, the individual work team members who were added to the team when the work team was created are not automatically subscribed to the topic. For information about subscribing workers’ email addresses to the topic, see Subscribing an Endpoint to an Amazon SNS Topic in the Amazon SNS Developer Guide.

The only situation in which workers are automatically subscribed to your topic is when you create or import an Amazon Cognito user group at the time that you create a work team and set up the topic subscription when you create that work team. For more information about creating and managing your workteams with Amazon Cognito, see Create Work Teams (Amazon Cognito Console) (p. 706).

Crowd HTML Elements Reference

Crowd HTML Elements are web components, a web standard that abstracts HTML markup, CSS, and JavaScript functionality into an HTML tag or set of tags. Amazon SageMaker provides customers with the ability to design their own custom task templates in HTML.

As a starting point, you can use a template built using Crowd HTML Elements from one of the following GitHub repositories:

- Example task UIs for Amazon SageMaker Ground Truth
- Over 60 example task UIs for Amazon Augmented AI (A2I)

These repositories include templates designed for audio, image, text, video, and other types of data labeling and annotation tasks.

For more information about how to implement custom templates in Amazon SageMaker Ground Truth, see Creating Custom Labeling Workflows (p. 509). To learn more about custom templates in Amazon Augmented AI, see Create Custom Worker Task Templates (p. 3448).

SageMaker Crowd HTML Elements

The following is a list of Crowd HTML Elements that make building a custom template easier and provide a familiar UI for workers. These elements are supported in Ground Truth, Augmented AI, and Mechanical Turk.

Topics

- crowd-alert (p. 721)
- crowd-badge (p. 723)
- crowd-button (p. 724)
- crowd-bounding-box (p. 726)
- crowd-card (p. 730)
- crowd-checkbox (p. 732)
- crowd-classifier (p. 734)
• crowd-classifier-multi-select (p. 736)
• crowd-entity-annotation (p. 738)
• crowd-fab (p. 741)
• crowd-form (p. 742)
• crowd-icon-button (p. 743)
• crowd-image-classifier (p. 745)
• crowd-image-classifier-multi-select (p. 748)
• crowd-input (p. 750)
• crowd-instance-segmentation (p. 753)
• crowd-instructions (p. 756)
• crowd-keypoint (p. 758)
• crowd-line (p. 762)
• crowd-modal (p. 765)
• crowd-polygon (p. 766)
• crowd-polyline (p. 771)
• crowd-radio-button (p. 775)
• crowd-radio-group (p. 777)
• crowd-semantic-segmentation (p. 779)
• crowd-slider (p. 782)
• crowd-tab (p. 784)
• crowd-tabs (p. 785)
• crowd-text-area (p. 787)
• crowd-toast (p. 789)
• crowd-toggle-button (p. 790)

**crowd-alert**

A message that alerts the worker to a current situation.

See an interactive example of an HTML template that uses this Crowd HTML Element in [CodePen](https://codepen.io).

The following is an example of a Liquid template that uses the `<crowd-alert>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <div id="errorBox"></div>

  <crowd-keypoint
    src="{{ task.input.taskObject | grant_read_access }}"
    labels="['Item A', 'Item B', 'Item C']"
    header="Please locate the centers of each item."
    name="annotatedResult">
    <short-instructions>
      Describe your task briefly here and give examples
    </short-instructions>
    <full-instructions>
      Give additional instructions and good/bad examples here
  </crowd-keypoint>
</crowd-form>
```
Attributes

The following attributes are supported by this element.

**dismissible**

A Boolean switch that, if present, allows the message to be closed by the worker.

**type**

A string that specifies the type of message to be displayed. The possible values are "info" (the default), "success", "error", and "warning".
Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-badge

An icon that floats over the top right corner of another element to which it is attached.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a template that uses the `<crowd-badge>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-image-classifier
    name="crowd-image-classifier"
    src="https://unsplash.com/photos/NLUkAA-nDdE"
    header="Choose the correct category for this image."
    categories="["Person", "Umbrella", "Chair", "Dolphin"]"
  >
    <full-instructions header="Classification Instructions">
      <p>Read the task carefully and inspect the image.</p>
      <p>Choose the appropriate label that best suits the image.</p>
    </full-instructions>

    <short-instructions id="short-instructions">
      <p>Read the task carefully and inspect the image.</p>
      <p>Choose the appropriate label that best suits the image.</p>
      <crowd-badge icon="star" for="short-instructions"/>
    </short-instructions>
  </crowd-image-classifier>
</crowd-form>
```

Attributes

The following attributes are supported by this element.

**for**

A string that specifies the ID of the element to which the badge is attached.

**icon**

A string that specifies the icon to be displayed in the badge. The string must be either the name of an icon from the open-source `iron-icons` set, which is pre-loaded, or the URL to a custom icon.
This attribute overrides the label attribute.

The following is an example of the syntax that you can use to add an iron-icon to a <crowd-badge> HTML element. Replace icon-name with the name of the icon you'd like to use from this [Icons set].

```html
<crowd-badge icon="icon-name" for="short-instructions"/>
```

**label**

The text to display in the badge. Three characters or less is recommended because text that is too large will overflow the badge area. An icon can be displayed instead of text by setting the icon attribute.

**Element Hierarchy**

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

**See Also**

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

**crowd-button**

A styled button that represents some action.

See an interactive example of an HTML template that uses this Crowd HTML Element in [CodePen](https://codepen.io).

The following is an example of a template that uses the <crowd-button> element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-image-classifier
    name="crowd-image-classifier"
    src="https://unsplash.com/photos/NLUkAA-nDdE"
    header="Please select the correct category for this image"
    categories="[Person', 'Umbrella', 'Chair', 'Dolphin']"
  >
    <full-instructions header="Classification Instructions">
      <p>Read the task carefully and inspect the image.</p>
      <p>Choose the appropriate label that best suits the image.</p>
    </full-instructions>
    <short-instructions>
      <p>Read the task carefully and inspect the image.</p>
      <p>Choose the appropriate label that best suits the image.</p>
    </short-instructions>
  </crowd-image-classifier>
</crowd-form>
```
Attributes

The following attributes are supported by this element.

disabled

A Boolean switch that, if present, displays the button as disabled and prevents clicks.

form-action

A switch that either submits its parent crowd-form (p. 742) element, if set to "submit", or resets its parent <crowd-form> element, if set to "reset".

href

The URL to an online resource. Use this property if you need a link styled as a button.

icon

A string that specifies the icon to be displayed next to the button's text. The string must be the name of an icon from the open-source iron-icons set, which is pre-loaded. For example, to insert the search iron-icon, use the following:

```
<crowd-button>
  <iron-icon icon="search"/>
</crowd-button>
```

The icon is positioned to either the left or the right of the text, as specified by the icon-align attribute.

To use a custom icon see icon-url.

icon-align

The left or right position of the icon relative to the button's text. The default is "left".

icon-url

A URL to a custom image for the icon. A custom image can be used in place of a standard icon that is specified by the icon attribute.

loading

A Boolean switch that, if present, displays the button as being in a loading state. This attribute has precedence over the disabled attribute if both attributes are present.

target

When you use the href attribute to make the button act as a hyperlink to a specific URL, the target attribute optionally targets a frame or window where the linked URL should load.

variant

The general style of the button. Use "primary" for primary buttons, "normal" for secondary buttons, "link" for tertiary buttons, or "icon" to display only the icon without text.
Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-bounding-box

A widget for drawing rectangles on an image and assigning a label to the portion of the image that is enclosed in each rectangle.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template that uses the `<crowd-bounding-box>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template. For more examples, see this GitHub repository.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-bounding-box
    name="annotatedResult"
    src="{{ task.input.taskObject | grant_read_access }}"
    header="Draw bounding boxes around all the cats and dogs in this image"
    labels=["'Cat', 'Dog']"
  >
    <full-instructions header="Bounding Box Instructions">
      <p>Use the bounding box tool to draw boxes around the requested target of interest:</p>
      <ol>
        <li>Draw a rectangle using your mouse over each instance of the target.</li>
        <li>Make sure the box does not cut into the target, leave a 2 - 3 pixel margin</li>
        <li>When targets are overlapping, draw a box around each object, include all contiguous parts of the target in the box. Do not include parts that are completely overlapped by another object.</li>
        <li>Do not include parts of the target that cannot be seen, even though you think you can interpolate the whole shape of the target.</li>
        <li>Avoid shadows, they're not considered as a part of the target.</li>
        <li>If the target goes off the screen, label up to the edge of the image.</li>
      </ol>
    </full-instructions>
    <short-instructions>
      Draw boxes around the requested target of interest.
    </short-instructions>
  </crowd-bounding-box>
</crowd-form>
```
Attributes

The following attributes are supported by this element.

header

The text to display above the image. This is typically a question or simple instruction for the worker.

initial-value

An array of JSON objects, each of which sets a bounding box when the component is loaded. Each JSON object in the array contains the following properties. Bounding boxes set via the initial-value property can be adjusted and whether or not a worker answer was adjusted is tracked via an initialValueModified boolean in the worker answer output.

- **height** – The height of the box in pixels.
- **label** – The text assigned to the box as part of the labeling task. This text must match one of the labels defined in the labels attribute of the <crowd-bounding-box> element.
- **left** – Distance of the top-left corner of the box from the left side of the image, measured in pixels.
- **top** – Distance of the top-left corner of the box from the top of the image, measured in pixels.
- **width** – The width of the box in pixels.

You can extract the bounding box initial value from a manifest file of a previous job in a custom template using the Liquid templating language:

```liquid
initial-value="[
{% for box in task.input.manifestLine.label-attribute-name-from-prior-job.annotations %}
  {% capture class_id %}{{ box.class_id }}{% endcapture %}
  {% assign label = task.input.manifestLine.label-attribute-name-from-prior-job
  metadata.class-map[class_id] %}
  {
    label: {{label | to_json}},
    left: {{box.left}},
    top: {{box.top}},
    width: {{box.width}},
    height: {{box.height}},
  },
{% endfor %}
]"
```

labels

A JSON formatted array of strings, each of which is a label that a worker can assign to the image portion enclosed by a rectangle. **Limit:** 10 labels.

name

The name of this widget. It's used as a key for the widget's input in the form output.

src

The URL of the image on which to draw bounding boxes.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements:** crowd-form (p. 742)
• **Child elements**: full-instructions (p. 728), short-instructions (p. 728)

**Regions**

The following regions are required by this element.

**full-instructions**

General instructions about how to draw bounding boxes.

**short-instructions**

Important task-specific instructions that are displayed in a prominent place.

**Output**

The following output is supported by this element.

**boundingBoxes**

An array of JSON objects, each of which specifies a bounding box that has been created by the worker. Each JSON object in the array contains the following properties.

- **height** – The height of the box in pixels.
- **label** – The text assigned to the box as part of the labeling task. This text must match one of the labels defined in the `labels` attribute of the `<crowd-bounding-box>` element.
- **left** – Distance of the top-left corner of the box from the left side of the image, measured in pixels.
- **top** – Distance of the top-left corner of the box from the top of the image, measured in pixels.
- **width** – The width of the box in pixels.

**inputImageProperties**

A JSON object that specifies the dimensions of the image that is being annotated by the worker. This object contains the following properties.

- **height** – The height, in pixels, of the image.
- **width** – The width, in pixels, of the image.

**Example: Sample Element Outputs**

The following are samples of outputs from common use scenarios for this element.

**Single Label, Single Box / Multiple Label, Single Box**

```
[
  {
    "annotatedResult": {
      "boundingBoxes": [
        {
          "height": 401,
          "label": "Dog",
          "left": 243,
          "top": 117,
          "width": 187
        }
      ],
      "inputImageProperties": {
        "height": 533,
        "width": 728
      }
    }
  ]
```
Single Label, Multiple Box

[
  {
    "annotatedResult": {
      "boundingBoxes": [
        {
          "height": 401,
          "label": "Dog",
          "left": 243,
          "top": 117,
          "width": 187
        },
        {
          "height": 283,
          "label": "Dog",
          "left": 684,
          "top": 120,
          "width": 116
        }
      ],
      "inputImageProperties": {
        "height": 533,
        "width": 800
      }
    }
  }
]

Multiple Label, Multiple Box

[
  {
    "annotatedResult": {
      "boundingBoxes": [
        {
          "height": 395,
          "label": "Dog",
          "left": 241,
          "top": 125,
          "width": 158
        },
        {
          "height": 298,
          "label": "Cat",
          "left": 699,
          "top": 116,
          "width": 101
        }
      ],
      "inputImageProperties": {
        "height": 533,
        "width": 800
      }
    }
  }
]
You could have many labels available, but only the ones that are used appear in the output.

**See Also**

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

**crowd-card**

A box with an elevated appearance for displaying information.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a template designed for sentiment analysis tasks that uses the `<crowd-card>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<style>
  h3 {
    margin-top: 0;
  }

  crowd-card {
    width: 100%;
  }

  .card {
    margin: 10px;
  }

  .left {
    width: 70%;
    margin-right: 10px;
    display: inline-block;
    height: 200px;
  }

  .right {
    width: 20%;
    height: 200px;
    display: inline-block;
  }
</style>

<crowd-form>
  <short-instructions>
    Your short instructions here.
  </short-instructions>

  <full-instructions>
    Your full instructions here.
  </full-instructions>

  <div class="left">
    <h3>What sentiment does this text convey?</h3>
    <crowd-card>
      <div class="card">
        730
      </div>
    </crowd-card>
  </div>
</crowd-form>
```
Nothing is great.
</div>
</crowd-card>
</div>

<div class="right">
<h3>Select an option</h3>
<select name="sentiment1" style="font-size: large" required>
<option value="">(Please select)</option>
<option>Negative</option>
<option>Neutral</option>
<option>Positive</option>
<option>Text is empty</option>
</select>
</div>

<div class="left">
<h3>What sentiment does this text convey?</h3>
</div>
</crowd-form>

Attributes

The following attributes are supported by this element.

heading

The text displayed at the top of the box.

image

A URL to an image to be displayed within the box.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

See Also

For more information, see the following.
crowd-checkbox

A UI component that can be checked or unchecked allowing a user to select multiple options from a set.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template that uses the `<crowd-checkbox>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  
  <p>Find the official website for: <strong>{{ task.input.company }}</strong></p>
  <p>Do not give Yelp pages, LinkedIn pages, etc.</p>
  <p>Include the http:// prefix from the website</p>
  <crowd-input name="website" placeholder="http://example.com"></crowd-input>

  <crowd-checkbox name="website-found">Website Found</crowd-checkbox>

</crowd-form>
```

**Attributes**

The following attributes are supported by this element.

**checked**

A Boolean switch that, if present, displays the check box as checked.

The following is an example of the syntax used to check a checkbox by default.

```html
<crowd-checkbox name="checkBox" value="checked" checked>This box is checked</crowd-checkbox>
```

**disabled**

A Boolean switch that, if present, displays the check box as disabled and prevents it from being checked.

The following is an example of the syntax used to disable a checkbox.

```html
<crowd-checkbox name="disabledCheckBox" value="Disabled" disabled>Cannot be selected</crowd-checkbox>
```

**name**

A string that is used to identify the answer submitted by the worker. This value will match a key in the JSON object that specifies the answer.

**required**

A Boolean switch that, if present, requires the worker to provide input.
The following is an example of the syntax used to require a checkbox be selected.

```xml
<crowd-checkbox name="work_verified" required>Instructions were clear</crowd-checkbox>
```

**value**

A string used as the name for the checkbox state in the output. Defaults to "on" if not specified.

**Element Hierarchy**

This element has the following parent and child elements.

- **Parent elements**: `crowd-form` (p. 742)
- **Child elements**: none

**Output**

Provides a JSON object. The `name` string is the object name and the `value` string is the property name for a Boolean value based on the checkbox state; true if checked, false if not checked.

**Example : Sample Element Outputs**

**Using the same name value for multiple boxes.**

```xml
<!-- INPUT -->
<div><crowd-checkbox name="image_attributes" value="blurry"> Blurry </crowd-checkbox></div>
<div><crowd-checkbox name="image_attributes" value="dim"> Too Dim </crowd-checkbox></div>
<div><crowd-checkbox name="image_attributes" value="exposed"> Too Bright </crowd-checkbox></div>
```

//Output with "blurry" and "dim" checked

```json
[
  {
    "image_attributes": {
      "blurry": true,
      "dim": true,
      "exposed": false
    }
  }
]
```

Note that all three color values are properties of a single object.

**Using different name values for each box.**

```xml
<!-- INPUT -->
<div><crowd-checkbox name="Stop" value="Red"> Red </crowd-checkbox></div>
<div><crowd-checkbox name="Slow" value="Yellow"> Yellow </crowd-checkbox></div>
<div><crowd-checkbox name="Go" value="Green"> Green </crowd-checkbox></div>
```

//Output with "Red" checked

```json
[
  {
    "Go": {
      "Green": false
    }
  }
]```
"Slow": {
  "Yellow": false
},
"Stop": {
  "Red": true
}
]}

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-classifier

A widget for classifying non-image content, such as audio, video, or text.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of an HTML worker task template built using crowd-classifier. This example uses the Liquid template language to automate:

- Label categories in the categories parameter
- The objects that are being classified in the classification-target parameter.

Copy the following code and save it in a file with the extension .html. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-classifier
    name="category"
    categories="{{ task.input.labels | to_json | escape }}"
    header="What type of a document is this?"
  >
    <classification-target>
      <iframe style="width: 100%; height: 600px;" src="{{ task.input.taskObject | grant_read_access }}" type="application/pdf"></iframe>
    </classification-target>

    <full-instructions header="Document Classification Instructions">
      <p>Read the task carefully and inspect the document.</p>
      <p>Choose the appropriate label that best suits the document.</p>
    </full-instructions>

    <short-instructions>
      Please choose the correct category for the document
    </short-instructions>
  </crowd-classifier>
</crowd-form>
```

Attributes

The following attributes are supported by this element.
categories
A JSON formatted array of strings, each of which is a category that a worker can assign to the text. You should include "other" as a category, otherwise the worker may not be able to provide an answer.

header
The text to display above the image. This is typically a question or simple instruction for the worker.

name
The name of this widget. It is used as a key for the widget's input in the form output.

Element Hierarchy
This element has the following parent and child elements.
- **Parent elements**: crowd-form (p. 742)
- **Child elements**: classification-target (p. 735), full-instructions (p. 735), short-instructions (p. 735)

Regions
The following regions are supported by this element.

classification-target
The content to be classified by the worker. This can be plain text or HTML. Examples of how the HTML can be used include *but are not limited to* embedding a video or audio player, embedding a PDF, or performing a comparison of two or more images.

full-instructions
General instructions about how to do text classification.

short-instructions
Important task-specific instructions that are displayed in a prominent place.

Output
The output of this element is an object using the specified name value as a property name, and a string from the categories as the property's value.

**Example : Sample Element Outputs**
The following is a sample of output from this element.

```
[
  {
    "<name>": {
      "label": "<value>"
    }
  }
]
```

See Also
For more information, see the following.
- **Use Amazon SageMaker Ground Truth to Label Data (p. 370)**
Crowd HTML Elements Reference (p. 720)

crowd-classifier-multi-select

A widget for classifying various forms of content—such as audio, video, or text—into one or more categories. The content to classify is referred to as an object.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of an HTML worker task template built using this element. Copy the following code and save it in a file with the extension .html. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-classifier-multi-select
    name="category"
    categories="['Positive', 'Negative', 'Neutral']"
    header="Select the relevant categories"
    exclusion-category="{ text: 'None of the above' }"
  >
    <classification-target>
      {{ task.input.taskObject }}
    </classification-target>
  </crowd-classifier-multi-select>
</crowd-form>

Attributes

The following attributes are supported by the crowd-classifier-multi-select element. Each attribute accepts a string value or string values.

categories

Required. A JSON-formatted array of strings, each of which is a category that a worker can assign to the object.

header

Required. The text to display above the image. This is typically a question or simple instruction for workers.

name

Required. The name of this widget. In the form output, the name is used as a key for the widget's input.
**exclusion-category**

Optional. A JSON-formatted string with the following format: 
```
{  text: 'default-value' }
```
This attribute sets a default value that workers can choose if none of the labels applies to the object shown in the worker UI.

**Element Hierarchy**

This element has the following parent and child elements:

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: classification-target (p. 735), full-instructions (p. 735), short-instructions (p. 735)

**Regions**

This element uses the following regions.

**classification-target**

The content to be classified by the worker. Content can be plain text or an object that you specify in the template using HTML. For example, you can use HTML elements to include a video or audio player, embedding a PDF file, or include a comparison of two or more images.

**full-instructions**

General instructions about how to classify text.

**short-instructions**

Important task-specific instructions. These instructions are displayed prominently.

**Output**

The output of this element is an object that uses the specified name value as a property name, and a string from categories as the property's value.

**Example : Sample Element Outputs**

The following is a sample of output from this element.

```
[
  {
    "<name>": {
      labels: ["label_a", "label_b"]
    }
  }
]
```

**See Also**

For more information, see the following:

- Text Classification (Multi-label) (p. 403)
- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)
Amazon SageMaker Developer Guide
SageMaker Crowd HTML Elements

crowd-entity-annotation
A widget for labeling words, phrases, or character strings within a longer text. Workers select a label, and
highlight the text that the label applies to.

Important: Self-contained Widget

Do not use <crowd-entity-annotation> element with the <crowd-form> element. It
contains its own form submission logic and Submit button.
See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.
The following is an example of a template that uses the <crowd-entity-annotation> element. Copy
the following code and save it in a ﬁle with the extension .html. Open the ﬁle in any browser to preview
and interact with this template.
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-entity-annotation
name="crowd-entity-annotation"
header="Highlight parts of the text below"
labels="[{'label': 'person', 'shortDisplayName': 'per', 'fullDisplayName': 'Person'},
{'label': 'date', 'shortDisplayName': 'dat', 'fullDisplayName': 'Date'}, {'label':
'company', 'shortDisplayName': 'com', 'fullDisplayName': 'Company'}]"
text="Amazon SageMaker Ground Truth helps you build highly accurate training datasets for
machine learning quickly."
>
<full-instructions header="Named entity recognition instructions">
<ol>
<li><strong>Read</strong> the text carefully.</li>
<li><strong>Highlight</strong> words, phrases, or sections of the text.</li>
<li><strong>Choose</strong> the label that best matches what you have highlighted.</
li>
<li>To <strong>change</strong> a label, choose highlighted text and select a new
label.</li>
<li>To <strong>remove</strong> a label from highlighted text, choose the X next to
the abbreviated label name on the highlighted text.</li>
<li>You can select all of a previously highlighted text, but not a portion of it.</
li>
</ol>
</full-instructions>
<short-instructions>
Apply labels to words or phrases.
</short-instructions>
<div id="additionalQuestions" style="margin-top: 20px">
<h3>
What is the overall subject of this text?
</h3>
<crowd-radio-group>
<crowd-radio-button name="tech" value="tech">Technology</crowd-radio-button>
<crowd-radio-button name="politics" value="politics">Politics</crowd-radio-button>
</crowd-radio-group>
</div>
</crowd-entity-annotation>
<script>
document.addEventListener('all-crowd-elements-ready', () => {
document
.querySelector('crowd-entity-annotation')
.shadowRoot
.querySelector('crowd-form')
.form
.appendChild(additionalQuestions);

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Attributes

The following attributes are supported by this element.

header

The text to display above the image. This is typically a question or simple instruction for the worker.

initial-value

A JSON formatted array of objects, each of which defines an annotation to apply to the text at initialization. Objects contain a label value that matches one in the labels attribute, an integer startOffset value for labeled span's starting unicode offset, and an integer endOffset value for the ending unicode offset.

Example

```json
[
  {
    label: 'person',
    startOffset: 0,
    endOffset: 16
  },
  ...
]
```

labels

A JSON formatted array of objects, each of which contains:

- **label** (required): The name used to identify entities.
- **fullDisplayName** (optional): Used for the label list in the task widget. Defaults to the label value if not specified.
- **shortDisplayName** (optional): An abbreviation of 3-4 letters to display above selected entities. Defaults to the label value if not specified.

  **shortDisplayName is highly recommended**

  Values displayed above the selections can overlap and create difficulty managing labeled entities in the workspace. Providing a 3-4 character shortDisplayName for each label is highly recommended to prevent overlap and keep the workspace manageable for your workers.

Example

```json
[
  {
    label: 'person',
    shortDisplayName: 'per',
    fullDisplayName: 'person'
  }
]
```

name

Serves as the widget's name in the DOM. It is also used as the label attribute name in form output and the output manifest.
text

The text to be annotated. The templating system escapes quotes and HTML strings by default. If your code is already escaped or partially escaped, see Variable filters (p. 514) for more ways to control escaping.

Element Hierarchy

This element has the following parent and child elements.

- **Child elements:** full-instructions (p. 740), short-instructions (p. 740)

Regions

The following regions are supported by this element.

**full-instructions**

General instructions about how to work with the widget.

**short-instructions**

Important task-specific instructions that are displayed in a prominent place.

Output

The following output is supported by this element.

**entities**

A JSON object that specifies the start, end, and label of an annotation. This object contains the following properties.

- **label** – The assigned label.
- **startOffset** – The Unicode offset of the beginning of the selected text.
- **endOffset** – The Unicode offset of the first character after the selection.

Example : Sample Element Outputs

The following is a sample of the output from this element.

```json
{
  "myAnnotatedResult": {
    "entities": [
      {
        "endOffset": 54,
        "label": "person",
        "startOffset": 47
      },
      {
        "endOffset": 97,
        "label": "event",
        "startOffset": 93
      },
      {
        "endOffset": 219,
        "label": "date",
        "startOffset": 212
      }
    ]
  }
}
```
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}

}

]

}

"endOffset": 271,
"label": "location",
"startOffset": 260

See Also
For more information, see the following.
• Use Amazon SageMaker Ground Truth to Label Data (p. 370)
• Crowd HTML Elements Reference (p. 720)

crowd-fab
A ﬂoating button with an image in its center.
See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.
The following is an example of a Liquid template designed for image classiﬁcation that uses the
<crowd-fab> element. This template uses JavaScript to enable workers to report issues with the worker
UI. Copy the following code and save it in a ﬁle with the extension .html. Open the ﬁle in any browser
to preview and interact with this template.
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
<crowd-image-classifier
src="${image_url}"
categories="['Cat', 'Dog', 'Bird', 'None of the Above']"
header="Choose the correct category for the image"
name="category">
<short-instructions>
<p>Read the task carefully and inspect the image.</p>
<p>Choose the appropriate label that best suits the image.</p>
<p>If there is an issue with the image or tools, please select
<b>None of the Above</b>, describe the issue in the text box and click the
button below.</p>
<crowd-input label="Report an Issue" name="template-issues"></crowd-input>
<crowd-fab id="button1" icon="report-problem" title="Issue"/>
</short-instructions>
<full-instructions header="Classification Instructions">
<p>Read the task carefully and inspect the image.</p>
<p>Choose the appropriate label that best suits the image.
Use the <b>None of the Above</b> option if none of the other labels suit the
image.</p>
</full-instructions>
</crowd-image-classifier>
</crowd-form>
<script>
[
button1,
].forEach(function(button) {
button.addEventListener('click', function() {
document.querySelector('crowd-form').submit();

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Attributes

The following attributes are supported by this element.

disabled

A Boolean switch that, if present, displays the floating button as disabled and prevents clicks.

icon

A string that specifies the icon to be displayed in the center of the button. The string must be either the name of an icon from the open-source iron-icons set, which is pre-loaded, or the URL to a custom icon.

The following is an example of the syntax that you can use to add an iron-icon to a <crowd-fab> HTML element. Replace icon-name with the name of the icon you’d like to use from this Icons set.

```html
<crowd-fab "id="button1" icon="icon-name" title="Issue"/>
```

label

A string consisting of a single character that can be used instead of an icon. Emojis or multiple characters may result in the button displaying an ellipsis instead.

title

A string that will display as a tool tip when the mouse hovers over the button.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-form

The form wrapper for all custom tasks. Sets and implements important actions for the proper submission of your form data.

If a crowd-button (p. 724) of type "submit" is not included inside the <crowd-form> element, it will automatically be appended within the <crowd-form> element.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of an image classification template that uses the <crowd-form> element. Copy the following code and save it in a file with the extension .html. Open the file in any browser to preview and interact with this template.
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
    <crowd-image-classifier
        src="${image_url}"
        categories="['Cat', 'Dog', 'Bird', 'None of the Above']"
        header="Choose the correct category for the image"
        name="category"
    
    <short-instructions>
        <p>Read the task carefully and inspect the image.</p>
        <p>Choose the appropriate label that best suits the image.</p>
    </short-instructions>

    <full-instructions header="Classification Instructions">
        <p>Read the task carefully and inspect the image.</p>
        <p>Choose the appropriate label that best suits the image. Use the <b>None of the Above</b> option if none of the other labels suit the image.</p>
    </full-instructions>

</crowd-image-classifier>
</crowd-form>

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: none
- **Child elements**: Any of the [UI Template](p. 720) elements

Element Events

The `crowd-form` element extends the standard HTML `form` element and inherits its events, such as `onclick` and `onsubmit`.

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-icon-button

A button with an image placed in the center. When the user touches the button, a ripple effect emanates from the center of the button.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template designed for image classification that uses the `<crowd-icon-button>` element. This template uses JavaScript to enable workers to report issues with the worker UI. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
Attributes

The following attributes are supported by this element.

**disabled**
A Boolean switch that, if present, displays the button as disabled and prevents clicks.

**icon**
A string that specifies the icon to be displayed in the center of the button. The string must be either the name of an icon from the open-source *iron-icons* set, which is pre-loaded, or the URL to a custom icon.

The following is an example of the syntax that you can use to add an iron-icon to a `<crowd-icon-button>` HTML element. Replace *icon-name* with the name of the icon you'd like to use from this *Icons* set.

```
<crowd-icon-button id="button1" icon="icon-name" title="Issue"/>
```

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
• **Child elements**: none

**See Also**

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

**crowd-image-classifier**

A widget for classifying an image. Use one of the following supported image formats: APNG, BMP, GIF, ICO, JPEG, PNG, SVG. Images do not have a size limit.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of an image classification template that uses the `<crowd-image-classifier>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-image-classifier
    src="${image_url}"
    categories="['Cat', 'Dog', 'Bird', 'None of the Above']"
    header="Choose the correct category for the image"
    name="category">
    <short-instructions>
      <p>Read the task carefully and inspect the image.</p>
      <p>Choose the appropriate label that best suits the image.</p>
    </short-instructions>
    <full-instructions header="Classification Instructions">
      <p>Read the task carefully and inspect the image.</p>
      <p>Choose the appropriate label that best suits the image. Use the &lt;b&gt;None of the Above&lt;/b&gt; option if none of the other labels suit the image.</p>
    </full-instructions>
  </crowd-image-classifier>
</crowd-form>
```

**Attributes**

The following attributes are required by this element.

**categories**

A JSON formatted array of strings, each of which is a category that a worker can assign to the image. You should include "other" as a category, so that the worker can provide an answer. You can specify up to 10 categories.

**header**

The text to display above the image. This is typically a question or simple instruction for the worker.
name

The name of this widget. It is used as a key for the widget's input in the form output.

overlay

Information to be overlaid on the source image. This is for verification workflows of bounding-box, semantic-segmentation, and instance-segmentation tasks.

It is a JSON object containing an object with the name of the task-type in camelCase as the key. That key's value is an object that contains the labels and other necessary information from the previous task.

An example of a `crowd-image-classifier` element with attributes for verifying a bounding-box task follows:

```xml
<crowd-image-classifier
    name="boundingBoxClassification"
    header="Rate the quality of the annotations based on the background section in the instructions on the left hand side."
    src="https://i.imgur.com/CIPKVJo.jpg"
    categories="['good', 'bad', 'okay']"
    overlay='{"boundingBox": {
        "labels": ["bird", "cat"],
        "value": [
            {
                height: 284,
                label: "bird",
                left: 230,
                top: 974,
                width: 223
            },
            {
                height: 69,
                label: "bird",
                left: 79,
                top: 889,
                width: 247
            }
        ]
    },
    "overlay": {
        "semanticSegmentation": {
            "labels": ["Cat", "Dog", "Bird", "Cow"],
            "labelMappings": {
                "Bird": {
                    "color": "#ff7f0e"
                },
                "Cat": {
                    "color": "#2ca02c"
                },
                "Cow": {
                    "color": "#d62728"
                }
            }
        }
    }
}> ... </crowd-image-classifier>
```

A semantic segmentation verification task would use the overlay value as follows:

```xml
<crowd-image-classifier
    name='crowd-image-classifier'
    categories='["good", "bad"]'
    src='URL of image to be classified'
    header='Please classify'
    overlay='{"semanticSegmentation": {
        "labels": ["Cat", "Dog", "Bird", "Cow"],
        "labelMappings": {
            "Bird": {
                "color": "#ff7f0e"
            },
            "Cat": {
                "color": "#2ca02c"
            },
            "Cow": {
                "color": "#d62728"
            }
        }
    }
}> ... </crowd-image-classifier>
```
An instance-segmentation task would use the overlay value as follows:

```html
crowd-image-classifier
  name='crowd-image-classifier'
  categories='["good", "bad"]'
  src='URL of image to be classified'
  header='Please classify instances of each category'
  overlay={
    "instanceSegmentation": {
      "labels": ["Cat", "Dog", "Bird", "Cow"],
      "instances": [{
        "color": "#2ca02c",
        "label": "Cat"
      },
      {
        "color": "#1f77b4",
        "label": "Cat"
      },
      {
        "color": "#d62728",
        "label": "Dog"
      }],
    "src": "URL of overlay image",
  }
}...
```

**src**

The URL of the image to be classified.

### Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: full-instructions (p. 747), short-instructions (p. 747), worker-comment (p. 748)

### Regions

The following regions are used by this element.

- **full-instructions**
  General instructions for the worker on how to classify an image.
- **short-instructions**
  Important task-specific instructions that are displayed in a prominent place.
worker-comment

Use this in verification workflows when you need workers to explain why they made the choice they did. Use the text between the opening and closing tags to provide instructions for workers on what information should be included in the comment.

It uses the following attributes:

header

A phrase with a call to action for leaving a comment. Used as the title text for a modal window where the comment is added.

Optional. Defaults to "Add a comment."

link-text

This text appears below the categories in the widget. When clicked, it opens a modal window where the worker may add a comment.

Optional. Defaults to "Add a comment."

placeholder

An example text in the comment text area that is overwritten when worker begins to type. This does not appear in output if the worker leaves the field blank.

Optional. Defaults to blank.

Output

The output of this element is a string that specifies one of the values defined in the categories attribute of the <crowd-image-classifier> element.

Example: Sample Element Outputs

The following is a sample of output from this element.

```
[
  {
"<name>": {
  "label": "<value>"
  "workerComment": "Comment - if no comment is provided, this field will not be present"
  }
  }
]
```

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-image-classifier-multi-select

A widget for classifying an image into one or more categories. Use one of the following supported image formats: APNG, BMP, GIF, ICO, JPEG, PNG, SVG. Images do not have a size limit.
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See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.
The following is an example of an HTML worker task template built using this crowd element. Copy the
following code and save it in a ﬁle with the extension .html. Open the ﬁle in any browser to preview
and interact with this template.
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
<crowd-image-classifier-multi-select
name="animals"
categories="['Cat', 'Dog', 'Horse', 'Pig', 'Bird']"
src="https://images.unsplash.com/photo-1509205477838-a534e43a849f?
ixlib=rb-1.2.1&ixid=eyJhcHBfaWQiOjEyMDd9&auto=format&fit=crop&w=1998&q=80"
header="Please identify the animals in this image"
exclusion-category="{ text: 'None of the above' }"
>
<full-instructions header="Classification Instructions">
<p>If more than one label applies to the image, select multiple labels.</p>
<p>If no labels apply, select <b>None of the above</b></p>
</full-instructions>
<short-instructions>
<p>Read the task carefully and inspect the image.</p>
<p>Choose the appropriate label(s) that best suit the image.</p>
</short-instructions>
</crowd-image-classifier-multi-select>
</crowd-form>

Attributes
The following attributes are supported by the crowd-image-classifier-multi-select element.
Each attribute accepts a string value or string values.

categories
Required. A JSON-formatted array of strings, each of which is a category that a worker can assign to the
image. A worker must choose at least one category and can choose all categories.

header
Required. The text to display above the image. This is typically a question or simple instruction for
workers.

name
Required. The name of this widget. In the form output, the name is used as a key for the widget's input.

src
Required. The URL of the image to be classiﬁed.

exclusion-category
Optional. A JSON-formatted string with the following format: "{ text: 'default-value' }". This
attribute sets a default value that workers can choose if none of the labels applies to the image shown in
the worker UI.

Element Hierarchy
This element has the following parent and child elements:

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• **Parent elements**: crowd-form (p. 742)
• **Child elements**: full-instructions (p. 747), short-instructions (p. 747), worker-comment (p. 748)

**Regions**

This element uses the following regions

**full-instructions**

General instructions for the worker on how to classify an image.

**short-instructions**

Important task-specific instructions. These instructions are displayed prominently.

**Output**

The output of this element is a string that specifies one or more of the values defined in the categories attribute of the `<crowd-image-classifier-multi-select>` element.

**Example : Sample Element Outputs**

The following is a sample of output from this element.

```json
[
  {
    "<name>": {
      "labels": ["label_a", "label_b"]
    }
  }
]
```

**See Also**

For more information, see the following:

• Image Classification (Multi-label) (p. 391)
• Use Amazon SageMaker Ground Truth to Label Data (p. 370)
• Crowd HTML Elements Reference (p. 720)

**crowd-input**

A box that accepts input data.

**Cannot be self-closing**

Unlike the `input` element in the HTML standard, this element cannot be self-closed by putting a slash before the ending bracket, e.g. `<crowd-input ... />`. It must be followed with a `</crowd-input>` to close the element.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template that uses the `<crowd-input>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
```
<crowd-form>
  <img style="max-width: 35vw; max-height: 50vh" src="{{ task.input.taskObject | grant_read_access }}">
  <crowd-input name="tag1" label="Word/phrase 1" required></crowd-input>
  <crowd-input name="tag2" label="Word/phrase 2" required></crowd-input>
  <crowd-input name="tag3" label="Word/phrase 3" required></crowd-input>
  
  <short-instructions>
    Your custom quick instructions and examples
  </short-instructions>
  
  <full-instructions>
    Your custom detailed instructions and more examples
  </full-instructions>
</crowd-form>

Attributes

The following attributes are supported by this element.

**allowed-pattern**

A regular expression that is used with the *auto-validate* attribute to ignore non-matching characters as the worker types.

**auto-focus**

When the value is set to true, the browser places focus inside the input area after loading. This way, the worker can start typing without having to select it first.

**auto-validate**

A Boolean switch that, if present, turns on input validation. The behavior of the validator can be modified by the *error-message* and *allowed-pattern* attributes.

**disabled**

A Boolean switch that, if present, displays the input area as disabled.

**error-message**

The text to be displayed below the input field, on the left side, if validation fails.

**label**

A string that is displayed inside a text field.

This text shrinks and rises up above a text field when the worker starts typing in the field or when the *value* attribute is set.

**max-length**

A maximum number of characters the input will accept. Input beyond this limit is ignored.

**min-length**

A minimum length for the input in the field

**name**

Sets the name of the input to be used in the DOM and the output of the form.
placeholder

A string value that is used as placeholder text, displayed until the worker starts entering data into the input. It is not used as a default value.

required

A Boolean switch that, if present, requires the worker to provide input.

type

Takes a string to set the HTML5 input-type behavior for the input. Examples include file and date.

value

A preset that becomes the default if the worker does not provide input. The preset appears in a text field.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

Output

Provides a name string as the property name, and the text that was entered in the field as its value.

Example: Sample JSON Output

The values for multiple elements are output in the same object, with their name attribute value as their property name. Elements with no input do not appear in the output. For example, let's use three inputs:

```
<crowd-input name="tag1" label="Word/phrase 1"></crowd-input>
<crowd-input name="tag2" label="Word/phrase 2"></crowd-input>
<crowd-input name="tag3" label="Word/phrase 3"></crowd-input>
```

This is the output if only two have input:

```
[
  { 
    "tag1": "blue",
    "tag2": "red"
  }
]
```

This means any code built to parse these results should be able to handle the presence or absence of each input in the answers.

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)
**crowd-instance-segmentation**

A widget for identifying individual instances of specific objects within an image and creating a colored overlay for each labeled instance.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template that uses the `<crowd-instance-segmentation>`.

Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<iframe src="https://example.com/interactive-example" width="100%" height="400"></iframe>
```

Use a template similar to the following to allow workers to add their own categories (labels).

```html
<iframe src="https://example.com/custom-label-template" width="100%" height="400"></iframe>
```
<full-instructions>
Describe your task in more detail here.
</full-instructions>
</crowd-instance-segmentation>
</crowd-form>

<script>
  document.addEventListener('all-crowd-elements-ready', function(event) {
    document.querySelector('crowd-instance-segmentation').labels = [];
  });

  function populateLabelsSection() {
    labelsSection.innerHTML = '
    annotator.labels.forEach(function(label) {
      const labelContainer = document.createElement('div');
      labelContainer.innerHTML = label + ' <a href="javascript:void(0)">(Delete)</a>';
      labelContainer.onclick = function() {
        annotator.labels = annotator.labels.filter(function(l) {
          return l !== label;
        });
        populateLabelsSection();
      };
      labelsSection.appendChild(labelContainer);
    });
  }

  addLabel.onclick = function() {
    annotator.labels = annotator.labels.concat([customLabel.value]);
    customLabel.value = null;
    populateLabelsSection();
  };
</script>

**Attributes**

The following attributes are supported by this element.

**header**

The text to display above the image. This is typically a question or simple instruction for the worker.

**labels**

A JSON formatted array of strings, each of which is a label that a worker can assign to an instance of an object in the image. Workers can generate different overlay colors for each relevant instance by selecting "add instance" under the label in the tool.

**name**

The name of this widget. It is used as a key for the labeling data in the form output.

**src**

The URL of the image that is to be labeled.

**initial-value**

A JSON object containing the color mappings of a prior instance segmentation job and a link to the overlay image output by the prior job. Include this when you want a human worker to verify the results of a prior labeling job and adjust it if necessary.

The attribute will appear as follows:
Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: full-instructions (p. 755), short-instructions (p. 755)

Regions

The following regions are supported by this element.

- **full-instructions**
  General instructions about how to do image segmentation.

- **short-instructions**
  Important task-specific instructions that are displayed in a prominent place.

Output

The following output is supported by this element.

- **labeledImage**
  A JSON Object containing a Base64 encoded PNG of the labels.

- **instances**
  A JSON Array containing objects with the instance labels and colors.
  - **color** – The hexadecimal value of the label's RGB color in the labeledImage PNG.
  - **label** – The label given to overlay(s) using that color. This value may repeat, because the different instances of the label are identified by their unique color.

- **inputImageProperties**
  A JSON object that specifies the dimensions of the image that is being annotated by the worker. This object contains the following properties.
  - **height** – The height, in pixels, of the image.
- **width** – The width, in pixels, of the image.

**Example : Sample Element Outputs**

The following is an example of output from this element.

```json
[
    {
        "annotatedResult": {
            "inputImageProperties": {
                "height": 533,
                "width": 800
            },
            "instances": [
                {
                    "color": "#1f77b4",
                    "label": "<Label 1>"
                },
                {
                    "color": "#2ca02c",
                    "label": "<Label 1>"
                },
                {
                    "color": "#ff7f0e",
                    "label": "<Label 3>"
                }
            ],
            "labeledImage": {
                "pngImageData": "<Base-64 Encoded Data>"
            }
        }
    }
]
```

**See Also**

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

**crowd-instructions**

An element that displays instructions on three tabbed pages, **Summary**, **Detailed Instructions**, and **Examples**, when the worker clicks on a link or button.

See an interactive example of an HTML template that uses this Crowd HTML Element in [CodePen](https://codepen.io).

The following is an example of a Liquid template that used the `<crowd-instructions>` element. Copy the following code and save it in a file with the extension .html. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
    <crowd-instructions link-text="View instructions" link-type="button">
        <short-summary>
            <p>Given an image, write three words or short phrases that summarize its contents.</p>
        </short-summary>
    </crowd-instructions>
</crowd-form>
```
Imagine that you are describing an image to a friend or tagging it for a news website. Provide three specific words or short phrases that describe it.

These are not specific enough:

- Trees
- Outside
- Daytime

Attributes

The following attributes are supported by this element.

**link-text**

The text to display for opening the instructions. The default is *Click for instructions*.

**link-type**

A string that specifies the type of trigger for the instructions. The possible values are "link" (default) and "button".

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

Regions

The following regions are supported by this element.
detailed-instructions
Content that provides specific instructions for a task. This appears on the page of the "Detailed Instructions" tab.

negative-example
Content that provides examples of inadequate task completion. This appears on the page of the "Examples" tab. More than one example may be provided within this element.

positive-example
Content that provides examples of proper task completion. This appears on the page of the "Examples" tab.

short-summary
A brief statement that summarizes the task to be completed. This appears on the page of the "Summary" tab. More than one example may be provided within this element.

See Also
For more information, see the following.
- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-keypoint
Generates a tool to select and annotate key points on an image.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of an Liquid template that uses the <crowd-keypoint> element. Copy the following code and save it in a file with the extension .html. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <div id="errorBox"></div>
  <crowd-keypoint
    src="{{ task.input.taskObject | grant_read_access }}"
    labels="['Item A', 'Item B', 'Item C']"
    header="Please locate the centers of each item."
    name="annotatedResult">
    <short-instructions>
      Describe your task briefly here and give examples
    </short-instructions>
    <full-instructions>
      Give additional instructions and good/bad examples here
    </full-instructions>
  </crowd-keypoint>
</crowd-form>
<script>
  var num_obj = 1;
  document.querySelector('crowd-form').onsubmit = function(e) {
    //...
  }
```
const keypoints = document.querySelector('crowd-keypoint').value.keypoints || document.querySelector('crowd-keypoint')._submittableValue.keypoints;
const labels = keypoints.map(function(p) {
  return p.label;
});

// 1. Make sure total number of keypoints is correct.
var original_num_labels = document.getElementsByTagName("crowd-keypoint")
[0].getAttribute("labels");
original_num_labels = original_num_labels.substring(2, original_num_labels.length - 2).split("","");
var goalNumKeypoints = num_obj*original_num_labels.length;
if (keypoints.length != goalNumKeypoints) {
  e.preventDefault();
  errorBox.innerHTML = '<crowd-alert type="error" dismissible>You must add all keypoint
   annotations and use each label only once.</crowd-alert>'';
  errorBox.scrollIntoView();
  return;
}

// 2. Make sure all labels are unique.
labelCounts = {};
for (var i = 0; i < labels.length; i++) {
  if (!labelCounts[labels[i]]) {
    labelCounts[labels[i]] = 0;
  }
  labelCounts[labels[i]]++;
}
const goalNumSingleLabel = num_obj;
const numLabels = Object.keys(labelCounts).length;
Object.entries(labelCounts).forEach(entry => {
  if (entry[1] != goalNumSingleLabel) {
    e.preventDefault();
    errorBox.innerHTML = '<crowd-alert type="error" dismissible>You must use each label
     only once.</crowd-alert>'';
    errorBox.scrollIntoView();
  }
});
</script>

**Attributes**

The following attributes are supported by this element.

**header**

The text to display above the image. This is typically a question or simple instruction for the worker.

**initial-value**

An array, in JSON format, of keypoints to be applied to the image on start. For example:

    initial-value="[
      { 'label': 'Left Eye',
        'x': 1022,
        'y': 429
      },
      { 'label': 'Beak',

{'x': 941,
'y': 403
}

**Note**

Please note that label values used in this attribute must have a matching value in the `labels` attribute or the point will not be rendered.

**labels**

An array, in JSON format, of strings to be used as keypoint annotation labels.

**name**

A string used to identify the answer submitted by the worker. This value will match a key in the JSON object that specifies the answer.

**src**

The source URI of the image to be annotated.

**Element Hierarchy**

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: full-instructions (p. 760), short-instructions (p. 760)

**Regions**

The following regions are required by this element.

**full-instructions**

General instructions about how to annotate the image.

**short-instructions**

Important task-specific instructions that are displayed in a prominent place.

**Output**

The following output is supported by this element.

**inputImageProperties**

A JSON object that specifies the dimensions of the image that is being annotated by the worker. This object contains the following properties.

- **height** – The height, in pixels, of the image.
- **width** – The width, in pixels, of the image.

**keypoints**

An array of JSON objects containing the coordinates and label of a keypoint. Each object contains the following properties.
• **label** – The assigned label for the keypoint.
• **x** – The X coordinate, in pixels, of the keypoint on the image.
• **y** – The Y coordinate, in pixels, of the keypoint on the image.

**Note**
X and Y coordinates are based on 0,0 being the top left corner of the image.

**Example : Sample Element Outputs**

The following is a sample output from using this element.

```
[
  {
    "crowdKeypoint": {
      "inputImageProperties": {
        "height": 1314,
        "width": 962
      },
      "keypoints": [
        {
          "label": "dog",
          "x": 155,
          "y": 275
        },
        {
          "label": "cat",
          "x": 341,
          "y": 447
        },
        {
          "label": "cat",
          "x": 491,
          "y": 513
        },
        {
          "label": "dog",
          "x": 714,
          "y": 578
        },
        {
          "label": "cat",
          "x": 712,
          "y": 763
        },
        {
          "label": "cat",
          "x": 397,
          "y": 814
        }
      ]
    }
  }
]
```

You may have many labels available, but only the ones that are used appear in the output.

**See Also**

For more information, see the following.

• **Use Amazon SageMaker Ground Truth to Label Data (p. 370)**
• Crowd HTML Elements Reference (p. 720)

crowd-line

A widget for drawing lines on an image. Each line is associated with a label, and output data will report the starting and ending points of each line.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template that uses the `<crowd-line>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template. For more examples, see this GitHub repository.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-line
    name="crowdLine"
    src="{{ task.input.taskObject | grant_read_access }}"
    header="Add header here to describe the task"
    labels="['car','pedestrian','street car']"
  >
    <short-instructions>
      <p>Read the task carefully and inspect the image.</p>
      <p>Choose the appropriate label that best suits the image.</p>
      <p>Draw a line on each objects that the label applies to.</p>
    </short-instructions>
    <full-instructions>
      <p>Read the task carefully and inspect the image.</p>
      <p>Choose the appropriate label that best suits the image.</p>
      <p>Draw a line along each object that the image applies to.</p>
      <p>Make sure that the line does not extend beyond the boundaries of the object.</p>
      <p>Each line is defined by a starting and ending point. Carefully place the starting and ending points on the boundaries of the object.</p>
    </full-instructions>
  </crowd-line>
</crowd-form>

Attributes

The following attributes are supported by this element.

header

Optional. The text to display above the image. This is typically a question or simple instruction for the worker.

initial-value

Optional. An array of JSON objects, each of which sets a line when the component is loaded. Each JSON object in the array contains the following properties:

- label – The text assigned to the line as part of the labeling task. This text must match one of the labels defined in the `labels` attribute of the `<crowd-line>` element.
- vertices – the x and y pixel coordinates of the start point and end point of the line, relative to the top-left corner of the image.
Lines set via the `initial-value` property can be adjusted. Whether or not a worker answer was adjusted is tracked via an `initialValueModified` boolean in the worker answer output.

**labels**

Required. A JSON formatted array of strings, each of which is a label that a worker can assign to the line.

**Limit:** 10 labels

**label-colors**

Optional. An array of strings. Each string is a hexadecimal (hex) code for a label.

**name**

Required. The name of this widget. It's used as a key for the widget's input in the form output.

**src**

Required. The URL of the image on which to draw lines.

**Regions**

The following regions are required by this element.

**full-instructions**

General instructions about how to draw lines.

**short-instructions**

Important task-specific instructions that are displayed in a prominent place.
Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: short-instructions (p. 763), full-instructions (p. 763)

Output

**inputImageProperties**

A JSON object that specifies the dimensions of the image that is being annotated by the worker. This object contains the following properties.

- **height** – The height, in pixels, of the image.
- **width** – The width, in pixels, of the image.

**lines**

A JSON Array containing objects with the line labels and vertices.

- **label** – The label given to a line.
- **vertices** – the x and y pixel coordinates of the start point and end point of the line, relative to the top-left corner of the image.

**Example: Sample Element Outputs**

The following is an example of output from this element.

```json
{
    "crowdLine": { //This is the name you set for the crowd-line
        "inputImageProperties": {
            "height": 1254,
            "width": 2048
        },
        "lines": [
            {
                "label": "yardline",
                "vertices": [
                    {
                        "x": 58,
                        "y": 295
                    },
                    {
                        "x": 1342,
                        "y": 398
                    }
                ]
            },
            {
                "label": "sideline",
                "vertices": [
                    {
                        "x": 472,
                        "y": 910
                    },
                    {
                        "x": 1480,
                        "y": 764
                    }
                ]
            }
        ]
    }
}
```
crowd-modal

A small window that pops up on the display when it is opened.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of the syntax that you can use with the `<crowd-modal>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-modal
  link-text = "See Examples"
  link-type = "button">
  Example Modal Text</crowd-modal>
```

Attributes

The following attributes are supported by this element.

- **link-text**
  
  The text to display for opening the modal. The default is "Click to open modal".

- **link-type**
  
  A string that specifies the type of trigger for the modal. The possible values are "link" (default) and "button".

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

See Also

For more information, see the following.
• Use Amazon SageMaker Ground Truth to Label Data (p. 370)
• Crowd HTML Elements Reference (p. 720)

**crowd-polygon**

A widget for drawing polygons on an image and assigning a label to the portion of the image that is enclosed in each polygon.

See an interactive example of an HTML template that uses this Crowd HTML Element in [CodePen](https://codepen.io).

The following is an example of a Liquid template that uses the `<crowd-polygon>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-polygon
      name="annotatedResult"
      src="{{ task.input.taskObject | grant_read_access }}"
      header="Draw a polygon around each of the requested target(s) of interest"
      labels="["Cat", "Dog", "Bird"]"
>
    <full-instructions header="Polygon instructions">
      <ul>
        <li>Make the polygon tight around the object</li>
        <li>You need to select a label before starting a polygon</li>
        <li>You will need to select a label again after completing a polygon</li>
        <li>To select a polygon, you can click on its borders</li>
        <li>You can start drawing a polygon from inside another polygon</li>
        <li>You can undo and redo while you're drawing a polygon to go back and forth between points you've placed</li>
        <li>You are prevented from drawing lines that overlap other lines from the same polygon</li>
      </ul>
    </full-instructions>

    <short-instructions>
      <p>Draw a polygon around each of the requested target(s) of interest</p>
      <p>Make the polygon tight around the object</p>
    </short-instructions>
  </crowd-polygon>
</crowd-form>
```

**Attributes**

The following attributes are supported by this element.

**header**

The text to display above the image. This is typically a question or simple instruction for the worker.

**labels**

A JSON formatted array of strings, each of which is a label that a worker can assign to the image portion enclosed by a polygon.

**name**

The name of this widget. It's used as a key for the widget's input in the form output.
src
The URL of the image on which to draw polygons.

initial-value
An array of JSON objects, each of which defines a polygon to be drawn when the component is loaded. Each JSON object in the array contains the following properties.

- **label** – The text assigned to the polygon as part of the labeling task. This text must match one of the labels defined in the `labels` attribute of the `<crowd-polygon>` element.
- **vertices** – An array of JSON objects. Each object contains an x and y coordinate value for a point in the polygon.

**Example**
An `initial-value` attribute might look something like this.

```json
initial-value =
'[
  {
    "label": "dog",
    "vertices":
      [
        {
          "x": 570,
          "y": 239
        },
        ...
        {
          "x": 759,
          "y": 281
        }
      ]
  }
]'
```

Because this will be within an HTML element, the JSON array must be enclosed in single or double quotes. The example above uses single quotes to encapsulate the JSON and double quotes within the JSON itself. If you must mix single and double quotes inside your JSON, replace them with their HTML entity codes (`&quot;` for double quote, `&#39;` for single) to safely escape them.

**Element Hierarchy**
This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: full-instructions (p. 767), short-instructions (p. 767)

**Regions**
The following regions are required.

**full-instructions**
General instructions about how to draw polygons.

**short-instructions**
Important task-specific instructions that are displayed in a prominent place.
Output

The following output is supported by this element.

polygons

An array of JSON objects, each of which describes a polygon that has been created by the worker. Each JSON object in the array contains the following properties.

- **label** – The text assigned to the polygon as part of the labeling task.
- **vertices** – An array of JSON objects. Each object contains an x and y coordinate value for a point in the polygon. The top left corner of the image is 0,0.

inputImageProperties

A JSON object that specifies the dimensions of the image that is being annotated by the worker. This object contains the following properties.

- **height** – The height, in pixels, of the image.
- **width** – The width, in pixels, of the image.

Example: Sample Element Outputs

The following are samples of outputs from common use scenarios for this element.

**Single Label, Single Polygon**

```json
{
    "annotatedResult": {
        "inputImageProperties": {
            "height": 853,
            "width": 1280
        },
        "polygons": [
            {
                "label": "dog",
                "vertices": [
                    {
                        "x": 570,
                        "y": 239
                    },
                    {
                        "x": 603,
                        "y": 513
                    },
                    {
                        "x": 823,
                        "y": 645
                    },
                    {
                        "x": 901,
                        "y": 417
                    },
                    {
                        "x": 759,
                        "y": 281
                    }
                ]
            }
        ]
    }
}
```
Single Label, Multiple Polygons

[
  {
    "annotatedResult": {
      "inputImageProperties": {
        "height": 853,
        "width": 1280
      },
      "polygons": [
        {
          "label": "dog",
          "vertices": [
            {
              "x": 570,
              "y": 239
            },
            {
              "x": 603,
              "y": 513
            },
            {
              "x": 823,
              "y": 645
            },
            {
              "x": 901,
              "y": 417
            },
            {
              "x": 759,
              "y": 281
            }
          ]
        },
        {
          "label": "dog",
          "vertices": [
            {
              "x": 870,
              "y": 278
            },
            {
              "x": 908,
              "y": 446
            },
            {
              "x": 1009,
              "y": 602
            },
            {
              "x": 1116,
              "y": 519
            },
            {
              "x": 1174,
              "y": 498
            }
          ]
        }
      ]
    }
  }
]
Multiple Labels, Multiple Polygons

[{
   "annotatedResult": {
      "inputImageProperties": {
         "height": 853,
         "width": 1280
      },
      "polygons": [
         {
            "label": "dog",
            "vertices": [
               {
                  "x": 570,
                  "y": 239
               },
               {
                  "x": 603,
                  "y": 513
               },
               {
                  "x": 823,
                  "y": 645
               },
               {
                  "x": 901,
                  "y": 417
               },
               {
                  "x": 759,
                  "y": 281
               }
            ]
         },
         {
            "label": "cat",
            "vertices": [
               {
                  "x": 870,
                  "y": 278
               },
               {
                  "x": 908,
                  "y": 446
               },
               {  
                  
               }  
            ]
         }
      ]
   }
}]}
You could have many labels available, but only the ones that are used appear in the output.

**See Also**

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

**crowd-polyline**

A widget for drawing polylines or lines on an image. Each polyline is associated with a label and can include two or more vertices. A polyline can intersect itself and its starting and ending points can be placed anywhere on the image.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template that uses the `<crowd-polyline>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template. For more examples, see this GitHub repository.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-polyline
    name="crowdPolyline"
    src="{{ task.input.taskObject | grant_read_access }}"
    header="Add header here to describe the task"
    labels="['car','pedestrian','street car']">
    <full-instructions>
```

---

771
Attributes

The following attributes are supported by this element.

header

Optional. The text to display above the image. This is typically a question or simple instruction for the worker.

initial-value

Optional. An array of JSON objects, each of which sets a polyline when the component is loaded. Each JSON object in the array contains the following properties:

- label – The text assigned to the polyline as part of the labeling task. This text must match one of the labels defined in the labels attribute of the <crowd-polyline> element.
- vertices – the x and y pixel coordinates of the vertices of a polyline, relative to the top-left corner of the image.

```json
initial-value= "{
  polylines: [
    {
      label: 'sideline', // label of this line annotation
      vertices:[         // an array of vertices which decide the position of the line
        { x: 84,         // an array of vertices which decide the position of the line
          y: 110
        },
        { x: 60,         // an array of vertices which decide the position of the line
          y: 100
        }
      ]
    },
    {
      label: 'yardline',
      vertices:[
        
```
Polylines set via the initial-value property can be adjusted. Whether or not a worker answer was adjusted is tracked via an initialValueModified boolean in the worker answer output.

**labels**

Required. A JSON formatted array of strings, each of which is a label that a worker can assign to the line.

**Limit:** 10 labels

**label-colors**

Optional. An array of strings. Each string is a hexadecimal (hex) code for a label.

**name**

Required. The name of this widget. It's used as a key for the widget's input in the form output.

**src**

Required. The URL of the image on which to draw polylines.

**Regions**

The following regions are required by this element.

**full-instructions**

General instructions about how to draw polylines.

**short-instructions**

Important task-specific instructions that are displayed in a prominent place.

**Element Hierarchy**

This element has the following parent and child elements.

- **Parent elements:** crowd-form (p. 742)
- **Child elements:** short-instructions (p. 773), full-instructions (p. 773)

**Output**

**inputImageProperties**

A JSON object that specifies the dimensions of the image that is being annotated by the worker. This object contains the following properties.
• **height** – The height, in pixels, of the image.
• **width** – The width, in pixels, of the image.

**polylines**

A JSON Array containing objects with polylines' labels and vertices.

• **label** – The label given to a line.
• **vertices** – the x and y pixel coordinates of the vertices of a polyline, relative to the top-left corner of the image.

**Example : Sample Element Outputs**

The following is an example of output from this element.

```json
{
    "crowdPolyline": { //This is the name you set for the crowd-polyline
        "inputImageProperties": {
            "height": 1254,
            "width": 2048
        },
        "polylines": [
            {
                "label": "sideline",
                "vertices": [
                    {
                        "x": 651,
                        "y": 498
                    },
                    {
                        "x": 862,
                        "y": 869
                    },
                    {
                        "x": 1449,
                        "y": 611
                    }
                ]
            },
            {
                "label": "yardline",
                "vertices": [
                    {
                        "x": 1148,
                        "y": 322
                    },
                    {
                        "x": 1705,
                        "y": 474
                    },
                    {
                        "x": 1755,
                        "y": 474
                    }
                ]
            }
        ]
    }
}
```
See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-radio-button

A button that can be either checked or unchecked. When radio buttons are inside a radio group, exactly one radio button in the group can be checked at any time. The following is an example of how to configure a crowd-radio-button element inside of a crowd-radio-group element.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of the syntax that you can use with the <crowd-radio-button> element. Copy the following code and save it in a file with the extension .html. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-radio-group>
    <crowd-radio-button name="tech" value="tech">Technology</crowd-radio-button>
    <crowd-radio-button name="politics" value="politics">Politics</crowd-radio-button>
  </crowd-radio-group>
</crowd-form>
```

The previous example can be seen in a custom worker task template in this GitHub example: entity recognition labeling job custom template.

Crowd HTML Element radio buttons do not support the HTML tag, required. To make a radio button selection required, use <input type="radio"> elements to create radio buttons and add the required tag. The name attribute for all <input> elements that belong to the same group of radio buttons must be the same. For example, the following template requires the user to select a radio button in the animal-type group before submitting.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <p>Select an animal type:</p>
  <img src="https://images.unsplash.com/photo-1537151608828-ea2b11777ee8?ixlib=rb-1.2.1&ixid=eyJhcHBfaWQiOjEyMDd9&auto=format&fit=crop&w=1539&q=80" style="height: 500; width: 400;"/>

  <div>
    <input type="radio" id="cat" name="animal-type" value="cat" required>
    <label for="cat">Cat</label>
  </div>
  <div>
    <input type="radio" id="dog" name="animal-type" value="dog">
    <label for="dog">Dog</label>
  </div>
  <div>
    <input type="radio" id="unknown" name="animal-type" value="unknown">
    <label for="unknown">Unknown</label>
  </div>

  <full-instructions header="Classification Instructions">
    <p>Read the task carefully and inspect the image.</p>
    <p>Choose the appropriate label that best suits the image.</p>
  </full-instructions>
</crowd-form>
```
Attributes

The following attributes are supported by this element.

**checked**
A Boolean switch that, if present, displays the radio button as checked.

**disabled**
A Boolean switch that, if present, displays the button as disabled and prevents it from being checked.

**name**
A string that is used to identify the answer submitted by the worker. This value will match a key in the JSON object that specifies the answer.

**Note**
If you use the buttons outside of a crowd-radio-group (p. 777) element, but with the same name string and different value strings, the name object in the output will contain a Boolean value for each value string. To ensure that only one button in a group is selected, make them children of a crowd-radio-group (p. 777) element and use different name values.

**value**
A property name for the element's boolean value. If not specified, it uses "on" as the default, e.g. 

```json
{ "<name>": { "<value>": <true or false> } }
```

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements:** crowd-radio-group (p. 777)
- **Child elements:** none

Output

Outputs an object with the following pattern: 

```json
{ "<name>": { "<value>": <true or false> } }
```

If you use the buttons outside of a crowd-radio-group (p. 777) element, but with the same name string and different value strings, the name object will contain a Boolean value for each value string. To ensure that only one button in a group is selected, make them children of a crowd-radio-group (p. 777) element and use different name values.

Example Sample output of this element

```json
[
  {
    "btn1": {
      "yes": true
    },
    "btn2": {
      "no": false
    }
  }
]
```
See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

**crowd-radio-group**

A group of radio buttons. Only one radio button within the group can be selected. Choosing one radio button clears any previously chosen radio button within the same group. For an example of a custom UI template that uses the `crowd-radio-group` element, see this [entity recognition labeling job custom template](#).

See an interactive example of an HTML template that uses this Crowd HTML Element in [CodePen](#).

The following is an example of the syntax that you can use with the `<crowd-radio-group>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<style>
body {
  padding-left: 20px;
  margin-bottom: 20px;
}
#outer-container {
  display: flex;
  justify-content: space-around;
  max-width: 900px;
  margin-left: 100px;
}
.left-container {
  margin-right: auto;
  padding-right: 50px;
}
.right-container {
  margin-left: auto;
  padding-left: 50px;
}
#vertical-separator {
  border: solid 1px #d5dbdb;
}
</style>

<crowd-form>
  <div>
    <h1>Instructions</h1>
    Lorem ipsum...
  </div>
  <div>
    <h2>Background</h2>
    Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat.
  </div>
</crowd-form>
```
**Attributes**

No special attributes are supported by this element.

**Element Hierarchy**

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: crowd-radio-button (p. 775)

**Output**

Outputs an array of objects representing the crowd-radio-button (p. 775) elements within it.

**Example Sample of Element Output**

```json
[
    {
        "btn1": {
            "yes": true
        },
        "btn2": {
            "no": false
        }
    }
]
```

**See Also**

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)
crowd-semantic-segmentation

A widget for segmenting an image and assigning a label to each image segment.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template that uses the `<crowd-semantic-segmentation>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-semantic-segmentation
    name="annotatedResult"
    src="{{ task.input.taskObject | grant_read_access }}"
    header="Please label each of the requested objects in this image"
    labels="['Cat', 'Dog', 'Bird']"
  >
    <full-instructions header="Segmentation Instructions">
      <ol>
        <li><strong>Read</strong> the task carefully and inspect the image.</li>
        <li><strong>Read</strong> the options and review the examples provided to understand more about the labels.</li>
        <li><strong>Choose</strong> the appropriate label that best suits the image.</li>
      </ol>
    </full-instructions>
    <short-instructions>
      <p>Use the tools to label the requested items in the image</p>
    </short-instructions>
  </crowd-semantic-segmentation>
</crowd-form>

Attributes

The following attributes are supported by this element.

**header**

The text to display above the image. This is typically a question or simple instruction for the worker.

**initial-value**

A JSON object containing the color mappings of a prior semantic segmentation job and a link to the overlay image output by the prior job. Include this when you want a human worker to verify the results of a prior labeling job and adjust it if necessary.

The attribute would appear as follows:

```json
initial-value='{
  "labelMappings": {
    "Bird": {
      "color": "#ff7f0e"
    },
    "Cat": {
      "color": "#2ca02c"
    },
    "Cow": {
      "color": "#62728"  
    }
}'}
```
When using Ground Truth built in task types with annotation consolidation (where more than one worker labels a single image), label mappings are included in individual worker output records, however the overall result is represented as the internal-color-map in the consolidated results.

You can convert the internal-color-map to label-mappings in a custom template using the Liquid templating language:

```liquid
initial-value="{
    'src': '{{ task.input.manifestLine.label-attribute-name-from-prior-job | grant_read_access }}',
    'labelMappings': {
        {% for box in task.input.manifestLine.label-attribute-name-from-prior-job-metadata.internal-color-map %}
            {% if box[1]['class-name'] != 'BACKGROUND' %}
                {{ box[1]['class-name'] | to_json }}: {
                    'color': {{ box[1]['hex-color'] | to_json }}
                },
            {% endif %}
        {% endfor %}
    }
}"
```

**labels**

A JSON formatted array of strings, each of which is a label that a worker can assign to a segment of the image.

**name**

The name of this widget. It is used as a key for the widget's input in the form output.

**src**

The URL of the image that is to be segmented.

**Element Hierarchy**

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: full-instructions (p. 780), short-instructions (p. 780)

**Regions**

The following regions are supported by this element.

- **full-instructions**
  General instructions about how to do image segmentation.

- **short-instructions**
  Important task-specific instructions that are displayed in a prominent place.
Output

The following output is supported by this element.

labeledImage

A JSON Object containing a Base64 encoded PNG of the labels.

labelMappings

A JSON Object containing objects with named with the segmentation labels.

- **color** – The hexadecimal value of the label's RGB color in the labeledImage PNG.

initialValueModified

A boolean representing whether the initial values have been modified. This is only included when the output is from an adjustment task.

inputImageProperties

A JSON object that specifies the dimensions of the image that is being annotated by the worker. This object contains the following properties.

- **height** – The height, in pixels, of the image.
- **width** – The width, in pixels, of the image.

Example: Sample Element Outputs

The following is a sample of output from this element.

```
[
  {
    "annotatedResult": {
      "inputImageProperties": {
        "height": 533,
        "width": 800
      },
      "labelMappings": {
        "<Label 2>": {
          "color": "#ff7f0e"
        },
        "<label 3>": {
          "color": "#2ca02c"
        },
        "<label 1>": {
          "color": "#1f77b4"
        }
      },
      "labeledImage": {
        "pngImageData": "<Base-64 Encoded Data>"
      }
    }
  }
]
```

See Also

For more information, see the following.
Amazon SageMaker Developer Guide
SageMaker Crowd HTML Elements

• Use Amazon SageMaker Ground Truth to Label Data (p. 370)
• Crowd HTML Elements Reference (p. 720)

crowd-slider
A bar with a sliding knob that allows a worker to select a value from a range of values by moving
the knob. The slider makes it a great choice for settings that reﬂect intensity levels, such as volume,
brightness, or color saturation.
See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.
The following is an example of a survey template that uses the <crowd-slider> element. Copy the
following code and save it in a ﬁle with the extension .html. Open the ﬁle in any browser to preview
and interact with this template.
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
<crowd-instructions link-text="View instructions" link-type="button">
<short-summary>
<p>Provide a brief instruction here</p>
</short-summary>
<detailed-instructions>
<h3>Provide more detailed instructions here</h3>
<p>Include additional information</p>
</detailed-instructions>
<positive-example>
<p>Provide an example of a good answer here</p>
<p>Explain why it's a good answer</p>
</positive-example>
<negative-example>
<p>Provide an example of a bad answer here</p>
<p>Explain why it's a bad answer</p>
</negative-example>
</crowd-instructions>
<div>
<p>What is your favorite color for a bird?</p>
<crowd-input name="favoriteColor" placeholder="example: pink" required></crowd-input>
</div>
<div>
<p>Check this box if you like birds</p>
<crowd-checkbox name="likeBirds" checked="true" required></crowd-checkbox>
</div>
<div>
<p>On a scale of 1-10, how much do you like birds?</p>
<crowd-slider name="howMuch" min="1" max="10" step="1" pin="true" required></crowdslider>
</div>
<div>
<p>Write a short essay describing your favorite bird</p>
<crowd-text-area name="essay" rows="4" placeholder="Lorem ipsum..." required></crowdtext-area>
</div>
</crowd-form>

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Attributes

The following attributes are supported by this element.

**disabled**

A Boolean switch that, if present, displays the slider as disabled.

**editable**

A Boolean switch that, if present, displays an up/down button that can be chosen to select the value.

Selecting the value via the up/down button is an alternative to selecting the value by moving the knob on the slider. The knob on the slider will move synchronously with the up/down button choices.

**max**

A number that specifies the maximum value on the slider.

**min**

A number that specifies the minimum value on the slider.

**name**

A string that is used to identify the answer submitted by the worker. This value will match a key in the JSON object that specifies the answer.

**pin**

A Boolean switch that, if present, displays the current value above the knob as the knob is moved.

**required**

A Boolean switch that, if present, requires the worker to provide input.

**secondary-progress**

When used with a `crowd-slider-secondary-color` CSS attribute, the progress bar is colored to the point represented by the secondary-progress. For example, if this was representing the progress on a streaming video, the value would represent where the viewer was in the video timeline. The secondary-progress value would represent the point on the timeline to which the video had buffered.

**step**

A number that specifies the difference between selectable values on the slider.

**value**

A preset that becomes the default if the worker does not provide input.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none
Amazon SageMaker Developer Guide
SageMaker Crowd HTML Elements

See Also
For more information, see the following.
• Use Amazon SageMaker Ground Truth to Label Data (p. 370)
• Crowd HTML Elements Reference (p. 720)

crowd-tab
A component styled to look like a tab with information below.
See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.
The following is an example template that uses the <crowd-tab> element. Copy the following code and
save it in a ﬁle with the extension .html. Open the ﬁle in any browser to preview and interact with this
template.
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
<crowd-tabs>
<crowd-tab header="Tab 1">
<h2>Image</h2>
<img
src="https://images.unsplash.com/photo-1478382188900-5bb598fe27d3?
ixlib=rb-1.2.1&ixid=eyJhcHBfaWQiOjEyMDd9&auto=format&fit=crop&w=1351&q=80"
style="max-width: 40%"
>
<h2>Text</h2>
<p>
Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor
incididunt ut labore et dolore magna aliqua.
</p>
<p>
Sed risus ultricies tristique nulla aliquet enim tortor at auctor. Tempus egestas sed
sed risus.
</p>
</crowd-tab>
<crowd-tab header="Tab 2">
<h2>Description</h2>
<p>
Sed risus ultricies tristique nulla aliquet enim tortor at auctor. Tempus egestas sed
sed risus.
</p>
</crowd-tab>
<crowd-tab header="Tab 3">
<div style="width: 40%; display: inline-block">
<img
src="https://images.unsplash.com/photo-1472747459646-91fd6f13995f?
ixlib=rb-1.2.1&ixid=eyJhcHBfaWQiOjEyMDd9&auto=format&fit=crop&w=1350&q=80"
style="max-width: 80%"
>
<crowd-input label="Input inside tab" name="inputInsideTab"></crowd-input>
<input type="checkbox" name="checkbox" value="foo">Foo
<input type="checkbox" name="checkbox" value="bar">Bar
<crowd-button>Some button</crowd-button>
</div>

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Attributes

The following attributes are supported by this element.

**header**

The text appearing on the tab. This is usually some short descriptive name indicative of the information contained below the tab.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-tabs (p. 785)
- **Child elements**: none

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)
See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example template that uses the `<crowd-tabs>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <crowd-tabs>
    <crowd-tab header="Tab 1">
      <h2>Image</h2>
      <img src="https://images.unsplash.com/photo-1478382188900-5bb598fe27d3?ixlib=rb-1.2.1&ixid=eyJhcHBfaWQiOjEyMDd9&auto=format&fit=crop&w=1351&q=80" style="max-width: 40%"/>
      
      <h2>Text</h2>
      <p>Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua.</p>
      <p>Sed risus ultricies tristique nulla aliquet enim tortor at auctor. Tempus egestas sed sed risus.</p>
    </crowd-tab>
    
    <crowd-tab header="Tab 2">
      <h2>Description</h2>
      <p>Sed risus ultricies tristique nulla aliquet enim tortor at auctor. Tempus egestas sed sed risus.</p>
    </crowd-tab>
    
    <crowd-tab header="Tab 3">
      <div style="width: 40%; display: inline-block">
        <img src="https://images.unsplash.com/photo-1472747459646-91fd6f13995f?ixlib=rb-1.2.1&ixid=eyJhcHBfaWQiOjEyMDd9&auto=format&fit=crop&w=1350&q=80" style="max-width: 80%"/>

        <crowd-input label="Input inside tab" name="inputInsideTab"></crowd-input>
        <input type="checkbox" name="checkbox" value="foo">Foo
        <input type="checkbox" name="checkbox" value="bar">Bar
        <crowd-button>Some button</crowd-button>
      </div>
      
      <div style="width: 40%; display: inline-block; vertical-align: top">
        Lorem ipsum dolor sit amet, lorem a wisi nibh, in pulvinar, consequat praesent vestibulum tellus ante felis auctor, vitae lobortis dictumst mauris. Pellentesque nulla ipsum ante quisque quam augue. Class lacus id eulismod, blandit tempor mauris quisque tortor mauris, urna gravida nullam pede libero, ut suscipit orci faucibus lascus varius ornare, pellentesque ipsum. At etiam suspendisse est elementum luctus netus, vel sem nulla sodales, potenti magna enim ipsum diam tortor rutrum, quam donec massa elit ac, nam adipiscing sed at leo ipsum consectetur. Ac turpis amet wisi, porttitor sint lacus ante, turpis accusantium, ac maecenas deleniti, nisl leo sem integer ac dignissim. Lobortis etiam luctus lectus odio auctor. Justo vitae, felis integer id, bibendum accumsan turpis eu est mus eros, ante id eros.
      </div>
    </crowd-tab>
  </crowd-tabs>
</crowd-form>
```
Attributes

This element has no attributes.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: crowd-tab (p. 784)

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-text-area

A field for text input.

See an interactive example of an HTML template that uses this Crowd HTML Element in CodePen.

The following is an example of a Liquid template designed to transcribe audio clips that uses the <crowd-text-area> element. Copy the following code and save it in a file with the extension .html. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
    <audio controls>
        <source src="{{ task.input.taskObject | grant_read_access }}" type="audio/mpeg">
        Your browser does not support the audio element.
    </audio>
    <h3>Instructions</h3>
    <p>Transcribe the audio</p>
    <p>Ignore "umms", "hmms", "uhs" and other non-textual phrases</p>
    <crowd-text-area name="transcription" rows="4"></crowd-text-area>
</crowd-form>
```
Attributes

The following attributes are supported by this element.

**allowed-pattern**

A regular expression that is used with the *auto-validate* attribute to ignore non-matching characters as the worker types.

**auto-focus**

A Boolean switch that, if present, puts the cursor in this element on-load so that users can immediately begin typing without having to click inside the element.

**auto-validate**

A Boolean switch that, if present, turns on input validation. The behavior of the validator can be modified by the *error-message* and *allowed-pattern* attributes.

**char-counter**

A Boolean switch that, if present, puts a small text field beneath the lower-right corner of the element, displaying the number of characters inside the element.

**disabled**

A Boolean switch that, if present, displays the input area as disabled.

**error-message**

The text to be displayed below the input field, on the left side, if validation fails.

**label**

A string that is displayed inside a text field.

This text shrinks and rises up above a text field when the worker starts typing in the field or when the *value* attribute is set.

**max-length**

An integer that specifies the maximum number of characters allowed by the element. Characters typed or pasted beyond the maximum are ignored.

**max-rows**

An integer that specifies the maximum number of rows of text that are allowed within a crowd-text-area. Normally the element expands to accommodate new rows. If this is set, after the number of rows exceeds it, content scrolls upward out of view and a scrollbar control appears.

**name**

A string used to represent the element's data in the output.

**placeholder**

A string presented to the user as placeholder text. It disappears after the user puts something in the input area.

**rows**

An integer that specifies the height of the element in rows of text.
value

A preset that becomes the default if the worker does not provide input. The preset appears in a text field.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

Output

This element outputs the name as a property name and the element's text contents as the value. Carriage returns in the text are represented as `\n`.

Example Sample output for this element

```
[
  {
    "textInput1": "This is the text; the text that\nmakes the crowd go wild."
  }
]
```

See Also

For more information, see the following.

- Use Amazon SageMaker Ground Truth to Label Data (p. 370)
- Crowd HTML Elements Reference (p. 720)

crowd-toast

A subtle notification that temporarily appears on the display. Only one crowd-toast is visible.

See an interactive example of an HTML template that uses this Crowd HTML Element in [CodePen](https://codepen.io).

The following is an example of a Liquid template that uses the `<crowd-toast>` element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<crowd-form>
  <p>Find the official website for: <strong>{{ task.input.company }}</strong></p>
  <p>Do not give Yelp pages, LinkedIn pages, etc.</p>
  <p>Include the http:// prefix from the website</p>
  <crowd-input name="website" placeholder="http://example.com"></crowd-input>

  <crowd-toast duration="10000" opened>
    This is a message that you want users to see when opening the template. This message will disappear in 10 seconds.
  </crowd-toast>
</crowd-form>
```
Attributes

The following attributes are supported by this element.

**duration**
A number that specifies the duration, in milliseconds, that the notification appears on the screen.

**text**
The text to display in the notification.

Element Hierarchy

This element has the following parent and child elements.

- **Parent elements**: crowd-form (p. 742)
- **Child elements**: none

See Also

For more information, see the following.

- [Use Amazon SageMaker Ground Truth to Label Data](p. 370)
- [Crowd HTML Elements Reference](p. 720)

crowd-toggle-button

A button that acts as an ON/OFF switch, toggling a state.

See an interactive example of an HTML template that uses this Crowd HTML Element in [CodePen](https://codepen.io).

The following example shows different ways you can use to use the `<crowd-toggle-button>` HTML element. Copy the following code and save it in a file with the extension `.html`. Open the file in any browser to preview and interact with this template.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>

<!--Toggle button without value-->
<crowd-toggle-button name="toggleButtonWithoutValue"></crowd-toggle-button>

<!--Toggle button with value-->
<crowd-toggle-button name="toggleButtonWithValue" value="someValue"></crowd-toggle-button>

<!--Toggle button disabled-->
<crowd-toggle-button name="toggleButtonDisabled" disabled></crowd-toggle-button>

<!--Toggle button marked invalid-->
<crowd-toggle-button name="toggleButtonInvalid" invalid></crowd-toggle-button>

<!--Toggle button marked required-->
<crowd-toggle-button name="toggleButtonRequired" required></crowd-toggle-button>
</crowd-form>
```
Attributes

The following attributes are supported by this element.

checked
A Boolean switch that, if present, displays the button switched to the ON position.

disabled
A Boolean switch that, if present, displays the button as disabled and prevents toggling.

invalid
When in an off position, a button using this attribute, will display in an alert color. The standard is red, but may be changed in CSS. When toggled on, the button will display in the same color as other buttons in the on position.

name
A string that is used to identify the answer submitted by the worker. This value matches a key in the JSON object that specifies the answer.

required
A Boolean switch that, if present, requires the worker to provide input.

value
A value used in the output as the property name for the element's Boolean state. Defaults to "on" if not provided.

Element Hierarchy

This element has the following parent and child elements.

- Parent elements: crowd-form (p. 742)
- Child elements: none

Output

This element outputs the name as the name of an object, containing the value as a property name and the element's state as Boolean value for the property. If no value for the element is specified, the property name defaults to "on."

Example Sample output for this element

```json
[
   {
      "theToggler": {
         "on": true
      }
   }
]
```

See Also

For more information, see the following.
Augmented AI Crowd HTML Elements

The following Crowd HTML Elements are only available for Amazon Augmented AI human workflow tasks.

Topics

• crowd-textract-analyze-document (p. 792)
• crowd-rekognition-detect-moderation-labels (p. 795)

crowd-textract-analyze-document

A widget to enable human review of an Amazon Textract document analysis result.

Attributes

The following attributes are supported by this element.

header

This is the text that is displayed as the header.

src

This is a link to the image to be analyzed by the worker.

initialValue

This sets initial values for attributes found in the worker UI.

The following is an example of an initialValue input:

```json
[
  {
    "blockType": "KEY_VALUE_SET",
    "confidence": 38.43309020996094,
    "geometry": {
      "boundingBox": {
        "width": 0.32613086700439453,
        "weight": 0.0942094624042511,
        "left": 0.483383575248718,
        "top": 0.5227988958558765
      },
      "polygon": [
        {
          "x": 0.123, "y": 0.345,
        }, ...]
    }
  },
  {
    "id": "8c97b240-0969-4678-834a-646c95da9cf4",
    "relationships": [
      {
        "type": "CHILD",
        "ids": [
          "7ee7b7da-ee1b-428d-a567-55a3e3affa56",
          "4d6da730-ba43-467c-a9a5-c6137ba0c472"
        ]
      }
    ]
  }
]
```
blockTypes

This determines the kind of analysis the workers can do. Only KEY_VALUE_SET is currently supported.

keys

This specifies new keys and the associated text value the worker can add. The input values for keys can include the following elements:

- importantFormKey accepts strings, and is used to specify a single key.
- importantFormKeyAliases can be used to specify aliases that are acceptable alternatives to the keys supplied. Use this element to identify alternative spellings or presentations of your keys. This parameter accepts a list of one or more strings.

The following is an example of an input for keys.

```
[  
  {  
    importantFormKey: 'Address',  
    importantFormKeyAliases: [  
      'address',  
      'Addr.',  
      'Add.',  
    ]  
  },  
  {  
    importantFormKey: 'Last name',  
    importantFormKeyAliases: ['Surname']  
  }  
]
```

no-key-edit

This prevents the workers from editing the keys of annotations passed through initialValu. This prevents workers from editing the keys that have been detected on your documents. This is required.

no-geometry-edit

This prevents workers from editing the polygons of annotations passed through initialValue. For example, this would prevent the worker from editing the bounding box around a given key. This is required.

Element Hierarchy

This element has the following parent and child elements.

- Parent elements – crowd-form
• Child elements – full-instructions (p. 794), short-instructions (p. 794)

Regions

The following regions are supported by this element. You can use custom HTML and CSS code within these regions to format your instructions to workers. For example, use the short-instructions section to provide good and bad examples of how to complete a task.

full-instructions

General instructions about how to work with the widget.

short-instructions

Important task-specific instructions that are displayed in a prominent place.

Example of a Worker Template Using the crowd Element

An example of a worker template using this crowd element would look like the following.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
{% capture s3_uri %}http://s3.amazonaws.com/{{ task.input.aiServiceRequest.document.s3Object.bucket }}/{{ task.input.aiServiceRequest.document.s3Object.name }}{% endcapture %}

<crowd-form>
  <crowd-textract-analyze-document
    src="{{ s3_uri | grant_read_access }}"
    initial-value="{{ task.input.selectedAiServiceResponse.blocks }}"
    header="Review the key-value pairs listed on the right and correct them if they don't match the following document."
    no-key-edit
    no-geometry-edit
    keys="{{ task.input.humanLoopContext.importantFormKeys }}"
    block-types="["KEY_VALUE_SET"]"
  >
  <short-instructions header="Instructions">
    <style>
      .instructions {
        white-space: pre-wrap;
      }
      .instructionsImage {
        display: inline-block;
        max-width: 100%;
      }
    </style>
    <p class='instructions'>Click on a key-value block to highlight the corresponding key-value pair in the document.

    If it is a valid key-value pair, review the content for the value. If the content is incorrect, correct it.

    The text of the value is incorrect, correct it.
    <img class='instructionsImage' src="https://assets.crowd.aws/images/a2i-console/correct-value-text.png"/>

    A wrong value is identified, correct it.
    <img class='instructionsImage' src="https://assets.crowd.aws/images/a2i-console/correct-value.png"/>

    If it is not a valid key-value relationship, choose No.
    <img class='instructionsImage' src="https://assets.crowd.aws/images/a2i-console/not-a-key-value-pair.png"/>
  </short-instructions>
</crowd-form>
```
Output

The following is a sample of the output from this element. You can find a detailed explanation of this output in the Amazon Textract `AnalyzeDocument` API documentation.

```
{
  "AWS/Textract/AnalyzeDocument/Forms/V1": {
    "blocks": [
      {
        "blockType": "KEY_VALUE_SET",
        "id": "8c97b240-0969-4678-834a-646c95da9cf4",
        "relationships": [
          {
            "type": "CHILD",
            "ids": ["7ee7b7da-ee1b-428d-a567-55a3e3affa56", "4d6da730-ba43-467c-a9a5-c6137ba0c472"]
          },
          {
            "type": "VALUE",
            "ids": ["6ee7b7da-ee1b-428d-a567-55a3e3affa54"]
          }
        ],
        "entityTypes": ["KEY"],
        "text": "Foo bar baz"
      }
    ]
  }
}
```

crowd-rekognition-detect-moderation-labels

A widget to enable human review of an Amazon Rekognition image moderation result.
Attributes

The following attributes are supported by this element.

**header**

This is the text that is displayed as the header.

**src**

This is a link to the image to be analyzed by the worker.

**categories**

This supports categories as an array of strings or an array of objects where each object has a name field.

If the categories come in as objects, the following applies:

- The displayed categories are the value of the name field.
- The returned answer contains the full objects of any selected categories.

If the categories come in as strings, the following applies:

- The returned answer is an array of all the strings that were selected.

**exclusion-category**

By setting this attribute you create a button underneath the categories in the UI.

- When a user chooses the button, all categories are deselected and disabled.
- Choosing the button again re-enables the categories so that users can choose them.
- If you submit after choosing the button, it returns an empty array.

Element Hierarchy

This element has the following parent and child elements.

- Parent elements – crowd-form
- Child elements – full-instructions (p. 796), short-instructions (p. 796)

AWS Regions

The following AWS Regions are supported by this element. You can use custom HTML and CSS code within these Regions to format your instructions to workers. For example, use the short-instructions section to provide good and bad examples of how to complete a task.

**full-instructions**

General instructions about how to work with the widget.

**short-instructions**

Important task-specific instructions that are displayed in a prominent place.
Example Worker Template with the crowd Element

An example of a worker template using the crowd element would look like the following.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
{% capture s3_uri %}http://s3.amazonaws.com/
{{ task.input.aiServiceRequest.image.s3Object.bucket }}/
{{ task.input.aiServiceRequest.image.s3Object.name }}{% endcapture %}

<crowd-form>
<crowd-rekognition-detect-moderation-labels
categories='[
    {% for label in task.input.selectedAiServiceResponse.moderationLabels %}
    {
        name: "{{ label.name }}",
        parentName: "{{ label.parentName }}",
    },
    {% endfor %}
]'
src="{{ s3_uri | grant_read_access }}"
header="Review the image and choose all applicable categories."
>
<short-instructions header="Instructions">
<style>
  .instructions {
    white-space: pre-wrap;
  }
</style>
<p class='instructions'>Review the image and choose all applicable categories. If no categories apply, choose None.

<b>Nudity</b>
Visuals depicting nude male or female person or persons

<b>Graphic Male Nudity</b>
Visuals depicting full frontal male nudity, often close ups

<b>Graphic Female Nudity</b>
Visuals depicting full frontal female nudity, often close ups

<b>Sexual Activity</b>
Visuals depicting various types of explicit sexual activities and pornography

<b>Illustrated Nudity or Sexual Activity</b>
Visuals depicting animated or drawn sexual activity, nudity or pornography

<b>Adult Toys</b>
Visuals depicting adult toys, often in a marketing context

<b>Female Swimwear or Underwear</b>
Visuals depicting female person wearing only swimwear or underwear

<b>Male Swimwear Or Underwear</b>
Visuals depicting male person wearing only swimwear or underwear

<b>Partial Nudity</b>
Visuals depicting covered up nudity, for example using hands or pose

<b>Revealing Clothes</b>
Visuals depicting revealing clothes and poses, such as deep cut dresses

<b>Graphic Violence or Gore</b>
Visuals depicting prominent blood or bloody injuries

<b>Physical Violence</b>
```
Visuals depicting violent physical assault, such as kicking or punching

<b>Weapon Violence</b>
Visuals depicting violence using weapons like firearms or blades, such as shooting

<b>Weapons</b>
Visuals depicting weapons like firearms and blades

<b>Self Injury</b>
Visuals depicting self-inflicted cutting on the body, typically in distinctive patterns using sharp objects

<b>Emaciated Bodies</b>
Visuals depicting extremely malnourished human bodies

<b>Corpses</b>
Visuals depicting human dead bodies

<b>Hanging</b>
Visuals depicting death by hanging

Output
The following is a sample of the output from this element. For details about this output, see Amazon Rekognition DetectModerationLabels API documentation.

```json
{
    "AWS/Rekognition/DetectModerationLabels/Image/V3": {
        "ModerationLabels": [
            { name: 'Gore', parentName: 'Violence' },
            { name: 'Corpses', parentName: 'Violence' }
        ]
    }
}
```
Prepare and Analyze Datasets

Import, prepare, transform, visualize and analyze data with Amazon SageMaker Data Wrangler. You can integrate Data Wrangler into your machine learning workflows to simplify and streamline data pre-processing and feature engineering using little to no coding. You can also add your own Python scripts and transformations to customize your data prep workflow.

Import data from Amazon S3, Amazon Redshift, Amazon Athena, and use Data Wrangler to create sophisticated machine learning data prep workflows with built-in and custom data transformations and analysis including feature target leakage and quick modeling.

After you have defined a data prep workflow, or data flow, you can integrate it with SageMaker Processing, SageMaker Pipelines, and SageMaker Feature Store, simplify the task of processing, sharing and storing ML training data. You can also export your data flow to a python script and create a custom ML data prep pipeline.

For more information, see Prepare ML Data with Amazon SageMaker Data Wrangler (p. 815).

Topics

- Detect Pretraining Data Bias (p. 799)
- Prepare ML Data with Amazon SageMaker Data Wrangler (p. 815)
- Prepare Data at Scale with Studio Notebooks (p. 983)

Detect Pretraining Data Bias

Algorithmic bias, discrimination, fairness, and related topics have been studied across disciplines such as law, policy, and computer science. A computer system might be considered biased if it discriminates against certain individuals or groups of individuals. The machine learning models powering these applications learn from data and this data could reflect disparities or other inherent biases. For example, the training data may not have sufficient representation of various demographic groups or may contain biased labels. The machine learning models trained on datasets that exhibit these biases could end up learning them and then reproduce or even exacerbate those biases in their predictions. The field of machine learning provides an opportunity to address biases by detecting them and measuring them at each stage of the ML lifecycle. You can use Amazon SageMaker Clarify to determine whether data used for training models encodes any bias.

Bias can be measured before training and after training, and monitored against baselines after deploying models to endpoints for inference. Pretraining bias metrics are designed to detect and measure bias in the raw data before it is used to train a model. The metrics used are model-agnostic because they do not depend on any model outputs. However, there are different concepts of fairness that require distinct measures of bias. Amazon SageMaker Clarify provides bias metrics to quantify various fairness criteria.

For additional information about bias metrics, see Learn How Amazon SageMaker Clarify Helps Detect Bias and Fairness Measures for Machine Learning in Finance.

Amazon SageMaker Clarify Terms for Bias and Fairness

SageMaker Clarify uses the following terminology to discuss bias and fairness.
Feature

An individual measurable property or characteristic of a phenomenon being observed, contained in a column for tabular data.

Label

Feature that is the target for training a machine learning model. Referred to as the observed label or observed outcome.

Predicted label

The label as predicted by the model. Also referred to as the predicted outcome.

Sample

An observed entity described by feature values and label value, contained in a row for tabular data.

Dataset

A collection of samples.

Bias

An imbalance in the training data or the prediction behavior of the model across different groups, such as age or income bracket. Biases can result from the data or algorithm used to train your model. For instance, if an ML model is trained primarily on data from middle-aged individuals, it may be less accurate when making predictions involving younger and older people.

Bias metric

A function that returns numerical values indicating the level of a potential bias.

Bias report

A collection of bias metrics for a given dataset, or a combination of a dataset and a model.

Positive label values

Label values that are favorable to a demographic group observed in a sample. In other words, designates a sample as having a positive result.

Negative label values

Label values that are unfavorable to a demographic group observed in a sample. In other words, designates a sample as having a negative result.

Group variable

Categorical column of the dataset that is used to form subgroups for the measurement of Conditional Demographic Disparity (CDD). Required only for this metric with regards to Simpson’s paradox.

Facet

A column or feature that contains the attributes with respect to which bias is measured.

Facet value

The feature values of attributes that bias might favor or disfavor.

Predicted probability

The probability, as predicted by the model, of a sample having a positive or negative outcome.

Sample Notebooks

Amazon SageMaker Clarify provides the following sample notebook for bias detection:
• **Explainability and bias detection with Amazon SageMaker Clarify** – Use SageMaker Clarify to create a processing job for the detecting bias and explaining model predictions with feature attributions.

This notebook has been verified to run in Amazon SageMaker Studio only. If you need instructions on how to open a notebook in Amazon SageMaker Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133). If you’re prompted to choose a kernel, choose Python 3 (Data Science).

**Topics**
- Measure Pretraining Bias (p. 801)
- Generate Reports for Bias in Pretraining Data in SageMaker Studio (p. 810)

**Measure Pretraining Bias**

Measuring bias in ML models is a first step to mitigating bias. Each measure of bias corresponds to a different notion of fairness. Even considering simple concepts of fairness leads to many different measures applicable in various contexts. For example, consider fairness with respect to age, and, for simplicity, that middle-aged and rest of the age groups are the two relevant demographics, referred to as **facets**. In the case of an ML model for lending, we may want small business loans to be issued to equal numbers of both demographics. Or, when processing job applicants, we may want to see equal numbers of members of each demographic hired. However, this approach may assume that equal numbers of both age groups apply to these jobs, so we may want to condition on the number that apply. Further, we may want to consider not whether equal numbers apply, but whether we have equal numbers of qualified applicants. Or, we may consider fairness to be an equal acceptance rate of qualified applicants across both age demographics, or, an equal rejection rate of applicants, or both. You might use datasets with different proportions of data on the attributes of interest. This imbalance can conflate the bias measure you choose. The models might be more accurate in classifying one facet than in the other. Thus, you need to choose bias metrics that are conceptually appropriate for the application and the situation.

We use the following notation to discuss the bias metrics. The conceptual model described here is for binary classification, where events are labeled as having only two possible outcomes in their sample space, referred to as positive (with value 1) and negative (with value 0). This framework is usually extensible to multiclassification in a straightforward way or to cases involving continuous valued outcomes when needed. In the binary classification case, positive and negative labels are assigned to outcomes recorded in a raw dataset for a favored facet \( a \) and for a disfavored facet \( d \). These labels \( y \) are referred to as **observed labels** to distinguish them from the **predicted labels** \( y' \) that are assigned by a machine learning model during the training or inferences stages of the ML lifecycle. These labels are used to define probability distributions \( P_a(y) \) and \( P_d(y) \) for their respective facet outcomes.

- **labels:**
  - \( y \) represents the \( n \) observed labels for event outcomes in a training dataset.
  - \( y' \) represents the predicted labels for the \( n \) observed labels in the dataset by a trained model.

- **outcomes:**
  - A positive outcome (with value 1) for a sample, such as an application acceptance.
    - \( n^{(1)} \) is the number of observed labels for positive outcomes (acceptances).
    - \( n^{(1)} \) is the number of predicted labels for positive outcomes (acceptances).
  - A negative outcome (with value 0) for a sample, such as an application rejection.
    - \( n^{(0)} \) is the number of observed labels for negative outcomes (rejections).
    - \( n^{(0)} \) is the number of predicted labels for negative outcomes (rejections).

- **facet values:**
  - facet \( a \) – The feature value that defines a demographic that bias favors.
    - \( n_a \) is the number of observed labels for the favored facet value: \( n_a = n_a^{(1)} + n_a^{(0)} \) the sum of the positive and negative observed labels for the value facet \( a \).
Measure Pretraining Bias

- \( n'_a \) is the number of predicted labels for the favored facet value: \( n'_a = n'_a^{(1)} + n'_a^{(0)} \) the sum of the positive and negative predicted outcome labels for the facet value \( a \). Note that \( n'_a = n_a \).
- facet \( d \) – The feature value that defines a demographic that bias disfavors.
- \( n_d \) is the number of observed labels for the disfavored facet value: \( n_d = n_d^{(1)} + n_d^{(0)} \) the sum of the positive and negative observed labels for the facet value \( d \).
- \( n'_d \) is the number of predicted labels for the disfavored facet value: \( n'_d = n'_d^{(1)} + n'_d^{(0)} \) the sum of the positive and negative predicted labels for the facet value \( d \). Note that \( n'_d = n_d \).

- probability distributions for outcomes of the labeled facet data outcomes:
  - \( P_a(y) \) is the probability distribution of the observed labels for facet \( a \). For binary labeled data, this distribution is given by the ratio of the number of samples in facet \( a \) labeled with positive outcomes to the total number, \( P_a(y^{(1)}) = n_a^{(1)}/n_a \), and the ratio of the number of samples with negative outcomes to the total number, \( P_a(y^{(0)}) = n_a^{(0)}/n_a \).
  - \( P_d(y) \) is the probability distribution of the observed labels for facet \( d \). For binary labeled data, this distribution is given by the number of samples in facet \( d \) labeled with positive outcomes to the total number, \( P_d(y^{(1)}) = n_d^{(1)}/n_d \), and the ratio of the number of samples with negative outcomes to the total number, \( P_d(y^{(0)}) = n_d^{(0)}/n_d \).

Models trained on data biased by demographic disparities might learn and even exacerbate them. To identify bias in the data before expending resources to train models on it, SageMaker Clarify provides data bias metrics that you can compute on raw datasets before training. All of the pretraining metrics are model-agnostic because they do not depend on model outputs and so are valid for any model. The first bias metric examines facet imbalance, but not outcomes. It determines the extent to which the amount of training data is representative across different facets, as desired for the application. The remaining bias metrics compare the distribution of outcome labels in various ways for facets \( a \) and \( d \) in the data. The metrics that range over negative values can detect negative bias. The following table contains a cheat sheet for quick guidance and links to the pretraining bias metrics.

### Pretraining Bias Metrics

<table>
<thead>
<tr>
<th>Bias metric</th>
<th>Description</th>
<th>Example question</th>
<th>Interpreting metric values</th>
</tr>
</thead>
</table>
| Class Imbalance (CI) (p. 805) | Measures the imbalance in the number of members between different facet values. | Could there be age-based biases due to not having enough data for the demographic outside a middle-aged facet? | Normalized range: \([-1, +1]\)  
Interpretation:  
- Positive values indicate the facet \( a \) has more training samples in the dataset.  
- Values near zero indicate the facets are balanced in the number of training samples in the dataset.  
- Negative values indicate the facet \( d \) has more training samples in the dataset. |
<table>
<thead>
<tr>
<th>Bias metric</th>
<th>Description</th>
<th>Example question</th>
<th>Interpreting metric values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Difference in Proportions of Labels (DPL) (p. 806)</td>
<td>Measures the imbalance of positive outcomes between different facet values.</td>
<td>Could there be age-based biases in ML predictions due to biased labeling of facet values in the data?</td>
<td>Range for normalized binary &amp; multicategory facet labels: [-1,+1] Range for continuous labels: (-∞, +∞) Interpretation: • Positive values indicate facet a has a higher proportion of positive outcomes. • Values near zero indicate a more equal proportion of positive outcomes between facets. • Negative values indicate facet d has a higher proportion of positive outcomes.</td>
</tr>
<tr>
<td>Kullback-Leibler Divergence (KL) (p. 806)</td>
<td>Measures how much the outcome distributions of different facets diverge from each other entropically.</td>
<td>How different are the distributions for loan application outcomes for different demographic groups?</td>
<td>Range for binary, multicategory, continuous: [0, +∞) Interpretation: • Values near zero indicate the labels are similarly distributed. • Positive values indicate the label distributions diverge, the more positive the larger the divergence.</td>
</tr>
<tr>
<td>Jensen-Shannon Divergence (JS) (p. 807)</td>
<td>Measures how much the outcome distributions of different facets diverge from each other entropically.</td>
<td>How different are the distributions for loan application outcomes for different demographic groups?</td>
<td>Range for binary, multicategory, continuous: [0, +∞) Interpretation: • Values near zero indicate the labels are similarly distributed. • Positive values indicate the label distributions diverge, the more positive the larger the divergence.</td>
</tr>
</tbody>
</table>
### Measure Pretraining Bias

<table>
<thead>
<tr>
<th>Bias metric</th>
<th>Description</th>
<th>Example question</th>
<th>Interpreting metric values</th>
</tr>
</thead>
</table>
| **L_p-norm (LP) (p. 807)** | Measures a p-norm difference between distinct demographic distributions of the outcomes associated with different facets in a dataset. | How different are the distributions for loan application outcomes for different demographics? | Range for binary, multicategory, continuous: [0, +∞)  
Interpretation:  
• Values near zero indicate the labels are similarly distributed.  
• Positive values indicate the label distributions diverge, the more positive the larger the divergence. |
| **Total Variation Distance (TVD) (p. 808)** | Measures half of the L_1-norm difference between distinct demographic distributions of the outcomes associated with different facets in a dataset. | How different are the distributions for loan application outcomes for different demographics? | Range for binary, multicategory, and continuous outcomes: [0, +∞)  
Interpretation:  
• Values near zero indicate the labels are similarly distributed.  
• Positive values indicate the label distributions diverge, the more positive the larger the divergence. |
| **Kolmogorov-Smirnov (KS) (p. 808)** | Measures maximum divergence between outcomes in distributions for different facets in a dataset. | Which college application outcomes manifest the greatest disparities by demographic group? | Range of KS values for binary, multicategory, and continuous outcomes: [0,1]  
Interpretation:  
• Values near zero indicate the labels were evenly distributed between facets in all outcome categories.  
• Values near one indicate the labels for one category were all in one facet, so very imbalanced.  
• Intermittent values indicate relative degrees of maximum label imbalance. |
### Bias metric

<table>
<thead>
<tr>
<th>Bias metric</th>
<th>Description</th>
<th>Example question</th>
<th>Interpreting metric values</th>
</tr>
</thead>
</table>
| **Conditional Demographic Disparity (CDD) (p. 809)** | Measures the disparity of outcomes between different facets as a whole, but also by subgroups. | Do some groups have a larger proportion of rejections for college admission outcomes than their proportion of acceptances? | Range of CDD: [-1, +1]  
• Positive values indicate outcomes where facet \(d\) is rejected more than accepted.  
• Near zero indicates no demographic disparity on average.  
• Negative values indicate outcomes where facet \(a\) is rejected more than accepted. |

For additional information about bias metrics, see *Fairness Measures for Machine Learning in Finance*.

**Topics**

- Class Imbalance (CI) (p. 805)
- Difference in Proportions of Labels (DPL) (p. 806)
- Kullback-Leibler Divergence (KL) (p. 806)
- Jensen-Shannon Divergence (JS) (p. 807)
- Lp-norm (LP) (p. 807)
- Total Variation Distance (TVD) (p. 808)
- Kolmogorov-Smirnov (KS) (p. 808)
- Conditional Demographic Disparity (CDD) (p. 809)

### Class Imbalance (CI)

Class imbalance (CI) bias occurs when a facet value \(d\) has fewer training samples when compared with another facet \(a\) in the dataset. This is because models preferentially fit the larger facets at the expense of the smaller facets and so can result in a higher training error for facet \(d\). Models are also at higher risk of overfitting the smaller data sets, which can cause a larger test error for facet \(d\). Consider the example where a machine learning model is trained primarily on data from middle-aged individuals (facet \(a\)), it might be less accurate when making predictions involving younger and older people (facet \(d\)).

The formula for the (normalized) facet imbalance measure:

\[
CI = \frac{(n_a - n_d)}{(n_a + n_d)}
\]

Where \(n_a\) is the number of members of facet \(a\) and \(n_d\) the number for facet \(d\). Its values range over the interval \([-1, 1]\).

- Positive CI values indicate the facet \(a\) has more training samples in the dataset and a value of 1 indicates the data only contains members of the facet \(a\).
- Values of CI near zero indicate a more equal distribution of members between facets and a value of zero indicates a perfectly equal partition between facets and represents a balanced distribution of samples in the training data.
• Negative CI values indicate the facet \( d \) has more training samples in the dataset and a value of -1 indicates the data only contains members of the facet \( d \).

• CI values near either of the extremes values of -1 or 1 are very imbalanced and are at a substantial risk of making biased predictions.

If a significant facet imbalance is found to exist among the facets, you might want to rebalance the sample before proceeding to train models on it.

**Difference in Proportions of Labels (DPL)**

The difference in proportions of labels (DPL) compares the proportion of observed outcomes with positive labels for facet \( d \) with the proportion of observed outcomes with positive labels of facet \( a \) in a training dataset. For example, you could use it to compare the proportion of middle-aged individuals (facet \( a \)) and other age groups (facet \( d \)) approved for financial loans. Machine learning models try to mimic the training data decisions as closely as possible. So a machine learning model trained on a dataset with a high DPL is likely to reflect the same imbalance in its future predictions.

The formula for the difference in proportions of labels is as follows:

\[
DPL = (q_a - q_d)
\]

Where:

• \( q_a = \frac{n_a^{(1)}}{n_a} \) is the proportion of facet \( a \) who have an observed label value of 1. For example, the proportion of a middle-aged demographic who get approved for loans. Here \( n_a^{(1)} \) represents the number of members of facet \( a \) who get a positive outcome and \( n_a \) the is number of members of facet \( a \).

• \( q_d = \frac{n_d^{(1)}}{n_d} \) is the proportion of facet \( d \) who have an observed label value of 1. For example, the proportion of people outside the middle-aged demographic who get approved for loans. Here \( n_d^{(1)} \) represents the number of members of the facet \( d \) who get a positive outcome and \( n_d \) the is number of members of the facet \( d \).

If DPL is close enough to 0, then we say that **demographic parity** has been achieved.

For binary and multiclass facet labels, the DPL values range over the interval (-1, 1). For continuous labels, we set a threshold to collapse the labels to binary.

• Positive DPL values indicate that facet \( a \) is has a higher proportion of positive outcomes when compared with facet \( d \).

• Values of DPL near zero indicate a more equal proportion of positive outcomes between facets and a value of zero indicates perfect demographic parity.

• Negative DPL values indicate that facet \( d \) has a higher proportion of positive outcomes when compared with facet \( a \).

Whether or not a high magnitude of DPL is problematic varies from one situation to another. In a problematic case, a high-magnitude DPL might be a signal of underlying issues in the data. For example, a dataset with high DPL might reflect historical biases or prejudices against age-based demographic groups that would be undesirable for a model to learn.

**Kullback-Leibler Divergence (KL)**

The Kullback-Leibler divergence (KL) measures how much the observed label distribution of facet \( a \), \( P_a(y) \), diverges from distribution of facet \( d \), \( P_d(y) \). It is also known as the relative entropy of \( P_a(y) \) with respect to \( P_d(y) \) and quantifies the amount of information lost when moving from \( P_a(y) \) to \( P_d(y) \).

The formula for the Kullback-Leibler divergence is as follows:
KL(P_a \| P_d) = \sum_y P_a(y) \cdot \log[P_a(y)/P_d(y)]

It is the expectation of the logarithmic difference between the probabilities $P_a(y)$ and $P_d(y)$, where the expectation is weighted by the probabilities $P_a(y)$. This is not a true distance between the distributions as it is asymmetric and does not satisfy the triangle inequality. The implementation uses natural logarithms, giving KL in units of nats. Using different logarithmic bases gives proportional results but in different units. For example, using base 2 gives KL in units of bits.

For example, assume that a group of applicants for loans have a 30% approval rate (facet $d$) and that the approval rate for other applicants (facet $a$) is 80%. The Kullback-Leibler formula gives you the label distribution divergence of facet $a$ from facet $d$ as follows:

$$KL = 0.8 \cdot \ln(0.8/0.3) + 0.2 \cdot \ln(0.2/0.7) = 0.53$$

There are two terms in the formula here because labels are binary in this example. This measure can be applied to multiple labels in addition to binary ones. For example, in a college admissions scenario, assume an applicant may be assigned one of three category labels: $y_i = \{y_0, y_1, y_2\} = \{\text{rejected}, \text{waitlisted}, \text{accepted}\}$.

Range of values for the KL metric for binary, multicategory, and continuous outcomes is $[0, +\infty)$.

- Values near zero mean the outcomes are similarly distributed for the different facets.
- Positive values mean the label distributions diverge, the more positive the larger the divergence.

### Jensen-Shannon Divergence (JS)

The Jensen-Shannon divergence (JS) measures how much the label distributions of different facets diverge from each other entropically. It is based on the Kullback-Leibler divergence, but it is symmetric.

The formula for the Jensen-Shannon divergence is as follows:

$$JS = \frac{1}{2} \cdot [KL(P_a \| P) + KL(P_d \| P)]$$

Where $P = \frac{1}{2} (P_a + P_d)$, the average label distribution across facets $a$ and $d$.

The range of JS values for binary, multicategory, continuous outcomes is $[0, \ln(2))$.

- Values near zero mean the labels are similarly distributed.
- Positive values mean the label distributions diverge, the more positive the larger the divergence.

This metric indicates whether there is a big divergence in one of the labels across facets.

### L_p-norm (LP)

The L_p-norm (LP) measures the p-norm distance between the facet distributions of the observed labels in a training dataset. This metric is non-negative and so cannot detect reverse bias.

The formula for the L_p-norm is as follows:

$$L_p(P_a, P_d) = (\sum ||P_a - P_d||^p)^{1/p}$$

Where the p-norm distance between the points $x$ and $y$ is defined as follows:

$$L_p(x, y) = (|x_1-y_1|^p + |x_2-y_2|^p + \ldots + |x_n-y_n|^p)^{1/p}$$

The 2-norm is the Euclidean norm. Assume you have an outcome distribution with three categories, for example, $y_i = \{y_0, y_1, y_2\} = \{\text{accepted}, \text{waitlisted}, \text{rejected}\}$ in a college admissions multicategory scenario. You take the sum of the squares of the differences between the outcome counts for facets $a$ and $d$. The resulting Euclidean distance is calculated as follows:
\[ L_2(P_a, P_d) = \left[ (n_a^{(0)} - n_d^{(0)})^2 + (n_a^{(1)} - n_d^{(1)})^2 + (n_a^{(2)} - n_d^{(2)})^2 \right]^{1/2} \]

Where:

- \( n_a^{(i)} \) is number of the \( i \)th category outcomes in facet \( a \): for example \( n_a^{(0)} \) is number of facet \( a \) acceptances.
- \( n_d^{(i)} \) is number of the \( i \)th category outcomes in facet \( d \): for example \( n_d^{(2)} \) is number of facet \( d \) rejections.

The range of LP values for binary, multicategory, and continuous outcomes is \([0, \sqrt{2})\), where:

- Values near zero mean the labels are similarly distributed.
- Positive values mean the label distributions diverge, the more positive the larger the divergence.

### Total Variation Distance (TVD)

The total variation distance data bias metric (TVD) is half the \( L_1 \)-norm. The TVD is the largest possible difference between the probability distributions for label outcomes of facets \( a \) and \( d \). The \( L_1 \)-norm is the Hamming distance, a metric used compare two binary data strings by determining the minimum number of substitutions required to change one string into another. If the strings were to be copies of each other, it determines the number of errors that occurred when copying. In the bias detection context, TVD quantifies how many outcomes in facet \( a \) would have to be changed to match the outcomes in facet \( d \).

The formula for the Total variation distance is as follows:

\[ \text{TVD} = \frac{1}{2} \cdot L_1(P_a, P_d) \]

For example, assume you have an outcome distribution with three categories, \( y_i = \{y_0, y_1, y_2\} = \{\text{accepted, waitlisted, rejected}\} \), in a college admissions multicategory scenario. You take the differences between the counts of facets \( a \) and \( d \) for each outcome to calculate TVD. The result is as follows:

\[ L_1(P_a, P_d) = |n_a^{(0)} - n_d^{(0)}| + |n_a^{(1)} - n_d^{(1)}| + |n_a^{(2)} - n_d^{(2)}| \]

Where:

- \( n_a^{(i)} \) is number of the \( i \)th category outcomes in facet \( a \): for example \( n_a^{(0)} \) is number of facet \( a \) acceptances.
- \( n_d^{(i)} \) is number of the \( i \)th category outcomes in facet \( d \): for example \( n_d^{(2)} \) is number of facet \( d \) rejections.

The range of TVD values for binary, multicategory, and continuous outcomes is \([0, 1)\), where:

- Values near zero mean the labels are similarly distributed.
- Positive values mean the label distributions diverge, the more positive the larger the divergence.

### Kolmogorov-Smirnov (KS)

The Kolmogorov-Smirnov bias metric (KS) is equal to the maximum divergence between labels in the distributions for facets \( a \) and \( d \) of a dataset. The two-sample KS test implemented by SageMaker Clarify complements the other measures of label imbalance by finding the most imbalanced label.

The formula for the Kolmogorov-Smirnov metric is as follows:

\[ KS = \max(|P_a(y) - P_d(y)|) \]

For example, assume a group of applicants (facet \( a \)) to college are rejected, waitlisted, or accepted at 40%, 40%, 20% respectively and that these rates for other applicants (facet \( d \)) are 20%, 10%, 70%. Then the Kolmogorov-Smirnov bias metric value is as follows:
KS = max(|0.4-0.2|, |0.4-0.1|, |0.2-0.7|) = 0.5

This tells us the maximum divergence between facet distributions is 0.5 and occurs in the acceptance rates. There are three terms in the equation because labels are multiclass of cardinality three.

The range of LP values for binary, multicategory, and continuous outcomes is \([0, +1]\), where:

- Values near zero indicate the labels were evenly distributed between facets in all outcome categories. For example, both facets applying for a loan got 50% of the acceptances and 50% of the rejections.
- Values near one indicate the labels for one outcome were all in one facet. For example, facet \(a\) got 100% of the acceptances and facet \(d\) got none.
- Intermittent values indicate relative degrees of maximum label imbalance.

### Conditional Demographic Disparity (CDD)

The demographic disparity metric (DD) determines whether a facet has a larger proportion of the rejected outcomes in the dataset than of the accepted outcomes. In the binary case where there are two facets, men and women for example, that constitute the dataset, the disfavored one is labelled facet \(d\) and the favored one is labelled facet \(a\). For example, in the case of college admissions, if women applicants comprised 46% of the rejected applicants and comprised only 32% of the accepted applicants, we say that there is demographic disparity because the rate at which women were rejected exceeds the rate at which they are accepted. Women applicants are labelled facet \(d\) in this case. If men applicants comprised 54% of the rejected applicants and 68% of the accepted applicants, then there is not a demographic disparity for this facet as the rate of rejection is less that the rate of acceptance. Men applicants are labelled facet \(a\) in this case.

The formula for the demographic disparity for the less favored facet \(d\) is as follows:

$$DD_d = \frac{n_d^{(0)}}{n^{(0)}} - \frac{n_d^{(1)}}{n^{(1)}} = P_d^R(y^0) - P_d^A(y^1)$$

Where:

- \(n^{(0)} = n_a^{(0)} + n_d^{(0)}\) is the total number of rejected outcomes in the dataset for the favored facet \(a\) and disadvantaged facet \(d\).
- \(n^{(1)} = n_a^{(1)} + n_d^{(1)}\) is the total number of accepted outcomes in the dataset for the favored facet \(a\) and disadvantaged facet \(d\).
- \(P_d^R(y^0)\) is the proportion of rejected outcomes (with value 0) in facet \(d\).
- \(P_d^A(y^1)\) is the proportion of accepted outcomes (value 1) in facet \(d\).

For the college admission example, the demographic disparity for women is \(DD_d = 0.46 - 0.32 = 0.14\). For men \(DD_a = 0.54 - 0.68 = -0.14\).

A conditional demographic disparity (CDD) metric that conditions DD on attributes that define a strata of subgroups on the dataset is needed to rule out Simpson's paradox. The regrouping can provide insights into the cause of apparent demographic disparities for less favored facets. The classic case arose in the case of Berkeley admissions where men were accepted at a higher rate overall than women. The statistics for this case were used in the example calculations of DD. However, when departmental subgroups were examined, women were shown to have higher admission rates than men when conditioned by department. The explanation was that women had applied to departments with lower acceptance rates than men had. Examining the subgrouped acceptance rates revealed that women were actually accepted at a higher rate than men for the departments with lower acceptance rates.

The CDD metric gives a single measure for all of the disparities found in the subgroups defined by an attribute of a dataset by averaging them. It is defined as the weighted average of demographic disparities (DD) for each of the subgroups, with each subgroup disparity weighted in proportion to the number of observations in contains. The formula for the conditional demographic disparity is as follows:
CDD = (1/n)\(\sum n_i \cdot DD_i\)

Where:
- \(\sum n_i = n\) is the total number of observations and \(n_i\) is the number of observations for each subgroup.
- \(DD_i = n_i^{(0)}/n^{(0)} - n_i^{(1)}/n^{(1)} = P_i^R(y^0) - P_i^A(y^1)\) is the demographic disparity for the \(i\)th subgroup.

The demographic disparity for a subgroup \((DD_i)\) are the difference between the proportion of rejected outcomes and the proportion of accepted outcomes for each subgroup.

The range of \(DD\) values for binary outcomes for the full dataset \(DD_d\) or for its conditionalized subgroups \(DD_i\) is \([-1, +1]\).

- +1: when there are no rejections in facet \(a\) or subgroup and no acceptances in facet \(d\) or subgroup
- Positive values indicate there is a demographic disparity as facet \(d\) or subgroup has a greater proportion of the rejected outcomes in the dataset than of the accepted outcomes. The higher the value the less favored the facet and the greater the disparity.
- Negative values indicate there is not a demographic disparity as facet \(d\) or subgroup has a larger proportion of the accepted outcomes in the dataset than of the rejected outcomes. The lower the value the more favored the facet.
- -1: when there are no rejections in facet \(d\) or subgroup and no acceptances in facet \(a\) or subgroup

If you don’t condition on anything then CDD is zero if and only if DPL is zero.

This metric is useful for exploring the concepts of direct and indirect discrimination and of objective justification in EU and UK non-discrimination law and jurisprudence. For additional information, see Why Fairness Cannot Be Automated. This paper also contains the relevant data and analysis of the Berkeley admissions case that shows how conditionalizing on departmental admission rate subgroups illustrates Simpson’s paradox.

**Generate Reports for Bias in Pretraining Data in SageMaker Studio**

SageMaker Clarify is integrated with Amazon SageMaker Data Wrangler, which can help you identify bias during data preparation without having to write your own code. Data Wrangler provides an end-to-end solution to import, prepare, transform, featurize, and analyze data with Amazon SageMaker Studio. For an overview of the Data Wrangler data prep workflow, see Prepare ML Data with Amazon SageMaker Data Wrangler (p. 815). You specify attributes of interest, such as gender or age, and SageMaker Clarify runs a set of algorithms to detect the presence of bias in those attributes. After the algorithm runs, SageMaker Clarify provides a visual report with a description of the sources and severity of possible bias so that you can plan steps to mitigate. For example, in a financial dataset that contains few examples of business loans to one age group as compared to others, SageMaker flags the imbalance so that you can avoid a model that disfavors that age group.

**To analyze and report on data bias**

To get started with Data Wrangler, see Get Started with Data Wrangler (p. 817).

1. Open Amazon SageMaker Studio and choose Create Data Flow from the Import and prepare your data tile.
2. From the Import data tab, choose Amazon S3 and then specify your data source on the Data sources/S3 source page.

3. After you have imported your data, choose the plus sign on the Data flow page and then choose Add Analysis.
4. On the Create Analysis page, go to the Configure panel and then choose Bias Report from the Chart menu.

5. Configure the bias report by providing the Name, the column to predict and whether it is a value or threshold, the column to analyze for bias (the facet) and whether it is a value or threshold.
6. Continue configuring the bias report by choosing the bias metrics.
7. Choose **Check for bias** to generate and view the bias report. Scroll down to view all of the reports.

8. Choose the caret to the right of the bias metric description to see documentation that can help you interpret the significance of the metric values.

9. To view a table summary of the bias metric values, choose the table. You can save the report for export by choosing **Create** in the lower-right corner of the page.
10. On the page where your data bias reports are stored, choose the Export tab to download the reports.

Prepare ML Data with Amazon SageMaker Data Wrangler

Amazon SageMaker Data Wrangler (Data Wrangler) is a feature of Amazon SageMaker Studio that provides an end-to-end solution to import, prepare, transform, featurize, and analyze data. You can integrate a Data Wrangler data preparation flow into your machine learning (ML) workflows to simplify and streamline data pre-processing and feature engineering using little to no coding. You can also add your own Python scripts and transformations to customize workflows.
Data Wrangler provides the following core functionalities to help you analyze and prepare data for machine learning applications.

- **Import** – Connect to and import data from Amazon Simple Storage Service (Amazon S3), Amazon Athena (Athena), Amazon Redshift, Snowflake, and Databricks.
- **Data Flow** – Create a data flow to define a series of ML data prep steps. You can use a flow to combine datasets from different data sources, identify the number and types of transformations you want to apply to datasets, and define a data prep workflow that can be integrated into an ML pipeline.
- **Transform** – Clean and transform your dataset using standard transforms like string, vector, and numeric data formatting tools. Featurize your data using transforms like text and date/time embedding and categorical encoding.
- **Generate Data Insights** – Automatically verify data quality and detect abnormalities in your data with Data Wrangler Data Insights and Quality Report.
- **Analyze** – Analyze features in your dataset at any point in your flow. Data Wrangler includes built-in data visualization tools like scatter plots and histograms, as well as data analysis tools like target leakage analysis and quick modeling to understand feature correlation.
- **Export** – Export your data preparation workflow to a different location. The following are example locations:
  - Amazon Simple Storage Service (Amazon S3) bucket
  - Amazon SageMaker Model Building Pipelines – Use SageMaker Pipelines to automate model deployment. You can export the data that you’ve transformed directly to the pipelines.
  - Amazon SageMaker Feature Store – Store the features and their data in a centralized store.
  - Python script – Store the data and their transformations in a Python script for your custom workflows.

To start using Data Wrangler, see [Get Started with Data Wrangler](#) (p. 817).

**Important**
Data Wrangler no longer supports Jupyter Lab Version 1 (JL1). To access the latest features and updates, update to Jupyter Lab Version 3. For more information about upgrading, see [View and update the JupyterLab version of an app from the console](#) (p. 125).

**Topics**
- [Get Started with Data Wrangler](#) (p. 817)
- [Import](#) (p. 827)
- [Create and Use a Data Wrangler Flow](#) (p. 864)
- [Get Insights On Data and Data Quality](#) (p. 875)
- [Automatically Train Models on Your Data Flow](#) (p. 888)
- [Transform Data](#) (p. 889)
- [Analyze and Visualize](#) (p. 930)
- [Reusing Data Flows for Different Datasets](#) (p. 938)
- [Export](#) (p. 945)
- [Security and Permissions](#) (p. 966)
- [Release Notes](#) (p. 974)
- [Troubleshoot](#) (p. 978)
- [Increase Amazon EC2 Instance Limit](#) (p. 980)
- [Update Data Wrangler](#) (p. 820)
- [Shut Down Data Wrangler](#) (p. 982)
Get Started with Data Wrangler

Amazon SageMaker Data Wrangler is a feature in Amazon SageMaker Studio. Use this section to learn how to access and get started using Data Wrangler. Do the following:

1. Complete each step in Prerequisites (p. 817).
2. Follow the procedure in Access Data Wrangler (p. 817) to start using Data Wrangler.

Prerequisites

To use Data Wrangler, you must complete the following prerequisites.

1. To use Data Wrangler, you need access to an Amazon Elastic Compute Cloud (Amazon EC2) instance. For more information about the Amazon EC2 instances that you can use, see Instances (p. 864). To learn how to view your quotas and, if necessary, request a quota increase, see AWS service quotas.
2. Configure the required permissions described in Security and Permissions (p. 966).

To use Data Wrangler, you need an active Studio instance. To learn how to launch a new instance, see Onboard to Amazon SageMaker Domain (p. 35). When your Studio instance is Ready, use the instructions in Access Data Wrangler (p. 817).

Access Data Wrangler

The following procedure assumes you have completed the Prerequisites (p. 817).

To access Data Wrangler in Studio:

1. Next to the user you want to use to launch Studio, select Open Studio.
2. When Studio opens, select the + sign on the New data flow card under ML tasks and components. This creates a new directory in Studio with a .flow file inside, which contains your data flow. The .flow file automatically opens in Studio.

You can also create a new flow by selecting File, then New, and choosing Data Wrangler Flow in the top navigation bar.
3. (Optional) Rename the new directory and the .flow file.

4. When you create a new .flow file in Studio, you might see a carousel that introduces you to Data Wrangler.

   This may take a few minutes.

   This messaging persists as long as the KernelGateway app on your User Details page is Pending. To see the status of this app, in the SageMaker console on the Amazon SageMaker Studio page, select the name of the user you are using to access Studio. On the User Details page, you see a KernelGateway app under Apps. Wait until this app status is Ready to start using Data Wrangler. This can take around 5 minutes the first time you launch Data Wrangler.
5. To get started, choose a data source and use it to import a dataset. See Import (p. 827) to learn more.

When you import a dataset, it appears in your data flow. To learn more, see Create and Use a Data Wrangler Flow (p. 864).

6. After you import a dataset, Data Wrangler automatically infers the type of data in each column. Choose + next to the Data types step and select Edit data types.

   **Important**
   After you add transforms to the Data types step, you cannot bulk-update column types using Update types.

7. Use the data flow to add transforms and analyses. To learn more see Transform Data (p. 889) and Analyze and Visualize (p. 930).

8. To export a complete data flow, choose Export and choose an export option. To learn more, see Export (p. 945).

9. Finally, choose the Components and registries icon, and select Data Wrangler from the dropdown list to see all the .flow files that you’ve created. You can use this menu to find and move between data flows.
After you have launched Data Wrangler, you can use the following section to walk through how you might use Data Wrangler to create an ML data prep flow.

**Update Data Wrangler**

We recommend that you periodically update the Data Wrangler Studio app to access the latest features and updates. The Data Wrangler app name starts with `sagemaker-data-wrang`. To learn how to update a Studio app, see [Shut down and Update Studio Apps](p. 180).

**Demo: Data Wrangler Titanic Dataset Walkthrough**

The following sections provide a walkthrough to help you get started using Data Wrangler. This walkthrough assumes that you have already followed the steps in [Access Data Wrangler](p. 817) and have a new data flow file open that you intend to use for the demo. You may want to rename this .flow file to something similar to `titanic-demo.flow`.

This walkthrough uses the Titanic dataset. It's a modified version of the Titanic dataset that you can import into your Data Wrangler flow more easily. This data set contains the survival status, age, gender, and class (which serves as a proxy for economic status) of passengers aboard the maiden voyage of the RMS Titanic in 1912.

In this tutorial, you perform the following steps.

1. Do one of the following:
   - Open your Data Wrangler flow and choose **Use Sample Dataset**.
   - Upload the Titanic dataset to Amazon Simple Storage Service (Amazon S3), and then import this dataset into Data Wrangler.
2. Analyze this dataset using Data Wrangler analyses.
3. Define a data flow using Data Wrangler data transforms.
4. Export your flow to a Jupyter Notebook that you can use to create a Data Wrangler job.
5. Process your data, and kick off a SageMaker training job to train a XGBoost Binary Classifier.

**Upload Dataset to S3 and Import**

To get started, you can use one of the following methods to import the Titanic dataset into Data Wrangler:

- Importing the dataset directly from the Data Wrangler flow
- Uploading the dataset to Amazon S3 and then importing it into Data Wrangler

To import the dataset directly into Data Wrangler, open the flow and choose **Use Sample Dataset**.

Uploading the dataset to Amazon S3 and importing it into Data Wrangler is closer to the experience you have importing your own data. The following information tells you how to upload your dataset and import it.

Before you start importing the data into Data Wrangler, download the Titanic dataset and upload it to an Amazon S3 (Amazon S3) bucket in the AWS Region in which you want to complete this demo.

If you are a new user of Amazon S3, you can do this using drag and drop in the Amazon S3 console. To learn how, see [Uploading Files and Folders by Using Drag and Drop](in the Amazon Simple Storage Service User Guide).

**Important**

Upload your dataset to an S3 bucket in the same AWS Region you want to use to complete this demo.
When your dataset has been successfully uploaded to Amazon S3, it you can import it into Data Wrangler.

**Import the Titanic dataset to Data Wrangler**

1. Select the **Import** tab in your Data Wrangler flow file.
2. Select **Amazon S3**.
3. Use the **Import a dataset from S3** table to find the bucket to which you added the Titanic dataset. Choose the Titanic dataset CSV file to open the **Details** pane.
4. Under **Details**, the **File type** should be CSV. Choose **Add header to table** to specify that the first row of the dataset is a header. You can also name the dataset something more friendly, such as **Titanic-train**.
5. Select **Import dataset**.

When your dataset is imported into Data Wrangler, it appears in your data flow. You can view your data flow at any time by selecting the **Data Flow** tab. You can double click on a node to enter the node detail view, which allows you to add transformations or analysis; otherwise, you can use the plus icon to navigate for a quick navigation. In the next section, you use this data flow to add analysis and transform steps.

**Data Flow**

In the data flow section, the only steps in the data flow are your recently imported dataset and a **Data type** step. After applying transformations, you can come back to this tab see what the data flow looks like. Now, add some basic transformations under the **Prepare** and **Analyze** tabs.

**Prepare and Visualize**

Data Wrangler has built-in transformations and visualizations that you can use to analyze, clean, and transform your data.

The **Data** tab of the node detail view lists all built-in transformations in the right panel, which also contains an area in which you can add custom transformations. The following use case showcases how to use these transformations.

To get information that might help you with data exploration and feature engineering, create a data quality and insights report. The information from the report can help you clean and process your data.
It gives you information such as the number of missing values and the number of outliers. If you have issues with your data, such as target leakage or imbalance, the insights report can bring those issues to your attention. For more information about creating a report, see Get Insights On Data and Data Quality (p. 875).

Data Exploration

First, create a table summary of the data using an analysis. Do the following:

1. Choose the + next to the Data type step in your data flow and select Add analysis.
2. In the Analysis area, select Table summary from the dropdown list.
3. Give the table summary a Name.
4. Select Preview to preview the table that will be created.
5. Choose Create to save it to your data flow. It appears under All Analyses.

Using the statistics you see, you can make observations similar to the following about this dataset:

• Fare average (mean) is around $33, while the max is over $500. This column likely has outliers.
• This dataset uses ? to indicate missing values. A number of columns have missing values: cabin, embarked, and home.dest
• The age category is missing over 250 values.

Choose Prepare to go back to the data flow. Next, clean your data using the insights gained from these stats.

Drop Unused Columns

Using the analysis from the previous section, clean up the dataset to prepare it for training. To add a new transform to your data flow, choose + next to the Data type step in your data flow and choose Add transform.

First, drop columns that you don't want to use for training. You can use pandas data analysis library to do this, or you can use one of the built-in transforms.

Use the following procedure to drop the unused columns.

To drop the unused columns, do the following.

1. Open the Data Wrangler flow.
2. There are two nodes in your Data Wrangler flow. For the node on the right, choose the +.
3. Choose Add transform.
4. Choose Manage columns.
5. Under Transform, make sure Drop column is selected.
6. Under Columns to drop, specify the following column names:

   • cabin
   • ticket
   • name
   • sibsp
   • parch
   • home.dest
   • boat
7. Choose **Preview**.
8. Choose **Add**.

To do this using pandas, follow these steps.

1. In the **Custom Transform** section, select **Python (Pandas)** from the dropdown list.
2. Enter the following in the code box.
   ```python
   cols = ['name', 'ticket', 'cabin', 'sibsp', 'parch', 'home.dest', 'boat', 'body']
   df = df.drop(cols, axis=1)
   ```
3. Choose **Preview** to preview the change and then choose **Add** to add the transformation.

To use the built-in transformations, do the following:

1. Choose **Manage columns** from the right panel.
2. For **Input column**, choose **cabin**, and choose **Preview**.
3. Verify that the **cabin** column has been dropped, then choose **Add**.
4. Repeat these steps for the following columns: **ticket**, **name**, **sibsp**, **parch**, **home.dest**, **boat**, and **body**.

**Clean up Missing Values**

Now, clean up missing values. You can do this with the **Handling missing values** transform group.

A number of columns have missing values. Of the remaining columns, **age** and **fare** contain missing values. Inspect this using the **Custom Transform**.

Using the **Python (Pandas)** option, use the following to quickly review the number of entries in each column:

```python
df.info()
```
To drop rows with missing values in the *age* category, do the following:

1. Choose **Handling missing values**.
2. Choose **Drop missing** for the **Transformer**.
3. Choose **Drop Rows** for the **Dimension**.
4. Choose **age** for the **Input column**.
5. Choose **Preview** to see the new data frame, and then choose **Add** to add the transform to your flow.
6. Repeat the same process for **fare**.

You can use `df.info()` in the **Custom transform** section to confirm that all rows now have 1,045 values.

---

**Custom Pandas: Encode**

Try flat encoding using Pandas. Encoding categorical data is the process of creating a numerical representation for categories. For example, if your categories are *Dog* and *Cat*, you may encode this information into two vectors: `[1, 0]` to represent *Dog*, and `[0, 1]` to represent *Cat*.

1. In the **Custom Transform** section, choose **Python (Pandas)** from the dropdown list.
2. Enter the following in the code box:
import pandas as pd

dummies = []
cols = ['pclass', 'sex', 'embarked']
for col in cols:
    dummies.append(pd.get_dummies(df[col]))

encoded = pd.concat(dummies, axis=1)
df = pd.concat((df, encoded), axis=1)

3. Choose Preview to preview the change. The encoded version of each column is added to the dataset.
4. Choose Add to add the transformation.

**Custom SQL: SELECT Columns**

Now, select the columns you want to keep using SQL. For this demo, select the columns listed in the following SELECT statement. Because survived is your target column for training, put that column first.

1. In the Custom Transform section, select SQL (PySpark SQL) from the dropdown list.
2. Enter the following in the code box.

   ```sql
   SELECT survived, age, fare, 1, 2, 3, female, male, C, Q, S FROM df;
   ```

3. Choose Preview to preview the change. The columns listed in your SELECT statement are the only remaining columns.
4. Choose Add to add the transformation.

**Export to a Data Wrangler Notebook**

When you've finished creating a data flow, you have a number of export options. The following section explains how to export to a Data Wrangler job notebook. A Data Wrangler job is used to process your data using the steps defined in your data flow. To learn more about all export options, see Export (p. 945).

**Export to Data Wrangler Job Notebook**

When you export your data flow using a Data Wrangler job, the process automatically creates a Jupyter Notebook. This notebook automatically opens in your Studio instance and is configured to run a SageMaker processing job to run your Data Wrangler data flow, which is referred to as a Data Wrangler job.

1. Save your data flow. Select File and then select Save Data Wrangler Flow.
2. Choose the Export tab.
3. Select the last step in your data flow.

   ![Image of data flow]

4. Choose Data Wrangler Job. This opens a Jupyter Notebook.
5. Choose any Python 3 (Data Science) kernel for the Kernel.
6. When the kernel starts, run the cells in the notebook book until Kick off SageMaker Training Job (Optional).
7. Optionally, you can run the cells in **Kick off SageMaker Training Job (Optional)** if you want to create a SageMaker training job to train an XGBoost classifier. You can find the cost to run an SageMaker training job in [Amazon SageMaker Pricing](https://aws.amazon.com/sagemaker/pricing/).

Alternatively, you can add the code blocks found in Training XGBoost Classifier (p. 826) to the notebook and run them to use the [XGBoost](https://xgboost.readthedocs.io/en/latest/) open source library to train an XGBoost classifier.

8. Uncomment and run the cell under **Cleanup** and run it to revert the SageMaker Python SDK to its original version.

You can monitor your Data Wrangler job status in the SageMaker console in the **Processing** tab. Additionally, you can monitor your Data Wrangler job using Amazon CloudWatch. For additional information, see [Monitor Amazon SageMaker Processing Jobs with CloudWatch Logs and Metrics](https://docs.aws.amazon.com/sagemaker/latest/dg/monitor-processing-jobs-log-metrics.html).

If you kicked off a training job, you can monitor its status using the SageMaker console under **Training jobs** in the Training section.

**Training XGBoost Classifier**

You can train an XGBoost Binary Classifier using either a Jupyter notebook or a Amazon SageMaker Autopilot. You can use Autopilot to automatically train and tune models on the data that you’ve transformed directly from your Data Wrangler flow. For information about Autopilot, see [Automatically Train Models on Your Data Flow](https://docs.aws.amazon.com/sagemaker/latest/dg/automate-data-flow.html) (p. 888).

In the same notebook that kicked off the Data Wrangler job, you can pull the data and train an XGBoost Binary Classifier using the prepared data with minimal data preparation.

1. First, upgrade necessary modules using `pip` and remove the `_SUCCESS` file (this last file is problematic when using `awswrangler`).

   ```bash
   ! pip install --upgrade awscli awswrangler boto sklearn
   ! aws s3 rm {output_path} --recursive --exclude "*" --include "*_SUCCESS*"
   ```

2. Read the data from Amazon S3. You can use `awswrangler` to recursively read all the CSV files in the S3 prefix. The data is then split into features and labels. The label is the first column of the dataframe.

   ```python
   import awswrangler as wr
   df = wr.s3.read_csv(path=output_path, dataset=True)
   X, y = df.iloc[:,:-1], df.iloc[:,-1]
   ```

   - Finally, create DMatrices (the XGBoost primitive structure for data) and do cross-validation using the XGBoost binary classification.

   ```python
   import xgboost as xgb
   dmatrix = xgb.DMatrix(data=X, label=y)
   params = {'objective':"binary:logistic",'learning_rate': 0.1, 'max_depth': 5, 'alpha': 10}
   xgb.cv(
       dtrain=dmatrix,
       params=params,
       nfold=3,
       num_boost_round=50,
       early_stopping_rounds=10,
       metrics="rmse",
       as_pandas=True,
   )
   ```
Shut down Data Wrangler

When you are finished using Data Wrangler, we recommend that you shut down the instance it runs on to avoid incurring additional charges. To learn how to shut down the Data Wrangler app and associated instance, see Shut Down Data Wrangler (p. 982).

Import

You can use Amazon SageMaker Data Wrangler to import data from the following data sources: Amazon Simple Storage Service (Amazon S3), Amazon Athena, Amazon Redshift, and Snowflake. The dataset that you import can include up to 1000 columns.

Topics

- Import data from Amazon S3 (p. 827)
- Import data from Athena (p. 832)
- Import data from Amazon Redshift (p. 835)
- Import data from Databricks (JDBC) (p. 839)
- Import data from Snowflake (p. 841)
- Imported Data Storage (p. 863)

Some data sources allow you to add multiple data connections:

- You can connect to multiple Amazon Redshift clusters. Each cluster becomes a data source.
- You can query any Athena database in your account to import data from that database.

When you import a dataset from a data source, it appears in your data flow. Data Wrangler automatically infers the data type of each column in your dataset. To modify these types, select the Data types step and select Edit data types.

When you import data from Athena or Amazon Redshift, the imported data is automatically stored in the default SageMaker S3 bucket for the AWS Region in which you are using Studio. Additionally, Athena stores data you preview in Data Wrangler in this bucket. To learn more, see Imported Data Storage (p. 863).

Important

The default Amazon S3 bucket may not have the least permissive security settings, such as bucket policy and server-side encryption (SSE). We strongly recommend that you Add a Bucket Policy To Restrict Access to Datasets Imported to Data Wrangler.

Important

In addition, if you use the managed policy for SageMaker, we strongly recommend that you scope it down to the most restrictive policy that allows you to perform your use case. For more information, see Grant an IAM Role Permission to Use Data Wrangler (p. 967).

Import data from Amazon S3

You can use Amazon Simple Storage Service (Amazon S3) to store and retrieve any amount of data, at any time, from anywhere on the web. You can accomplish these tasks using the AWS Management Console, which is a simple and intuitive web interface, and the Amazon S3 API. If you've stored your
dataset locally, we recommend that you add it to an S3 bucket for import into Data Wrangler. To learn how, see Uploading an object to a bucket in the Amazon Simple Storage Service User Guide.

Data Wrangler uses S3 Select to allow you to preview your Amazon S3 files in Data Wrangler. You incur standard charges for each file preview. To learn more about pricing, see the Requests & data retrievals tab on Amazon S3 pricing.

**Important**
If you plan to export a data flow and launch a Data Wrangler job, ingest data into a SageMaker feature store, or create a SageMaker pipeline, be aware that these integrations require Amazon S3 input data to be located in the same AWS region.

**Important**
If you're importing a CSV file, make sure it meets the following requirements:

- A record in your dataset can't be longer than one line.
- A backslash, \, is the only valid escape character.
- Your dataset must use one of the following delimiters:
  - Comma – ,
  - Colon – :
  - Semicolon – ;
  - Pipe – |  
  - Tab – [TAB]

To save space, you can import compressed CSV files.

Data Wrangler gives you the ability to either import the entire dataset or sample a portion of it. For Amazon S3, it provides the following sampling options:

- None – Import the entire dataset.
- First K – Sample the first K rows of the dataset, where K is an integer that you specify.
- Randomized – Takes a random sample of a size that you specify.
- Stratified – Takes a stratified random sample. A stratified sample preserves the ratio of values in a column.

After you've imported your data, you can also use the sampling transformer to take one or more samples from your entire dataset. For more information about the sampling transformer, see Sampling (p. 923).

You can import either a single file or multiple files as a dataset. You can use the multifile import operation when you have a dataset that is partitioned into separate files. It takes all of the files from an Amazon S3 directory and imports them as a single dataset. For information on the types of files that you can import and how to import them, see the following sections.

**Single File Import**

You can import single files in the following formats:

- Comma Separated Values (CSV)
- Parquet
- Javascript Object Notation (JSON)
- Optimized Row Columnar (ORC)

For files formatted in JSON, Data Wrangler supports both JSON lines (.jsonl) and JSON documents (.json). When you preview your data, it automatically shows the JSON in tabular format. For nested
JSON documents that are larger than 5 MB, Data Wrangler shows the schema for the structure and the arrays as values in the dataset. Use the Flatten structured and Explode array operators to display the nested values in tabular format. For more information, see Unnest JSON Data (p. 928) and Explode Array (p. 929).

When you choose a dataset, you can rename it, specify the file type, and identify the first row as a header.

You can import a dataset that you've partitioned into multiple files in an Amazon S3 bucket in a single import step.

To import a dataset into Data Wrangler from a single file that you've stored in Amazon S3:

1. If you are not currently on the Import tab, choose Import.
2. Under Data Preparation, choose Amazon S3 to see the Import S3 Data Source view.
3. From the table of available S3 buckets, select a bucket and navigate to the dataset you want to import.
4. Select the file that you want to import. If your dataset does not have a .csv or .parquet extension, select the data type from the File Type dropdown list.
5. If your CSV file has a header, select the checkbox next to Add header to table.
6. Use the Preview table to preview your dataset. This table shows up to 100 rows.
7. In the Details pane, verify or change the Name and File Type for your dataset. If you add a Name that contains spaces, these spaces are replaced with underscores when your dataset is imported.
8. Specify the sampling configuration that you'd like to use.
9. Choose Import dataset.
Multifile Import

The following are the requirements for importing multiple files:

- The files must be in the same folder of your Amazon S3 bucket.
- The files must either share the same header or have no header.

Each file must be in one of the following formats:

- CSV
- Parquet
- Optimized Row Columnar (ORC)
- JSON

Use the following procedure to import multiple files.

**To import a dataset into Data Wrangler from multiple files that you've stored in an Amazon S3 directory**

1. If you are not currently on the Import tab, choose Import.
2. Under Data Preparation, choose Amazon S3 to see the Import S3 Data Source view.
3. From the table of available S3 buckets, select the bucket containing the folder that you want to import.

4. Select the folder containing the files that you want to import. Each file must be in one of the supported formats. Your files must be the same data type.

5. If your folder contains CSV files with headers, select the checkbox next to **First row is header**.

6. If your files are nested within other folders, select the checkbox next to **Include nested directories**.

7. (Optional) Choose **Add filename column** add a column to the dataset that shows the filename for each observation.

8. (Optional) By default, Data Wrangler doesn't show you a preview of a folder. You can activate previewing by choosing the blue **Preview off** button. A preview shows the first 10 rows of the first 10 files in the folder. The following images show you how to activate a preview for a dataset created from nested directories.
9. In the Details pane, verify or change the Name and File Type for your dataset. If you add a Name that contains spaces, these spaces are replaced with underscores when your dataset is imported.

10. Specify the sampling configuration that you'd like to use.

11. Choose Import dataset.

Import data from Athena

Use Amazon Athena to import your data from Amazon Simple Storage Service (Amazon S3) into Data Wrangler. In Athena, you write standard SQL queries to select the data that you're importing from Amazon S3. For more information, see What is Amazon Athena?

You can use the AWS Management Console to set up Amazon Athena. You must create at least one database in Athena before you start running queries. For more information about getting started with Athena, see Getting started.

Athena is directly integrated with Data Wrangler. You can write Athena queries without having to leave the Data Wrangler UI.

In addition to writing simple Athena queries in Data Wrangler, you can also use:

- Athena workgroups for query result management. For more information about workgroups, see Managing query results (p. 834).
- Lifecycle configurations for setting data retention periods. For more information about data retention, see Setting data retention periods (p. 834).

Query Athena within Data Wrangler

Note
Data Wrangler does not support federated queries.
If you use AWS Lake Formation with Athena, make sure your Lake Formation IAM permissions do not override IAM permissions for the database sagemaker_data_wrangler.

Data Wrangler gives you the ability to either import the entire dataset or sample a portion of it. For Athena, it provides the following sampling options:

- None – Import the entire dataset.
- First K – Sample the first K rows of the dataset, where K is an integer that you specify.
- Randomized – Takes a random sample of a size that you specify.
- Stratified – Takes a stratified random sample. A stratified sample preserves the ratio of values in a column.

The following procedure shows how to import a dataset from Athena into Data Wrangler.

To import a dataset into Data Wrangler from Athena

1. On the Import data screen, choose Amazon Athena.
2. For Data Catalog, choose a data catalog.
3. Use the Database dropdown list to select the database that you want to query. When you select a database, you can preview all tables in your database using the Tables listed under Details.
4. (Optional) Choose Advanced configuration.
   a. Choose a Workgroup.
   b. If your workgroup hasn't enforced the Amazon S3 output location or if you don't use a workgroup, specify a value for Amazon S3 location of query results.
   c. (Optional) For Data retention period, select the checkbox to set a data retention period and specify the number of days to store the data before it's deleted.
   d. (Optional) By default, Data Wrangler saves the connection. You can choose to deselect the checkbox and not save the connection.
5. For Sampling, choose a sampling method. Choose None to turn off sampling.
6. Enter your query in the query editor and use the Run button to run the query. After a successful query, you can preview your result under the editor.

   Note
   Salesforce data uses the timestamptz type. If you're querying the timestamp column that you've imported to Athena from Salesforce, cast the data in the column to the timestamp type. The following query casts the timestamp column to the correct type.

   ```sql
   # cast column timestamptz_col as timestamp type, and name it as timestamp_col
   select cast(timestamptz_col as timestamp) as timestamp_col from table
   ```

7. To import the results of your query, select Import.

After you complete the preceding procedure, the dataset that you've queried and imported appears in the Data Wrangler flow.

By default, Data Wrangler saves the connection settings as a new connection. When you import your data, the query that you've already specified appears as a new connection. The saved connections store information about the Athena workgroups and Amazon S3 buckets that you're using. When you're connecting to the data source again, you can choose the saved connection.
Managing query results

Data Wrangler supports using Athena workgroups to manage the query results within an AWS account. You can specify an Amazon S3 output location for each workgroup. You can also specify whether the output of the query can go to different Amazon S3 locations. For more information, see Using Workgroups to Control Query Access and Costs.

Your workgroup might be configured to enforce the Amazon S3 query output location. You can't change the output location of the query results for those workgroups.

If you don't use a workgroup or specify an output location for your queries, Data Wrangler uses the default Amazon S3 bucket in the same AWS Region in which your Studio instance is located to store Athena query results. It creates temporary tables in this database to move the query output to this Amazon S3 bucket. It deletes these tables after data has been imported; however the database, sagemaker_data_wrangler, persists. To learn more, see Imported Data Storage (p. 863).

To use Athena workgroups, set up the IAM policy that gives access to workgroups. If you're using a SageMaker-Execution-Role, we recommend adding the policy to the role. For more information about IAM policies for workgroups, see IAM policies for accessing workgroups. For example workgroup policies, see Workgroup example policies.

Setting data retention periods

Data Wrangler automatically sets a data retention period for the query results. The results are deleted after the length of the retention period. For example, the default retention period is five days. The results of the query are deleted after five days. This configuration is designed to help you clean up data that you're no longer using. Cleaning up your data prevents unauthorized users from gaining access. It also helps control the costs of storing your data on Amazon S3.

If you don't set a retention period, the Amazon S3 lifecycle configuration determines the duration that the objects are stored. The data retention policy that you've specified for the lifecycle configuration removes any query results that are older than the Lifecycle configuration that you've specified. For more information, see Setting lifecycle configuration on a bucket.

Data Wrangler uses S3 lifecycle configurations to manage data retention and expiration. You must give your Amazon SageMaker Studio IAM execution role permissions to manage bucket lifecycle configurations. Use the following procedure to give permissions.

To give permissions to manage the lifecycle configuration do the following.

1. Sign in to the AWS Management Console and open the IAM console at https://console.aws.amazon.com/iam/.
2. Choose Roles.
3. In the search bar, specify the Amazon SageMaker execution role that Amazon SageMaker Studio is using.
4. Choose the role.
5. Choose Add permissions.
6. Choose Create inline policy.
7. For Service, specify S3 and choose it.
8. Under the Read section, choose GetLifecycleConfiguration.
9. Under the Write section, choose PutLifecycleConfiguration.
10. For Resources, choose Specific.
11. For Actions, select the arrow icon next to Permissions management.
13. For Resources, choose Specific.
14. Choose the checkbox next to Any in this account.
15. Choose Review policy.
16. For Name, specify a name.
17. Choose Create policy.

Import data from Amazon Redshift

Amazon Redshift is a fully managed, petabyte-scale data warehouse service in the cloud. The first step to create a data warehouse is to launch a set of nodes, called an Amazon Redshift cluster. After you provision your cluster, you can upload your dataset and then perform data analysis queries.

You can connect to and query one or more Amazon Redshift clusters in Data Wrangler. To use this import option, you must create at least one cluster in Amazon Redshift. To learn how, see Getting started with Amazon Redshift.

You can output the results of your Amazon Redshift query in one of the following locations:

- The default Amazon S3 bucket
- An Amazon S3 output location that you specify

You can either import the entire dataset or sample a portion of it. For Amazon Redshift, it provides the following sampling options:

- None – Import the entire dataset.
- First K – Sample the first K rows of the dataset, where K is an integer that you specify.
- Randomized – Takes a random sample of a size that you specify.
- Stratified – Takes a stratified random sample. A stratified sample preserves the ratio of values in a column.

The default Amazon S3 bucket is in the same AWS Region in which your Studio instance is located to store Amazon Redshift query results. For more information, see Imported Data Storage (p. 863).

For either the default Amazon S3 bucket or the bucket that you specify, you have the following encryption options:

- The default AWS service-side encryption with an Amazon S3 managed key (SSE-S3)
- An AWS Key Management Service (AWS KMS) key that you specify

An AWS KMS key is an encryption key that you create and manage. For more information on KMS keys, see AWS Key Management Service.

You can specify an AWS KMS key using either the key ARN or the ARN of your AWS account.

If you use the IAM managed policy, AmazonSageMakerFullAccess, to grant a role permission to use Data Wrangler in Studio, your Database User name must have the prefix sagemaker_access.

Use the following procedures to learn how to add a new cluster.

**Note**

Data Wrangler uses the Amazon Redshift Data API with temporary credentials. To learn more about this API, refer to Using the Amazon Redshift Data API in the Amazon Redshift Management Guide.
To connect to a Amazon Redshift cluster

1. Choose **Import**.
2. Choose + under **Add data connection**.
3. Choose **Amazon Redshift**.
4. Choose **Temporary credentials (IAM)** for **Type**.
5. Enter a **Connection Name**. This is a name used by Data Wrangler to identify this connection.
6. Enter the **Cluster Identifier** to specify to which cluster you want to connect. Note: Enter only the cluster identifier and not the full endpoint of the Amazon Redshift cluster.
7. Enter the **Database Name** of the database to which you want to connect.
8. Enter a **Database User** to identify the user you want to use to connect to the database.
9. For **UNLOAD IAM Role**, enter the IAM role ARN of the role that the Amazon Redshift cluster should assume to move and write data to Amazon S3. For more information about this role, see Authorizing Amazon Redshift to access other AWS services on your behalf in the Amazon Redshift Management Guide.
10. Choose **Connect**.
11. (Optional) For **Amazon S3 output location**, specify the S3 URI to store the query results.
12. (Optional) For **KMS key ID**, specify the ARN of the AWS KMS key or alias. The following image shows you where you can find either key in the AWS Management Console.
The following image shows all the fields from the preceding procedure.

After your connection is successfully established, it appears as a data source under Data Import. Select this data source to query your database and import data.

To query and import data from Amazon Redshift

1. Select the connection that you want to query from Data Sources.
2. Select a Schema. To learn more about Amazon Redshift Schemas, see Schemas in the Amazon Redshift Database Developer Guide.
3. (Optional) Under Advanced configuration, specify the Sampling method that you'd like to use.
4. Enter your query in the query editor and choose Run to run the query. After a successful query, you can preview your result under the editor.
5. Select Import dataset to import the dataset that has been queried.
6. Enter a Dataset name. If you add a Dataset name that contains spaces, these spaces are replaced with underscores when your dataset is imported.
7. Choose Add.
Import data from Databricks (JDBC)

You can use Databricks as a data source for your Amazon SageMaker Data Wrangler flow. To import a dataset from Databricks, use the JDBC (Java Database Connectivity) import functionality to access to your Databricks database. After you access the database, specify a SQL query to get the data and import it.

We assume that you have a running Databricks cluster and that you've configured your JDBC driver to it. For more information, see the following Databricks documentation pages:

- JDBC driver
- JDBC configuration and connection parameters
- Authentication parameters

Data Wrangler stores your JDBC URL in AWS Secrets Manager. You must give your Amazon SageMaker Studio IAM execution role permissions to use Secrets Manager. Use the following procedure to give permissions.

To give permissions to Secrets Manager, do the following.

1. Sign in to the AWS Management Console and open the IAM console at https://console.aws.amazon.com/iam/.
2. Choose Roles.
3. In the search bar, specify the Amazon SageMaker execution role that Amazon SageMaker Studio is using.
4. Choose the role.
5. Choose Add permissions.
6. Choose Create inline policy.
7. For Service, specify Secrets Manager and choose it.
8. For Actions, select the arrow icon next to Permissions management.
10. For Resources, choose Specific.
11. Choose the checkbox next to Any in this account.
13. For Name, specify a name.
14. Choose Create policy.

You can use partitions to import your data more quickly. Partitions give Data Wrangler the ability to process the data in parallel. By default, Data Wrangler uses 2 partitions. For most use cases, 2 partitions give you near-optimal data processing speeds.

If you choose to specify more than 2 partitions, you can also specify a column to partition the data. The type of the values in the column must be numeric or date.

We recommend using partitions only if you understand the structure of the data and how it's processed.

You can either import the entire dataset or sample a portion of it. For a Databricks database, it provides the following sampling options:

- None – Import the entire dataset.
- First K – Sample the first K rows of the dataset, where K is an integer that you specify.
- Randomized – Takes a random sample of a size that you specify.
Stratified – Takes a stratified random sample. A stratified sample preserves the ratio of values in a column.

Use the following procedure to import your data from a Databricks database.

To import data from Databricks, do the following.

1. Sign into Amazon SageMaker Console.
2. Choose Studio.
3. Choose Launch app.
4. From the dropdown list, select Studio.
5. From the Import data tab of your Data Wrangler flow, choose Add data source.

7. Specify the following fields:
   - **Dataset name** – A name that you want to use for the dataset in your Data Wrangler flow.
   - **Driver** – `com.simba.spark.jdbc.Driver`.
   - **JDBC URL** – The URL of the Databricks database. The URL formatting can vary between Databricks instances. For information about finding the URL and the specifying the parameters within it, see JDBC configuration and connection parameters. The following is an example of how a URL can be formatted: `jdbc:spark://aws-sagemaker-datawrangler.cloud.databricks.com:443/default;transportMode=http;httpPath=sql/protocolv1/o/3122619508517275/0909-200301-cut318;AuthMech=3;UID=token;PWD=personal-access-token`.
     
     **Note**
     You can specify a secret ARN that contains the JDBC URL instead of specifying the JDBC URL itself. The secret must contain a key-value pair with the following format: `jdbcURL: JDBC-URL`. For more information, see What is Secrets Manager?.

8. Specify a SQL SELECT statement.
   
   **Note**
   Data Wrangler doesn't support Common Table Expressions (CTE) or temporary tables within a query.
9. For **Sampling**, choose a sampling method.

10. Choose **Run**.

11. (Optional) For the **PREVIEW**, choose the gear to open the **Partition settings**.
    The gear for the additional settings is located to the far right of the **PREVIEW** title.
    - Specify the number of partitions. You can partition by column if you specify the number of partitions:
      - **Enter number of partitions** – Specify a value greater than 2.
      - (Optional) **Partition by column** – Specify the following fields. You can only partition by a column if you've specified a value for **Enter number of partitions**.
        - **Select column** – Select the column that you're using for the data partition. The data type of the column must be numeric or date.
        - **Upper bound** – From the values in the column that you've specified, the upper bound is the value that you're using in the partition. The value that you specify doesn't change the data that you're importing. It only affects the speed of the import. For the best performance, specify an upper bound that's close to the column's maximum.
        - **Lower bound** – From the values in the column that you've specified, the lower bound is the value that you're using in the partition. The value that you specify doesn't change the data that you're importing. It only affects the speed of the import. For the best performance, specify a lower bound that's close to the column's minimum.

12. Choose **Import**.

### Import data from Snowflake

You can use Snowflake as a data source in SageMaker Data Wrangler to prepare data in Snowflake for machine learning.

With Snowflake as a data source in Data Wrangler, you can quickly connect to Snowflake without writing a single line of code. Additionally, you can join your data in Snowflake with data stored in Amazon S3 and data queried through Amazon Athena and Amazon Redshift to prepare data for machine learning.

Once connected, you can interactively query data stored in Snowflake, transform data with more than 300 preconfigured data transformations, understand data and identify potential errors and extreme values with a set of robust preconfigured visualization templates, quickly identify inconsistencies in your data preparation workflow, and diagnose issues before models are deployed into production. Finally, you can export your data preparation workflow to Amazon S3 for use with other SageMaker features such as Amazon SageMaker Autopilot, Amazon SageMaker Feature Store and Amazon SageMaker Model Building Pipelines.

You can encrypt the output of your queries using an AWS Key Management Service key that you've created. For more information about AWS KMS, see [AWS Key Management Service](#).

### Administrator Guide

**Important**
To learn more about granular access control and best practices, see [Security Access Control](#).

This section is for Snowflake administrators who are setting up access to Snowflake from within SageMaker Data Wrangler.

**Important**
Your administrator is responsible for managing and monitoring the access control within Snowflake. This includes what data a user can access, what storage integration a user can use, and what queries a user can run. Data Wrangler does not add a layer of access control with respect to Snowflake.
Important
Note that granting monitor privileges can permit users to see details within an object, such as queries or usage within a warehouse.

Configure Snowflake with Data Wrangler

To import data from Snowflake, Snowflake admins must configure access from Data Wrangler using Amazon S3.

This feature is currently not available in the opt-in Regions.

To configure access, follow these steps.

1. Configure access permissions for the S3 bucket.

AWS Access Control Requirements

Snowflake requires the following permissions on an S3 bucket and directory to be able to access files in the directory.

- s3:GetObject
- s3:GetObjectVersion
- s3:ListBucket
- s3:ListObjects
- s3:GetBucketLocation

Create an IAM policy

The following steps describe how to configure access permissions for Snowflake in your AWS Management Console so you can use an S3 bucket to load and unload data:

- Log in to the AWS Management Console.
- From the home dashboard, choose IAM.
• Choose Policies.
• Choose Create Policy.
• Select the JSON tab.
• Add a policy document that allows Snowflake to access the S3 bucket and directory.

The following policy (in JSON format) provides Snowflake with the required permissions to load and unload data using a single bucket and directory path. Make sure to replace `bucket` and `prefix` with your actual bucket name and directory path prefix.

```json
# Example policy for S3 write access
# This needs to be updated
{
```

843
"Version": "2012-10-17",
"Statement": [
{
  "Effect": "Allow",
  "Action": [
    "s3:PutObject",
    "s3:GetObject",
    "s3:GetObjectVersion",
    "s3:DeleteObject",
    "s3:DeleteObjectVersion"
  ],
  "Resource": "arn:aws:s3:::bucket/prefix/*"
},
{
  "Effect": "Allow",
  "Action": [
    "s3:ListBucket"
  ],
  "Resource": "arn:aws:s3:::bucket/",
  "Condition": {
    "StringLike": {
      "s3:prefix": "["prefix/**"]
    }
  }
}
]

• Choose Next: Tags.
• Choose Next: Review.

Enter the policy name (such as snowflake_access) and an optional description. Choose Create policy.

2. Create the IAM Role in AWS.
3. Create a Cloud Storage Integration in Snowflake.
4. Retrieve the AWS IAM User for your Snowflake Account.
5. Grant the IAM User Permissions to Access Bucket.
6. Grant the data scientist's Snowflake role usage permission to the storage integration.
   • In the Snowflake console, run GRANT USAGE ON INTEGRATION integration_name TO snowflake_role;
• integration_name is the name of your storage integration.
• snowflake_role is the name of the default Snowflake role given to the data scientist user.

Provide information to the data scientist

Provide the data scientist with the information that they need to access Snowflake from Amazon SageMaker Data Wrangler.

1. To allow your data scientist to access Snowflake from SageMaker Data Wrangler, provide them with one of the following:
   • A Snowflake account name, user name, and password.
   • A secret created with AWS Secrets Manager and the ARN of the secret. Use the following procedure below to create the secret for Snowflake if you choose this option.

   **Important**
   If your data scientists use the Snowflake Credentials (User name and Password) option to connect to Snowflake, you can use Secrets Manager to store the credentials in a secret. Secrets Manager rotates secrets as part of a best practice security plan. The secret created in Secrets Manager is only accessible with the Studio role configured when you set up a Studio user profile. This requires you to add this permission, secretsmanager:PutResourcePolicy, to the policy that is attached to your Studio role.
   We strongly recommend that you scope the role policy to use different roles for different groups of Studio users. You can add additional resource-based permissions for the Secrets Manager secrets. See Manage Secret Policy for condition keys you can use.
   For information about creating a secret, see Create a secret. You're charged for the secrets that you create.

2. Provide the data scientist with the name of the storage integration you created in Step 3: Create a Cloud Storage Integration in Snowflake. This is the name of the new integration and is called integration_name in the CREATE INTEGRATION SQL command you ran, which is shown in the following snippet:

   ```sql
   CREATE STORAGE INTEGRATION integration_name
   TYPE = EXTERNAL_STAGE
   STORAGE_PROVIDER = S3
   ENABLED = 'true'
   STORAGE_AWS_ROLE_ARN = 'iam_role'
   [ STORAGE_AWS_OBJECT_ACL = 'bucket-owner-full-control' ]
   STORAGE_ALLOWED_LOCATIONS = ('s3://bucket/path/', 's3://bucket/path/')
   [ STORAGE_BLOCKED_LOCATIONS = ('s3://bucket/path/', 's3://bucket/path/') ]
   ```

Data Scientist Guide

This section outlines how to access your Snowflake data warehouse from within SageMaker Data Wrangler and how to use Data Wrangler features.

**Important**
Note: Your administrator needs to follow the Administer Guide set up in the preceding section before you can use Data Wrangler within Snowflake.

Use the following procedure to open Amazon SageMaker Studio and see which version you're running.

To open Studio and check its version, see the following procedure.
1. Use the steps in Prerequisites (p. 817) to access Data Wrangler through Amazon SageMaker Studio.
2. Next to the user you want to use to launch Studio, select Launch app.
3. Choose Studio.
4. After Studio loads, select File, then New, and then Terminal.

5. Once you have launched Studio, select File, then New, and then Terminal.

6. Enter `cat /opt/conda/share/jupyter/lab/staging/yarn.lock | grep -A 1 "@amzn/sagemaker-ui-data-prep-plugin@"` to print the version of your Studio instance. You must have Studio version 1.3.0 to use Snowflake.

Use the following procedure to check that you're running version 1.3.0 or greater.

To check the version of Studio, do the following.

1. If you do not have this version, then update your Studio version. To do this, close your Studio window and navigate to the SageMaker Studio Console.
2. Next, select the user you are using to access Studio and then select **Delete app**. After the deletion is complete, launch Studio again by selecting **Open Studio**.

3. Follow Step 3 again to verify that your Studio version is 1.3.0.

Use the following procedure to connect to Snowflake.

1. Create a new data flow from within Data Wrangler

   Once you have accessed Data Wrangler from within Studio and have version 1.3.0, select the + sign on the **New data flow** card under **ML tasks and components**. This creates a new directory in Studio with a .flow file inside, which contains your data flow. The .flow file automatically opens in Studio.

   Alternatively, you can also create a new flow by selecting **File**, then **New**, and then choosing **Flow**.
When you create a new .flow file in Studio, you may see a message at the top of the Data Wrangler interface that says:

**Connecting to engine**

**Establishing connection to engine...**

2. Connect to Snowflake.

There are two ways to connect to Snowflake from within Data Wrangler. You only need to choose one of the two ways.

1. Specify your Snowflake credentials (account name, user name, and password) in Data Wrangler.
2. Provide an Amazon Resource Name (ARN) of a secret.
Important
If you do not have your Snowflake credentials or ARN, reach out to your administrator. Your administrator can tell you which of the preceding methods to use to connect to Snowflake.

Start on the Import data screen and first select Add data source from the dropdown menu, and then select Snowflake. The following screenshot illustrates where to find the Snowflake option.

Choose an authentication method. For this step, as previously mentioned, you can use your Snowflake credentials or ARN name. One of the two is provided by your administrator.

Next, we explain both authentication methods and provide screenshots for each.

1. **Snowflake Credentials Option.**

   Select the Basic (user name and password) option from the Authentication method dropdown list. Then, enter your credentials in the following fields:
   
   - **Storage integration**: Provide the name of the storage integration. Your administrator provides this name.
   - **Snowflake account name**: The full name of your Snowflake account.
   - **User name**: Snowflake account user name.
   - **Password**: Snowflake account password.
   - **Connection name**: Choose a connection name for your choice.
   - (Optional) **KMS key ID**: Choose the AWS KMS key to encrypt the output of the Snowflake query. For more information about AWS Key Management Service, see https://docs.aws.amazon.com/kms/latest/developerguide/overview.html. If you don't specify a AWS KMS key, Data Wrangler uses the default SSE-KMS encryption method.

   Select Connect.

   The following screenshot shows how to complete these fields.
2. ARN Option

Select the ARN option from the Authentication method dropdown list. Then, provide your ARN name under Secrets Manager ARN and your Storage integration, which is provided by your administrator. If you've created a KMS key, you can specify its ID for KMS key ID. For more information about AWS Key Management Service, see https://docs.aws.amazon.com/kms/latest/developerguide/overview.html. Create a Connection name and select Connect, as shown in the following screenshot.
3. The workflow at this point is to connect your Snowflake account to Data Wrangler, then run some queries on your data and then finally use Data Wrangler for performing data transformations.

The following steps explain the import and querying step from within Data Wrangler.

After creating your Snowflake connection, you are taken to the Import data from Snowflake screen, as shown in the following screenshot.
From here, select your warehouse. You can also optionally select your database and schema, in which case the written query should specify them. If **Database** and **Schema** are provided in the dropdown list, the written query does not need to specify the database and schema names.

Your schemas and tables from your Snowflake account are listed in the left panel. You can select and unravel these entities. When you select a specific table, select the eye icon on the right side of each table name to preview the table.

**Important**

If you’re importing a dataset with columns of type `TIMESTAMP_TZ` or `TIMESTAMP_LTZ`, add `::string` to the column names of your query. For more information, see [How To: Unload TIMESTAMP_TZ and TIMESTAMP_LTZ data to a Parquet file](#).

The following screenshot shows the panel with your data warehouses, databases, and schemas, along with the eye icon with which you can preview your table. Once you select the **Preview Table** icon, the schema preview of that table is generated. You must select a warehouse before you can preview a table.

After selecting a data warehouse, database and schema, you can now write queries and run them. The output of your query shows under **Query results**, as shown in the following screenshot.
Once you have settled on the output of your query, you can then import the output of your query into a Data Wrangler flow to perform data transformations.

To do this, select **Import**, then specify a name and select **Go**, as shown in the following screenshot.
From here, transition to the **Data flow** screen to prepare your data transformation, as shown in the following screenshot.
Private Connectivity between Data Wrangler and Snowflake via AWS PrivateLink

This section explains how to use AWS PrivateLink to establish a private connection between Data Wrangler and Snowflake. The steps are explained in the following sections.

Create a VPC

If you do not have a VPC set up, then follow the Create a new VPC instructions to create one.

Once you have a chosen VPC you would like to use for establishing a private connection, provide the following credentials to your Snowflake Administrator to enable AWS PrivateLink:

- VPC ID
- AWS Account ID
- Your corresponding account URL you use to access Snowflake

Important
As described in Snowflake's documentation, enabling your Snowflake account can take up to two business days.

Set up Snowflake AWS PrivateLink Integration

After AWS PrivateLink is activated, retrieve the AWS PrivateLink configuration for your Region by running the following command in a Snowflake worksheet. Log into your Snowflake console and enter the following under Worksheets: select SYSTEM$GET_PRIVATELINK_CONFIG();

1. Retrieve the values for the following: privatelink-account-name, privatelink_ocsp-url, privatelink-account-url, and privatelink_ocsp-url from the resulting JSON object. Examples of each value are shown in the following snippet. Store these values for later use.

| privatelink-account-name: xxxxxxxx.region.privatelink |
| privatelink-vpce-id: com.amazonaws.vpce.region.vpce-svc-xxxxxxxxxxxxxxxxxx |
| privatelink-account-url: xxxxxxxx.region.privatelink.snowflakecomputing.com |
2. Switch to your AWS Console and navigate to the VPC menu.
3. From the left side panel, choose the Endpoints link to navigate to the VPC Endpoints setup.

Once there, choose Create Endpoint.
4. Select the radio button for Find service by name, as shown in the following screenshot.

5. In the Service Name field, paste in the value for privatelink-vpce-id that you retrieved in the preceding step and choose Verify.

If the connection is successful, a green alert saying Service name found appears on your screen and the VPC and Subnet options automatically expand, as shown in the following screenshot. Depending on your targeted Region, your resulting screen may show another AWS Region name.

6. Select the same VPC ID that you sent to Snowflake from the VPC dropdown list.
7. If you have not yet created a subnet, then perform the following set of instructions on creating a subnet.

8. Select Subnets from the VPC dropdown list. Then select Create subnet and follow the prompts to create a subnet in your VPC. Ensure you select the VPC ID you sent Snowflake.


10. Provide a name for the new security group (such as datawrangler-doc-snowflake-privatelink-connection) and a description. Be sure to select the VPC ID you have used in previous steps.
11 Add two rules to allow traffic from within your VPC to this VPC endpoint.

Navigate to your VPC under Your VPCs in a separate tab, and retrieve your CIDR block for your VPC. Then choose Add Rule in the Inbound Rules section. Select HTTPS for the type, leave the Source as Custom in the form, and paste in the value retrieved from the preceding describe-vpcs call (such as 10.0.0.0/16).

12 Choose Create Security Group. Retrieve the Security Group ID from the newly created security group (such as sg-xxxxxxxxxxxxxxxx).

13 In the VPC Endpoint configuration screen, remove the default security group. Paste in the security group ID in the search field and select the checkbox.

14 Select Create Endpoint.

15 If the endpoint creation is successful, you see a page that has a link to your VPC endpoint configuration, specified by the VPC ID. Select the link to view the configuration in full.

Retrieve the topmost record in the DNS names list. This can be differentiated from other DNS names because it only includes the Region name (such as us-west-2), and no Availability Zone letter notation (such as us-west-2a). Store this information for later use.

Configure DNS for Snowflake Endpoints in your VPC

This section explains how to configure DNS for Snowflake endpoints in your VPC. This allows your VPC to resolve requests to the Snowflake AWS PrivateLink endpoint.

1. Navigate to the Route 53 menu within your AWS console.
2. Select the Hosted Zones option (if necessary, expand the left-hand menu to find this option).
3. Choose Create Hosted Zone.
   a. In the Domain name field, reference the value that was stored for privatelink-account-url in the preceding steps. In this field, your Snowflake account ID is removed from the DNS name and only uses the value starting with the Region identifier. A Resource Record Set is also created later for the subdomain, such as, region.privatelink.snowflakecomputing.com.
   b. Select the radio button for Private Hosted Zone in the Type section. Your Region code may not be us-west-2. Reference the DNS name returned to you by Snowflake.
c. In the **VPCs to associate with the hosted zone** section, select the Region in which your VPC is located and the VPC ID used in previous steps.

d. Choose **Create hosted zone**.

4. Next, create two records, one for `privatelink-account-url` and one for `privatelink_ocsp-url`.
   - In the **Hosted Zone** menu, choose **Create Record Set**.
     a. Under **Record name**, enter your Snowflake Account ID only (the first 8 characters in `privatelink-account-url`).
     b. Under **Record type**, select **CNAME**.
     c. Under **Value**, enter the DNS name for the regional VPC endpoint you retrieved in the last step of the **Set up the Snowflake AWS PrivateLink Integration** section.
d. Choose Create records.

e. Repeat the preceding steps for the OCSP record we notated as privatelink-ocsp-url, starting with ocsp through the 8-character Snowflake ID for the record name (such as ocsp.xxxxxxxx).

Configure Route 53 Resolver Inbound Endpoint for your VPC

This section explains how to configure Route 53 resolvers inbound endpoints for your VPC.

1. Navigate to the Route 53 menu within your AWS console.
   - In the left hand panel in the Security section, select the Security Groups option.
   - Provide a name for your security group (such as datawranger-doc-route53-resolver-sg) and a description.
   - Select the VPC ID used in previous steps.
   - Create rules that allow for DNS over UDP and TCP from within the VPC CIDR block.
3. Navigate to the **Route 53 menu** within your AWS console.
   - In the **Resolver** section, select the **Inbound Endpoint** option.
4. Choose **Create Inbound Endpoint**.
   - Provide an endpoint name.
   - From the **VPC in the Region** dropdown list, select the VPC ID you have used in all previous steps.
   - In the **Security group for this endpoint** dropdown list, select the security group ID from Step 2 in this section.

   - In the **IP Address** section, select an Availability Zones, select a subnet, and leave the radio selector for **Use an IP address that is selected automatically** selected for each IP address.
5. Select the Inbound endpoint after it has been created.

6. Once the inbound endpoint is created, note the two IP addresses for the resolvers.

- Choose Submit.

SageMaker VPC Endpoints

This section explains how to create VPC endpoints for the following: Amazon SageMaker Studio, SageMaker Notebooks, the SageMaker API, SageMaker Runtime, and Amazon SageMaker Feature Store Runtime.

Create a security group that is applied to all endpoints.

1. Navigate to the EC2 menu in the AWS Console.
2. In the Network & Security section, select the Security groups option.
3. Choose **Create security group**.
4. Provide a security group name and description (such as `datawrangler-doc-sagemaker-vpce-sg`).
   A rule is added later to allow traffic over HTTPS from SageMaker to this group.

**Creating the endpoints**

1. Navigate to the **VPC menu** in the AWS console.
2. Select the **Endpoints** option.
3. Choose **Create Endpoint**.
4. Search for the service by entering its name in the **Search** field.
5. From the **VPC** dropdown list, select the VPC in which your Snowflake AWS PrivateLink connection exists.
6. In the **Subnets** section, select the subnets which have access to the Snowflake PrivateLink connection.
7. Leave the **Enable DNS Name** checkbox selected.
8. In the **Security Groups** section, select the security group you created in the preceding section.
9. Choose **Create Endpoint**.

**Configure Studio and Data Wrangler**

This section explains how to configure Studio and Data Wrangler.

1. Configure the security group.
   a. Navigate to the Amazon EC2 menu in the AWS Console.
   b. Select the **Security Groups** option in the **Network & Security** section.
   c. Choose **Create Security Group**.
   d. Provide a name and description for your security group (such as `datawrangler-doc-sagemaker-studio`).
   e. Create the following inbound rules.
      • The HTTPS connection to the security group you provisioned for the Snowflake PrivateLink connection you created in the **Set up the Snowflake PrivateLink Integration** step.
      • The HTTP connection to the security group you provisioned for the Snowflake PrivateLink connection you created in the **Set up the Snowflake PrivateLink Integration step**.
      • The UDP and TCP for DNS (port 53) to Route 53 Resolver Inbound Endpoint security group you create in step 2 of **Configure Route 53 Resolver Inbound Endpoint for your VPC**.
   f. Choose **Create Security Group** button in the lower right hand corner.
2. Configure Studio.
   • Navigate to the SageMaker menu in the AWS console.
   • From the left hand console, Select the **SageMaker Studio** option.
   • If you do not have any domains configured, the **Get Started** menu is present.
   • Select the **Standard Setup** option from the **Get Started** menu.
   • Under **Authentication method**, select **AWS Identity and Access Management (IAM)**.
   • From the **Permissions** menu, you can create a new role or use a pre-existing role, depending on your use case.
      • If you choose **Create a new role**, you are presented the option to provide an S3 bucket name, and a policy is generated for you.
      • If you already have a role created with permissions for the S3 buckets to which you require access, select the role from the dropdown list. This role should have the **AmazonSageMakerFullAccess** policy attached to it.
- Select the **Network and Storage** dropdown list to configure the VPC, security, and subnets SageMaker uses.
  - Under **VPC**, select the VPC in which your Snowflake PrivateLink connection exists.
  - Under **Subnet(s)**, select the subnets which have access to the Snowflake PrivateLink connection.
  - Under **Network Access for Studio**, select **VPC Only**.
  - Under **Security Group(s)**, select the security group you created in step 1.
  - Choose **Submit**.

3. Edit the SageMaker security group.
   - Create the following inbound rules:
     - Port 2049 to the inbound and outbound NFS Security Groups created automatically by SageMaker in step 2 (the security group names contain the Studio domain ID).
     - Access to all TCP ports to itself (required for SageMaker for VPC Only).

4. Edit the VPC Endpoint Security Groups:
   - Navigate to the Amazon EC2 menu in the AWS console.
   - Locate the security group you created in a preceding step.
   - Add an inbound rule allowing for HTTPS traffic from the security group created in step 1.

5. Create a user profile.
   - From the **SageMaker Studio Control Panel**, choose **Add User**.
   - Provide a user name.
   - For the **Execution Role**, choose to create a new role or to use a pre-existing role.
     - If you choose **Create a new role**, you are presented the option to provide an Amazon S3 bucket name, and a policy is generated for you.
     - If you already have a role created with permissions to the Amazon S3 buckets to which you require access, select the role from the dropdown list. This role should have the AmazonSageMakerFullAccess policy attached to it.
   - Choose **Submit**.

6. Create a data flow (follow the data scientist guide outlined in a preceding section).
   - When adding a Snowflake connection, enter the value of `privatelink-account-name` (from the **Set up Snowflake PrivateLink Integration** step) into the **Snowflake account name (alphanumeric)** field, instead of the plain Snowflake account name. Everything else is left unchanged.

## Imported Data Storage

### Important
We strongly recommend that you follow the best practices around protecting your Amazon S3 bucket by following **Security best practices**.

When you query data from Amazon Athena or Amazon Redshift, the queried dataset is automatically stored in Amazon S3. Data is stored in the default SageMaker S3 bucket for the AWS Region in which you are using Studio.

Default S3 buckets have the following naming convention: `sagemaker-region-account number`. For example, if your account number is 111122223333 and you are using Studio in `us-east-1`, your imported datasets are stored in `sagemaker-us-east-1-111122223333`.

Data Wrangler flows depend on this Amazon S3 dataset location, so you should not modify this dataset in Amazon S3 while you are using a dependent flow. If you do modify this S3 location, and you want to continue using your data flow, you must remove all objects in `trained_parameters` in your .flow file.

To do this, download the .flow file from Studio and for each instance of `trained_parameters`, delete all entries. When you are done, `trained_parameters` should be an empty JSON object.
When you export and use your data flow to process your data, the .flow file you export refers to this dataset in Amazon S3. Use the following sections to learn more.

**Amazon Redshift Import Storage**

Data Wrangler stores the datasets that result from your query in a Parquet file in your default SageMaker S3 bucket.

This file is stored under the following prefix (directory): redshift/uuid/data/, where uuid is a unique identifier that gets created for each query.

For example, if your default bucket is sagemaker-us-east-1-111122223333, a single dataset queried from Amazon Redshift is located in s3://sagemaker-us-east-1-111122223333/redshift/uuid/data/.

**Amazon Athena Import Storage**

When you query an Athena database and import a dataset, Data Wrangler stores the dataset, as well as a subset of that dataset, or preview files, in Amazon S3.

The dataset you import by selecting **Import dataset** is stored in Parquet format in Amazon S3.

Preview files are written in CSV format when you select **Run** on the Athena import screen, and contain up to 100 rows from your queried dataset.

The subset of the dataset that is stored to preview dataframes in Data Wrangler is stored under the prefix: athena/.

**Create and Use a Data Wrangler Flow**

Use an Amazon SageMaker Data Wrangler flow, or a **data flow**, to create and modify a data preparation pipeline. The data flow connects the datasets, transformations, and analyses, or steps, you create and can be used to define your pipeline.

**Instances**

When you create a Data Wrangler flow in Amazon SageMaker Studio, Data Wrangler uses an Amazon EC2 instance to run the analyses and transformations in your flow. By default, Data Wrangler uses the m5.4xlarge instance. m5 instances are general purpose instances that provide a balance between compute and memory. You can use m5 instances for a variety of compute workloads.

Data Wrangler also gives you the option of using r5 instances. r5 instances are designed to deliver fast performance that process large datasets in memory.

We recommend that you choose an instance that is best optimized around your workloads. For example, the r5.8xlarge might have a higher price than the m5.4xlarge, but the r5.8xlarge might be better optimized for your workloads. With better optimized instances, you can run your data flows in less time at lower cost.
The following table shows the instances that you can use to run your Data Wrangler flow.

<table>
<thead>
<tr>
<th>Standard Instances</th>
<th>vCPU</th>
<th>Memory</th>
</tr>
</thead>
<tbody>
<tr>
<td>ml.m5.4xlarge</td>
<td>16</td>
<td>64 GiB</td>
</tr>
<tr>
<td>ml.m5.8xlarge</td>
<td>32</td>
<td>128 GiB</td>
</tr>
<tr>
<td>ml.m5.16xlarge</td>
<td>64</td>
<td>256 GiB</td>
</tr>
<tr>
<td>ml.m5.24xlarge</td>
<td>96</td>
<td>384 GiB</td>
</tr>
<tr>
<td>r5.4xlarge</td>
<td>16</td>
<td>128 GiB</td>
</tr>
<tr>
<td>r5.8xlarge</td>
<td>32</td>
<td>256 GiB</td>
</tr>
<tr>
<td>r5.24xlarge</td>
<td>96</td>
<td>768 GiB</td>
</tr>
</tbody>
</table>

For more information about r5 instances, see Amazon EC2 R5 Instances. For more information about m5 instances, see Amazon EC2 M5 Instances.

Each Data Wrangler flow has an Amazon EC2 instance associated with it. You might have multiple flows that are associated with a single instance.

For each flow file, you can seamlessly switch the instance type. If you switch the instance type, the instance that you used to run the flow continues to run.

To switch the instance type of your flow, do the following.

1. Navigate to the instance that you're currently using and choose it. The following image shows you where to choose the instance.

2. Choose the instance type that you want to use.
3. Choose **Save**.

You are charged for all running instances. To avoid incurring additional charges, shut down the instances that you aren't using manually. To shut down an instance that is running, use the following procedure.

To shut down a running instance.

1. Choose the instance icon on the left of the UI. The following image shows you where to select the **RUNNING INSTANCES** icon.

2. Choose **Shut down** next to the instance that you want to shut down.

   If you shut down an instance used to run a flow, you temporarily can't access the flow. If you get an error while attempting to open the flow running an instance you previously shut down, wait for five minutes and try opening it again.

   When you export your data flow to a location such as Amazon Simple Storage Service or Amazon SageMaker Feature Store, Data Wrangler runs an Amazon SageMaker processing job. You can use one of the following instances for the processing job. For more information on exporting your data, see **Export** (p. 945).
### Standard Instances

<table>
<thead>
<tr>
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</tr>
<tr>
<td>ml.m5.12xlarge</td>
<td>48</td>
<td>192 GiB</td>
</tr>
<tr>
<td>ml.m5.24xlarge</td>
<td>96</td>
<td>384 GiB</td>
</tr>
</tbody>
</table>

For more information about the cost per hour for using the available instance types, see [SageMaker Pricing](#).

## The Data Flow UI

When you import a dataset, the original dataset appears on the data flow and is named **Source**. If you turned on sampling when you imported your data, this dataset is named **Source - sampled**. Data Wrangler automatically infers the types of each column in your dataset and creates a new dataframe named **Data types**. You can select this frame to update the inferred data types. You see results similar to those shown in the following image after you upload a single dataset:

![Data Flow UI](https://example.com/data-flow-ui.png)

Each time you add a transform step, you create a new dataframe. When multiple transform steps (other than **Join** or **Concatenate**) are added to the same dataset, they are stacked.

**Join** and **Concatenate** create standalone steps that contain the new joined or concatenated dataset.

The following diagram shows a data flow with a join between two datasets, as well as two stacks of steps. The first stack (**Steps (2)**) adds two transforms to the type inferred in the **Data types** dataset. The **downstream** stack, or the stack to the right, adds transforms to the dataset resulting from a join named **demo-join**.
The small, gray box in the bottom right corner of the data flow provides an overview of number of stacks and steps in the flow and the layout of the flow. The lighter box inside the gray box indicates the steps that are within the UI view. You can use this box to see sections of your data flow that fall outside of the UI view. Use the fit screen icon ( ) to fit all steps and datasets into your UI view.

The bottom left navigation bar includes icons that you can use to zoom in ( ) and out ( ) of your data flow and resize the data flow to fit the screen ( ). Use the lock icon ( ) to lock and unlock the location of each step on the screen.
Add a Step to Your Data Flow

Select + next to any dataset or previously added step and then select one of the following options:

- **Edit data types** (For a Data types step only): If you have not added any transforms to a Data types step, you can select **Edit data types** to update the data types Data Wrangler inferred when importing your dataset.

- **Add transform**: Adds a new transform step. See Transform Data (p. 889) to learn more about the data transformations you can add.

- **Add analysis**: Adds an analysis. You can use this option to analyze your data at any point in the data flow. When you add one or more analyses to a step, an analysis icon (●) appears on that step. See Analyze and Visualize (p. 930) to learn more about the analyses you can add.

- **Join**: Joins two datasets and adds the resulting dataset to the data flow. To learn more, see Join Datasets (p. 895).

- **Concatenate**: Concatenates two datasets and adds the resulting dataset to the data flow. To learn more, see Concatenate Datasets (p. 895).

Delete a Step from Your Data Flow

To delete a step, select the step and select **Delete**. If the node is a node that has a single input, you delete only the step that you select. Deleting a step that has a single input doesn't delete the steps that follow it. If you're deleting a step for a source, join, or concatenate node, all the steps that follow it are also deleted.

To delete a step from a stack of steps, select the stack and then select the step you want to delete.

You can use one of the following procedures to delete a step without deleting the downstream steps.

Delete a step in the Data Wrangler flow

You can delete an individual step for nodes in your data flow that have a single input. You can't delete individual steps for source, join, and concatenate nodes.

Use the following procedure to delete a step in the Data Wrangler flow.

1. Choose the group of steps that has the step that you're deleting.
2. Choose the icon next to the step.
3. Choose **Delete**.
Data flow
Choose the plus sign to add a step to the flow. Select a step to modify.
Source - sampled
S3: titanic-train.csv
Delete a step in the table view

Use the following procedure to delete a step in the table view.

You can delete an individual step for nodes in your data flow that have a single input. You can't delete individual steps for source, join, and concatenate nodes.

1. Choose the step and open the table view for the step.
2. Move your cursor over the step.
3. Choose the icon next to the step.
4. Choose Delete.
### Step 3. Standard deviation numeric outliers

<table>
<thead>
<tr>
<th>pclass (long)</th>
<th>survived (long)</th>
<th>name (string)</th>
<th>sex (string)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>Allen, Miss. Elisabeth W...</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Allison, Master. Hudson...</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Allison, Miss. Helen Lor...</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Allison, Mr. Hudson Jos...</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Allison, Mrs. Hudson J C...</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Anderson, Mr. Harry</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Andrews, Miss. Kornelia...</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Andrews, Mr. Thomas Jr</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Appleton, Mrs. Edward ...</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Artagaveytia, Mr. Ramon</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Astor, Col. John Jacob</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Astor, Mrs. John Jacob (...</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Aubart, Mme. Leontine ...</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Barber, Miss. Ellen ’Nellie’</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Baxter, Mr. Quigg Edmo...</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Baxter, Mrs. James (Hel...</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Bazzani, Miss. Albina</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Beattie, Mr. Thomson</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Beckwith, Mr. Richard L</td>
<td>male</td>
</tr>
</tbody>
</table>
Edit a Step in Your Data Wrangler Flow

You can edit each step that you've added in your Data Wrangler flow. Editing steps gives you the ability to change the transformations or the data types of the columns. You can edit the steps to make changes that give you the ability to perform better analyses.

There are many ways that you can edit a step. Some examples include changing the imputation method or changing the threshold for considering a value to be an outlier.

Use the following procedure to edit a step.

To edit a step, do the following.

1. Choose a step in the Data Wrangler flow to open the table view.
2. Choose a step in the data flow.
3. Edit the step.

The following is an example of editing a step.
Use the **Data Quality and Insights Report** to perform an analysis of the data that you've imported into Data Wrangler. We recommend that you create the report after you import your dataset. You can use the report to help you clean and process your data. It gives you information such as the number of missing values.

### Get Insights On Data and Data Quality

<table>
<thead>
<tr>
<th>Pclass (long)</th>
<th>Survived (long)</th>
<th>Name (string)</th>
<th>Sex (string)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>Allen, Miss. Elisabeth</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Allison, Master. Hudson</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Allison, Miss. Helen</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Allison, Mr. Hudson</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Allison, Mrs. Hudson</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>Anderson, Mr. Harry</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Andrews, Miss. Kornelia</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Andrews, Mr. Thomas</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Appleton, Mrs. Edward</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Artagaveyta, Mr. Ramon</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Astor, Col. John</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Astor, Mrs. John</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Aubart, Mme. Leontine</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Barber, Miss. Ellen</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Barkworth, Mr. Algerno</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Baumann, Mr. John</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Baxter, Mr. Quigg</td>
<td>male</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Baxter, Mrs. James</td>
<td>female</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>Bavaria, Mrs. Albina</td>
<td>female</td>
</tr>
</tbody>
</table>

[Back to data flow]
values and the number of outliers. If you have issues with your data, such as target leakage or imbalance, the insights report can bring those issues to your attention.

**Note**
If you've sampled the data that you've imported, Data Wrangler creates the report from the sampled data. For information about turning off sampling, see Import (p. 827).

The following topics show the sections of the report:

**Topics**
- Summary (p. 876)
- Target column (p. 878)
- Quick model (p. 881)
- Feature summary (p. 883)
- Samples (p. 885)
- Definitions (p. 886)

You can either download the report or view it online. To download the report, choose the download button at the top right corner of the screen. The following image shows the button.

**Summary**

The insights report has a brief summary of the data that includes general information such as missing values, invalid values, feature types, outlier counts, and more. It can also include high severity warnings that point to probable issues with the data. We recommend that you investigate the warnings.

The following is an example of a report summary.
### SUMMARY

**Dataset statistics**

<table>
<thead>
<tr>
<th>Key</th>
<th>Value</th>
<th>Feature type</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of features</td>
<td>13</td>
<td>numeric</td>
<td>9</td>
</tr>
<tr>
<td>Number of rows</td>
<td>8553</td>
<td>categorical</td>
<td>1</td>
</tr>
<tr>
<td>Missing</td>
<td>0%</td>
<td>text</td>
<td>0</td>
</tr>
<tr>
<td>Valid</td>
<td>100%</td>
<td>datetime</td>
<td>0</td>
</tr>
<tr>
<td>Duplicate rows</td>
<td>4.63%</td>
<td>binary</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td>vector</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td></td>
<td>None</td>
<td>0</td>
</tr>
</tbody>
</table>

**High Priority Warnings**

2 high severity warnings were detected. See the list below.

- **Skewed target** **High**
  
The target column is skewed and contains outliers. Because the outliers induce lower prediction quality for the non-outlier samples. In case you are interested in prediction quality, there is no need for further action. However, if extreme values are not the point, this can be handled under **Handle outliers**.

- **Target leakage** **High**
  
The feature hoa_(BRL) predicts the target extremely well on its own. A feature that perfectly predicts the target column in the dataset can result in a high level of leakage. Alternatively, if the machine learning task is "easy", then a single feature can have only leaking anything further. However, if you think there's target leakage, we recommend...
Target column

When you create the data quality and insights report, Data Wrangler gives you the option to select a target column. A target column is a column that you're trying to predict. When you choose a target column, Data Wrangler automatically creates a target column analysis. It also ranks the features in the order of their predictive power. When you select a target column, you must specify whether you’re trying to solve a regression or a classification problem.

For classification, Data Wrangler shows a table and a histogram of the most common classes. A class is a category. It also presents observations, or rows, with a missing or invalid target value.

The following image shows an example target column analysis for a classification problem.
For regression, Data Wrangler shows a histogram of all the values in the target column. It also presents observations, or rows, with a missing, invalid, or outlier target value.

The following image shows an example target column analysis for a regression problem.
### TARGET COLUMN

<table>
<thead>
<tr>
<th>key</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valid</td>
<td>100%</td>
</tr>
<tr>
<td>Missing</td>
<td>0%</td>
</tr>
<tr>
<td>Outliers</td>
<td>0.103%</td>
</tr>
<tr>
<td>Min</td>
<td>450</td>
</tr>
<tr>
<td>Max</td>
<td>4.5e+04</td>
</tr>
<tr>
<td>Mean</td>
<td>3.9e+03</td>
</tr>
<tr>
<td>Median</td>
<td>2.66e+03</td>
</tr>
<tr>
<td>Skew</td>
<td>1.84</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>4.62</td>
</tr>
<tr>
<td>Number of unique</td>
<td>1195</td>
</tr>
</tbody>
</table>

Histogram of the target column average.

See below several samples with outlier target values.

<table>
<thead>
<tr>
<th>city</th>
<th>area</th>
<th>rooms</th>
<th>bathroom</th>
<th>parking spaces</th>
<th>floor</th>
<th>animal</th>
<th>furniture</th>
</tr>
</thead>
<tbody>
<tr>
<td>São Paulo</td>
<td>700</td>
<td>4</td>
<td>7</td>
<td>8</td>
<td>-</td>
<td>accept</td>
<td>not full</td>
</tr>
<tr>
<td>São Paulo</td>
<td>350</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>-</td>
<td>accept</td>
<td>not full</td>
</tr>
<tr>
<td>São Paulo</td>
<td>486</td>
<td>8</td>
<td>4</td>
<td>6</td>
<td>-</td>
<td>accept</td>
<td>not full</td>
</tr>
<tr>
<td>São Paulo</td>
<td>80</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>accept</td>
<td>not full</td>
</tr>
<tr>
<td>São Paulo</td>
<td>900</td>
<td>3</td>
<td>4</td>
<td>8</td>
<td>-</td>
<td>accept</td>
<td>not full</td>
</tr>
</tbody>
</table>
Quick model

The Quick model provides an estimate of the expected predicted quality of a model that you train on your data.

Data Wrangler splits your data into training and validation folds. It uses 80% of the samples for training and 20% of the values for validation. For classification, the sample is stratified split. For a stratified split, each data partition has the same ratio of labels. For classification problems, it's important to have the same ratio of labels between the training and classification folds. Data Wrangler trains the XGBoost model with the default hyperparameters. It applies early stopping on the validation data and performs minimal feature preprocessing.

For classification models, Data Wrangler returns both a model summary and a confusion matrix.

The following is an example of a classification model summary. To learn more about the information that it returns, see Definitions (p. 886).

<table>
<thead>
<tr>
<th>Metric</th>
<th>Validation scores</th>
<th>Train scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>0.977</td>
<td>0.992</td>
</tr>
<tr>
<td>Balanced accuracy</td>
<td>0.972</td>
<td>0.99</td>
</tr>
<tr>
<td>ROC-AUC</td>
<td>0.995</td>
<td>1</td>
</tr>
<tr>
<td>F1</td>
<td>0.969</td>
<td>0.99</td>
</tr>
<tr>
<td>Precision</td>
<td>0.99</td>
<td>0.997</td>
</tr>
<tr>
<td>Recall</td>
<td>0.95</td>
<td>0.983</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>class</th>
<th>precision</th>
<th>recall</th>
<th>f1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.9698795180722891</td>
<td>0.9938271604938271</td>
<td>0.9811</td>
</tr>
<tr>
<td>1</td>
<td>0.9895833333333334</td>
<td>0.95</td>
<td>0.9695</td>
</tr>
</tbody>
</table>

The following is an example of a confusion matrix that the quick model returns.
A confusion matrix gives you the following information:

- The number of times the predicted label matches the true label.
- The number of times the predicted label doesn't match the true label.

The true label represents an actual observation in your data. For example, if you're using a model to detect fraudulent transactions, the true label represents a transaction that is actually fraudulent or non-fraudulent. The predicted label represents the label that your model assigns to the data.

You can use the confusion matrix to see how well the model predicts the presence or the absence of a condition. If you're predicting fraudulent transactions, you can use the confusion matrix to get a sense of both the sensitivity and the specificity of the model. The sensitivity refers to the model's ability to detect fraudulent transactions. The specificity refers to the model's ability to avoid detecting non-fraudulent transactions as fraudulent.

The following is an example of the quick model outputs for a regression problem.
Feature summary

When you specify a target column, Data Wrangler orders the features by their prediction power. Prediction power is measured on the data after it was split into 80% training and 20% validation folds. Data Wrangler fits a model for each feature separately on the training fold. It applies minimal feature preprocessing and measures prediction performance on the validation data.

It normalizes the scores to the range [0,1]. Higher prediction scores indicate columns that are more useful for predicting the target on their own. Lower scores point to columns that aren't predictive of the target column.

It's uncommon for a column that isn't predictive on its own to be predictive when it's used in tandem with other columns. You can confidently use the prediction scores to determine whether a feature in your dataset is predictive.

A low score usually indicates the feature is redundant. A score of 1 implies perfect predictive abilities, which often indicates target leakage. Target leakage usually happens when the dataset contains a column that isn't available at the prediction time. For example, it could be a duplicate of the target column.

The following are examples of the table and the histogram that show the prediction value of each feature.
<table>
<thead>
<tr>
<th>Feature</th>
<th>Prediction power</th>
<th>Type</th>
<th>Valid</th>
<th>Missing</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Name</td>
<td>0.274276</td>
<td>text</td>
<td>100.0%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Pclass</td>
<td>0.154638</td>
<td>numeric</td>
<td>100.0%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>SibSp</td>
<td>0.141675</td>
<td>numeric</td>
<td>100.0%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Parch</td>
<td>0.127353</td>
<td>numeric</td>
<td>100.0%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Cabin</td>
<td>0.112283</td>
<td>text</td>
<td>25.91%</td>
<td>74.09%</td>
<td></td>
</tr>
<tr>
<td>Ticket</td>
<td>0.0869433</td>
<td>numeric</td>
<td>72.97%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Fare</td>
<td>0.0625847</td>
<td>numeric</td>
<td>100.0%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Embarked</td>
<td>0.00600914</td>
<td>categorical</td>
<td>99.72%</td>
<td>0.28%</td>
<td></td>
</tr>
<tr>
<td>Survived</td>
<td>0.00434197</td>
<td>binary</td>
<td>100.0%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>PassengerId</td>
<td>0</td>
<td>numeric</td>
<td>100.0%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td>0</td>
<td>binary</td>
<td>100.0%</td>
<td>0.0%</td>
<td></td>
</tr>
</tbody>
</table>
Data Wrangler provides information about whether your samples are anomalous or if there are duplicates in your dataset.

Data Wrangler detects anomalous samples using the isolation forest algorithm. The isolation forest associates an anomaly score with each sample (row) of the dataset. Low anomaly scores indicate anomalous samples. High scores are associated with non-anomalous samples. Samples with a negative anomaly score are usually considered anomalous and samples with positive anomaly score are considered non-anomalous.

When you look at a sample that might be anomalous, we recommend that you pay attention to unusual values. For example, you might have anomalous values that result from errors in gathering and processing the data. The following is an example of the most anomalous samples according to the Data Wrangler’s implementation of the isolation forest algorithm. We recommend using domain knowledge and business logic when you examine the anomalous samples.

Data Wrangler detects duplicate rows and calculates the ratio of duplicate rows in your data. Some data sources could include valid duplicates. Other data sources could have duplicates that point to problems in data collection. Duplicate samples that result from faulty data collection could interfere with machine learning processes that rely on splitting the data into independent training and validation folds.

The following are elements of the insights report that can be impacted by duplicated samples:

- Quick model
Get Insights On Data and Data Quality

- Prediction power estimation
- Automatic hyperparameter tuning

You can remove duplicate samples from the dataset using the **Drop duplicates** transform under **Manage rows**. Data Wrangler shows you the most frequently duplicated rows.

**Definitions**

The following are definitions for the technical terms that are used in the data insights report.

**Feature types**

The following are the definitions for each of the feature types:

- **Numeric** – Numeric values can be either floats or integers, such as age or income. The machine learning models assume that numeric values are ordered and a distance is defined over them. For example, 3 is closer to 4 than to 10 and $3 < 4 < 10$.

- **Categorical** – The column entries belong to a set of unique values, which is usually much smaller than the number of entries in the column. For example, a column of length 100 could contain the unique values Dog, Cat, and Mouse. The values could be numeric, text, or a combination of both. Horse, House, 8, Love, and 3.1 would all be valid values and could be found in the same categorical column. The machine learning model does not assume order or distance on the values of categorical features, as opposed to numeric features, even when all the values are numbers.

- **Binary** – Binary features are a special categorical feature type in which the cardinality of the set of unique values is 2.

- **Text** – A text column contains many non-numeric unique values. In extreme cases, all the elements of the column are unique. In an extreme case, no two entries are the same.

- **Datetime** – A datetime column contains information about the date or time. It can have information about both the date and time.

**Feature statistics**

The following are definitions for each of the feature statistics:

- **Prediction power** – Prediction power measures how useful the column is in predicting the target.

- **Outliers** (in numeric columns) – Data Wrangler detects outliers using two statistics that are robust to outliers: median and robust standard deviation (RSTD). RSTD is derived by clipping the feature values to the range [5 percentile, 95 percentile] and calculating the standard deviation of the clipped vector. All values larger than median + 5 * RSTD or smaller than median - 5 * RSTD are considered to be outliers.

- **Skew** (in numeric columns) – Skew measures the symmetry of the distribution and is defined as the third moment of the distribution divided by the third power of the standard deviation. The skewness of the normal distribution or any other symmetric distribution is zero. Positive values imply that the right tail of the distribution is longer than the left tail. Negative values imply that the left tail of the distribution is longer than the right tail. As a rule of thumb, a distribution is considered skewed when the absolute value of the skew is larger than 3.

- **Kurtosis** (in numeric columns) – Pearson's kurtosis measures the heaviness of the tail of the distribution. It's defined as the fourth moment of the distribution divided by the square of the second moment. The kurtosis of the normal distribution is 3. Kurtosis values lower than 3 imply that the distribution is concentrated around the mean and the tails are lighter than the tails of the normal distribution. Kurtosis values higher than 3 imply heavier tails or outliers.

- **Missing values** – Null-like objects, empty strings and strings composed of only white spaces are considered missing.
• **Valid values for numeric features or regression target** – All values that you can cast to finite floats are valid. Missing values are not valid.

• **Valid values for categorical, binary, or text features, or for classification target** – All values that are not missing are valid.

• **Datetime features** – All values that you can cast to a datetime object are valid. Missing values are not valid.

• **Invalid values** – Values that are either missing or you can’t properly cast. For example, in a numeric column, you can’t cast the string "six" or a null value.

**Quick model metrics for regression**

The following are the definitions for the quick model metrics:

• **R2 or coefficient of determination** – R2 is the proportion of the variation in the target that is predicted by the model. R2 is in the range of [-infty, 1]. 1 is the score of the model that predicts the target perfectly and 0 is the score of the trivial model that always predicts the target mean.

• **MSE or mean squared error** – MSE is in the range [0, infty]. 0 is the score of the model that predicts the target perfectly.

• **MAE or mean absolute error** – MAE is in the range [0, infty] where 0 is the score of the model that predicts the target perfectly.

• **RMSE or root mean square error** – RMSE is in the range [0, infty] where 0 is the score of the model that predicts the target perfectly.

• **Max error** – The maximum absolute value of the error over the dataset. Max error is in the range [0, infty]. 0 is the score of the model that predicts the target perfectly.

• **Median absolute error** – Median absolute error is in the range [0, infty]. 0 is the score of the model that predicts the target perfectly.

**Quick model metrics for classification**

The following are the definitions for the quick model metrics:

• **Accuracy** – Accuracy is the ratio of samples that are predicted accurately. Accuracy is in the range [0, 1]. 0 is the score of the model that predicts all samples incorrectly and 1 is the score of the perfect model.

• **Balanced accuracy** – Balanced accuracy is the ratio of samples that are predicted accurately when the class weights are adjusted to balance the data. All classes are given the same importance, regardless of their frequency. Balanced accuracy is in the range [0, 1]. 0 is the score of the model that predicts all samples wrong. 1 is the score of the perfect model.

• **AUC (binary classification)** – This is the area under the receiver operating characteristic curve. AUC is in the range [0, 1] where a random model returns a score of 0.5 and the perfect model returns a score of 1.

• **AUC (OVR)** – For multiclass classification, this is the area under the receiver operating characteristic curve calculated separately for each label using one versus rest. Data Wrangler reports the average of the areas. AUC is in the range [0, 1] where a random model returns a score of 0.5 and the perfect model returns a score of 1.

• **Precision** – Precision is defined for a specific class. Precision is the fraction of true positives out of all the instances that the model classified as that class. Precision is in the range [0, 1]. 1 is the score of the model that has no false positives for the class. For binary classification, Data Wrangler reports the precision of the positive class.

• **Recall** – Recall is defined for a specific class. Recall is the fraction of the relevant class instances that are successfully retrieved. Recall is in the range [0, 1]. 1 is the score of the model that classifies all the instances of the class correctly. For binary classification, Data Wrangler reports the recall of the positive class.
• **F1** – F1 is defined for a specific class. It's the harmonic mean of the precision and recall. F1 is in the range \([0, 1]\). 1 is the score of the perfect model. For binary classification, Data Wrangler reports the F1 for classes with positive values.

**Textual patterns**

Patterns describe the textual format of a string using an easy to read format. The following are examples of textual patterns:

- "\{digits:4-7\}" describes a sequence of digits that have a length between 4 and 7.
- "\{alnum:5\}" describes an alpha-numeric string with a length of exactly 5.

Data Wrangler infers the patterns by looking at samples of non-empty strings from your data. It can describe many of the commonly used patterns. The confidence expressed as a percentage indicates how much of the data is estimated to match the pattern. Using the textual pattern, you can see which rows in your data you need to correct or drop.

The following describes the patterns that Data Wrangler can recognize:

<table>
<thead>
<tr>
<th>Pattern</th>
<th>Textual Format</th>
</tr>
</thead>
<tbody>
<tr>
<td>{alnum}</td>
<td>Alphanumeric strings</td>
</tr>
<tr>
<td>{any}</td>
<td>Any string of word characters</td>
</tr>
<tr>
<td>{digits}</td>
<td>A sequence of digits</td>
</tr>
<tr>
<td>{lower}</td>
<td>A lowercase word</td>
</tr>
<tr>
<td>{mixed}</td>
<td>A mixed-case word</td>
</tr>
<tr>
<td>{name}</td>
<td>A word beginning with a capital letter</td>
</tr>
<tr>
<td>{upper}</td>
<td>An uppercase word</td>
</tr>
<tr>
<td>{whitespace}</td>
<td>whitespace characters</td>
</tr>
</tbody>
</table>

A word character is either an underscore or a character that might appear in a word in any language. For example, the strings 'Hello_word' and 'écoute' both consist of word characters. 'H' and 'é' are both examples of word characters.

**Automatically Train Models on Your Data Flow**

You can use Amazon SageMaker Autopilot to automatically train, tune, and deploy models on the data that you've transformed in your data flow. Amazon SageMaker Autopilot can go through several algorithms and use the one that works best with your data. For more information about Amazon SageMaker Autopilot, see [Automate model development with Amazon SageMaker Autopilot](#).

When you train and tune a model, Data Wrangler exports your data to an Amazon S3 location where Amazon SageMaker Autopilot can access it.

You can prepare and deploy a model by choosing a node in your Data Wrangler flow and choosing **Export and Train** in the data preview. You can use this method to view your dataset before you choose to train a model on it.

You can also train and deploy a model directly from your data flow.
Transform Data

The following procedure prepares and deploys a model from the data flow. For Data Wrangler flows with multi-row transforms, you can't use the transforms from the Data Wrangler flow when you're deploying the model. You can use the following procedure to process the data before you use it to perform inference.

To train and deploy a model directly from your data flow, do the following.

1. Choose the + next to the node containing the training data.
2. Choose Train model.
3. (Optional) Specify a AWS KMS key or ID. For more information about creating and controlling cryptographic keys to protect your data, see AWS Key Management Service.
4. Choose Export and train.
5. After Amazon SageMaker Autopilot trains the model on the data that Data Wrangler exported, specify a name for Experiment name.
6. Under Input data, choose Preview to verify that Data Wrangler properly exported your data to Amazon SageMaker Autopilot.
7. For Target, choose the target column.
8. (Optional) For S3 location under Output data, specify an Amazon S3 location other than the default location.
10. Choose a training method. For more information, see 
??? (p. 325).
11. (Optional) For Auto deploy endpoint, specify a name for the endpoint.
12. For Deployment option, choose a deployment method. You can choose to deploy with or without the transformations that you've made to your data.

Important
You can't deploy an Amazon SageMaker Autopilot model with the transformations that you've made in your Data Wrangler flow if you've used the following transformations:

- Join
- Concatenate
- Group by

You can export the dataset from a join to Amazon S3. You can create a new flow using the dataset that you've exported. You can use the dataset to train and deploy a model.

13. Choose Next: Review and create.
14. Choose Create experiment.

For more information about model training and deployment, see Create an Amazon SageMaker Autopilot experiment (p. 321). Autopilot shows you analyses about the best model's performance. For more information about model performance, see Autopilot Model Insights (p. 354).

Transform Data

Amazon SageMaker Data Wrangler provides numerous ML data transforms to streamline cleaning, transforming, and featurizing your data. When you add a transform, it adds a step to the data flow. Each transform you add modifies your dataset and produces a new dataframe. All subsequent transforms apply to the resulting dataframe.

Data Wrangler includes built-in transforms, which you can use to transform columns without any code. You can also add custom transformations using PySpark, Python (User-Defined Function), pandas,
and PySpark SQL. Some transforms operate in place, while others create a new output column in your dataset.

You can apply transforms to multiple columns at once. For example, you can delete multiple columns in a single step.

You can apply the **Process numeric** and **Handle missing** transforms only to a single column.

Use this page to learn more about these built-in and custom transforms.

**Transform UI**

Most of the built-in transforms are located in the **Prepare** tab of the Data Wrangler UI. You can access the join and concatenate transforms through the data flow view. Use the following table to preview these two views.

**Transform**

You can add a transform to any step in your data flow. Use the following procedure to add a transform to your data flow.

To add a step to your data flow, do the following.

1. Choose the + next to the step in the data flow.
2. Choose **Add transform**.
3. Choose **Add step**.
4. Choose a transform.

5. (Optional) You can search for the transform that you want to use. Data Wrangler highlights the query in the results.
Join View

To join two datasets, select the first dataset in your data flow and choose Join. When you choose Join, you see results similar to those shown in the following image. Your left and right datasets are displayed in the left panel. The main panel displays your data flow, with the newly joined dataset added.
When you choose Configure to configure your join, you see results similar to those shown in the following image. Your join configuration is displayed in the left panel. You can use this panel to choose the joined dataset name, join type, and columns to join. The main panel displays three tables. The top two tables display the left and right datasets on the left and right respectively. Under this table, you can preview the joined dataset.

See Join Datasets (p. 895) to learn more.

Concatenate View

To concatenate two datasets, you select the first dataset in your data flow and choose Concatenate. When you select Concatenate, you see results similar to those shown in the following image. Your
left and right datasets are displayed in the left panel. The main panel displays your data flow, with the newly concatenated dataset added.

When you choose Configure to configure your concatenation, you see results similar to those shown in the following image. Your concatenate configuration displays in the left panel. You can use this panel to choose the concatenated dataset's name, and choose to remove duplicates after concatenation and add columns to indicate the source dataframe. The main panel displays three tables. The top two tables display the left and right datasets on the left and right respectively. Under this table, you can preview the concatenated dataset.

See Concatenate Datasets (p. 895) to learn more.
Join Datasets

You join dataframes directly in your data flow. When you join two datasets, the resulting joined dataset appears in your flow. The following join types are supported by Data Wrangler.

- **Left Outer** – Include all rows from the left table. If the value for the column joined on a left table row does not match any right table row values, that row contains null values for all right table columns in the joined table.
- **Left Anti** – Include rows from the left table that do not contain values in the right table for the joined column.
- **Left semi** – Include a single row from the left table for all identical rows that satisfy the criteria in the join statement. This excludes duplicate rows from the left table that match the criteria of the join.
- **Right Outer** – Include all rows from the right table. If the value for the joined column in a right table row does not match any left table row values, that row contains null values for all left table columns in the joined table.
- **Inner** – Include rows from left and right tables that contain matching values in the joined column.
- **Full Outer** – Include all rows from the left and right tables. If the row value for the joined column in either table does not match, separate rows are created in the joined table. If a row doesn't contain a value for a column in the joined table, null is inserted for that column.
- **Cartesian Cross** – Include rows which combine each row from the first table with each row from the second table. This is a Cartesian product of rows from tables in the join. The result of this product is the size of the left table times the size of the right table. Therefore, we recommend caution in using this join between very large datasets.

Use the following procedure to join two dataframes.

1. Select + next to the left dataframe that you want to join. The first dataframe you select is always the left table in your join.
2. Choose Join.
3. Select the right dataframe. The second dataframe you select is always the right table in your join.
4. Choose Configure to configure your join.
5. Give your joined dataset a name using the Name field.
6. Select a Join type.
7. Select a column from the left and right tables to join.
8. Choose Apply to preview the joined dataset on the right.
9. To add the joined table to your data flow, choose Add.

Concatenate Datasets

**Concatenate two datasets:**

1. Choose + next to the left dataframe that you want to concatenate. The first dataframe you select is always the left table in your concatenate.
2. Choose Concatenate.
3. Select the right dataframe. The second dataframe you select is always the right table in your concatenate.
4. Choose Configure to configure your concatenate.
5. Give your concatenated dataset a name using the Name field.
6. (Optional) Select the checkbox next to **Remove duplicates after concatenation** to remove duplicate columns.

7. (Optional) Select the checkbox next to **Add column to indicate source dataframe** if, for each column in the new dataset, you want to add an indicator of the column's source.

8. Choose **Apply** to preview the new dataset.

9. Choose **Add** to add the new dataset to your data flow.

## Balance Data

You can balance the data for datasets with an underrepresented category. Balancing a dataset can help you create better models for binary classification.

**Note**

You can't balance datasets containing column vectors.

You can use the **Balance data** operation to balance your data using one of the following operators:

- **Random oversampling** – Randomly duplicates samples in the minority category. For example, if you're trying to detect fraud, you might only have cases of fraud in 10% of your data. For an equal proportion of fraudulent and non-fraudulent cases, this operator randomly duplicates fraud cases within the dataset 8 times.

- **Random undersampling** – Roughly equivalent to random oversampling. Randomly removes samples from the overrepresented category to get the proportion of samples that you desire.

- **Synthetic Minority Oversampling Technique (SMOTE)** – Uses samples from the underrepresented category to interpolate new synthetic minority samples. For more information about SMOTE, see the following description.

You can use all transforms for datasets containing both numeric and non-numeric features. SMOTE interpolates values by using neighboring samples. Data Wrangler uses the R-squared distance to determine the neighborhood to interpolate the additional samples. Data Wrangler only uses numeric features to calculate the distances between samples in the underrepresented group.

For two real samples in the underrepresented group, Data Wrangler interpolates the numeric features by using a weighted average. It randomly assigns weights to those samples in the range of [0, 1]. For numeric features, Data Wrangler interpolates samples using a weighted average of the samples. For samples A and B, Data Wrangler could randomly assign a weight of 0.7 to A and 0.3 to B. The interpolated sample has a value of 0.7A + 0.3B.

Data Wrangler interpolates non-numeric features by copying from either of the interpolated real samples. It copies the samples with a probability that it randomly assigns to each sample. For samples A and B, it can assign probabilities 0.8 to A and 0.2 to B. For the probabilities it assigned, it copies A 80% of the time.

## Custom Transforms

The **Custom Transforms** group allows you to use Python (User-Defined Function), PySpark, pandas, or PySpark (SQL) to define custom transformations. For all three options, you use the variable `df` to access the dataframe to which you want to apply the transform. If you're not using Python (User-Defined Function), you don't need to include a return statement. Choose **Preview** to preview the result of the custom transform. Choose **Add** to add the custom transform to your list of Previous steps.

You can import the popular libraries with an `import` statement in the custom transform code block, such as the following:

- NumPy version 1.19.0
Important

Custom transform doesn't support columns with spaces or special characters in the name. We recommend that you specify column names that only have alphanumeric characters and underscores. You can use the Rename column transform in the Manage columns transform group to remove spaces from a column's name. You can also add a Python (Pandas) Custom transform similar to the following to remove spaces from multiple columns in a single step. This example changes columns named A column and B column to A_column and B_column respectively.

```python
df.rename(columns={"A column": "A_column", "B column": "B_column"})
```

If you include print statements in the code block, the result appears when you select Preview. You can resize the custom code transformer panel. Resizing the panel provides more space to write code. The following image shows the resizing of the panel.
Data flow

Choose the plus sign to add a step to the flow. Select a step to modify.

Source - sampled

S3: titanic.csv
The following sections provide additional context and examples for writing custom transform code.

**Python (User-Defined Function)**

The Python function gives you the ability to write custom transformations without needing to know Apache Spark or pandas. Data Wrangler is optimized to run your custom code quickly. You get similar performance using custom Python code and an Apache Spark plugin.

To use the Python (User-Defined Function) code block, you specify the following:

- **Input column** – The input column where you're applying the transform.
- **Mode** – The scripting mode, either pandas or Python.
- **Return type** – The data type of the value that you're returning.

Using the pandas mode gives better performance. The Python mode makes it easier for you to write transformations by using pure Python functions.

The following video shows an example of how to use custom code to create a transformation. It uses the Titanic dataset to create a column with the person's salutation.
Data flow

Choose the plus sign to add a step to the flow. Select a step to move...
**PySpark**

The following example extracts date and time from a timestamp.

```python
from pyspark.sql.functions import from_unixtime, to_date, date_format
df = df.withColumn('DATE_TIME', from_unixtime('TIMESTAMP'))
df = df.withColumn( 'EVENT_DATE', to_date('DATE_TIME')).withColumn('EVENT_TIME', date_format('DATE_TIME', 'HH:mm:ss'))
```

**pandas**

The following example provides an overview of the dataframe to which you are adding transforms.

```python
df.info()
```

**PySpark (SQL)**

The following example creates a new dataframe with four columns: `name`, `fare`, `pclass`, `survived`.

```sql
SELECT name, fare, pclass, survived FROM df
```

If you don’t know how to use PySpark, you can use custom code snippets to help you get started.

Data Wrangler has a searchable collection of code snippets. You can use code snippets to perform tasks such as dropping columns, grouping by columns, or modelling.

To use a code snippet, choose **Search example snippets** and specify a query in the search bar. The text you specify in the query doesn’t have to match the name of the code snippet exactly.

The following example shows a **Drop duplicate rows** code snippet that can delete rows with similar data in your dataset. You can find the code snippet by searching for one of the following:

- Duplicates
- Identical
- Remove

The following snippet has comments to help you understand the changes that you need to make. For most snippets, you must specify the column names of your dataset in the code.

```python
# Specify the subset of columns
# all rows having identical values in these columns will be dropped
subset = ["col1", "col2", "col3"]
df = df.dropDuplicates(subset)
# to drop the full-duplicate rows run
# df = df.dropDuplicates()
```

To use a snippet, copy and paste its content into the **Custom transform** field. You can copy and paste multiple code snippets into the custom transform field.

**Custom Formula**

Use **Custom formula** to define a new column using a Spark SQL expression to query data in the current dataframe. The query must use the conventions of Spark SQL expressions.
**Important**

**Custom formula** doesn't support columns with spaces or special characters in the name. We recommend that you specify column names that only have alphanumeric characters and underscores. You can use the **Rename column** transform in the **Manage columns** transform group to remove spaces from a column's name. You can also add a **Python (Pandas) Custom transform** similar to the following to remove spaces from multiple columns in a single step. This example changes columns named A_column and B_column to A_column and B_column respectively.

```python
df.rename(columns={"A column": "A_column", "B column": "B_column"})
```

You can use this transform to perform operations on columns, referencing the columns by name. For example, assuming the current dataframe contains columns named col_a and col_b, you can use the following operation to produce an **Output column** that is the product of these two columns with the following code:

```python
col_a * col_b
```

Other common operations include the following, assuming a dataframe contains col_a and col_b columns:

- Concatenate two columns: `concat(col_a, col_b)`
- Add two columns: `col_a + col_b`
- Subtract two columns: `col_a - col_b`
- Divide two columns: `col_a / col_b`
- Take the absolute value of a column: `abs(col_a)`

For more information, see the **Spark documentation** on selecting data.

### Reduce Dimensionality within a Dataset

Reduce the dimensionality in your data by using Principal Component Analysis (PCA). The dimensionality of your dataset corresponds to the number of features. When you use dimensionality reduction in Data Wrangler, you get a new set of features called components. Each component accounts for some variability in the data.

The first component accounts for the largest amount of variation in the data. The second component accounts for the second largest amount of variation in the data, and so on.

You can use dimensionality reduction to reduce the size of the data sets that you use to train models. Instead of using the features in your dataset, you can use the principal components instead.

To perform PCA, Data Wrangler creates axes for your data. An axis is an affine combination of columns in your dataset. The first principal component is the value on the axis that has the largest amount of variance. The second principal component is the value on the axis that has the second largest amount of variance. The nth principal component is the value on the axis that has the nth largest amount of variance.

You can configure the number of principal components that Data Wrangler returns. You can either specify the number of principal components directly or you can specify the variance threshold percentage. Each principal component explains an amount of variance in the data. For example, you might have a principal component with a value of 0.5. The component would explain 50% of the variation in the data. When you specify a variance threshold percentage, Data Wrangler returns the smallest number of components that meet the percentage that you specify.
The following are example principal components with the amount of variance that they explain in the data.

- Component 1 – 0.5
- Component 2 – 0.45
- Component 3 – 0.05

If you specify a variance threshold percentage of 94 or 95, Data Wrangler returns Component 1 and Component 2. If you specify a variance threshold percentage of 96, Data Wrangler returns all three principal components.

You can use the following procedure to run PCA on your dataset.

To run PCA on your dataset, do the following.

1. Open your Data Wrangler data flow.
2. Choose the +, and select Add transform.
3. Choose Add step.
4. Choose Dimensionality Reduction.
5. For Input Columns, choose the features that you’re reducing into the principal components.
6. (Optional) For Number of principal components, choose the number of principal components that Data Wrangler returns in your dataset. If specify a value for the field, you can’t specify a value for Variance threshold percentage.
7. (Optional) For Variance threshold percentage, specify the percentage of variation in the data that you want explained by the principal components. Data Wrangler uses the default value of 95 if you don’t specify a value for the variance threshold. You can’t specify a variance threshold percentage if you’ve specified a value for Number of principal components.
8. (Optional) Deselect Center to not use the mean of the columns as the center of the data. By default, Data Wrangler centers the data with the mean before scaling.
9. (Optional) Deselect Scale to not scale the data with the unit standard deviation.
10. (Optional) Choose Columns to output the components to separate columns. Choose Vector to output the components as a single vector.
11. (Optional) For Output column, specify a name for an output column. If you’re outputting the components to separate columns, the name that you specify is a prefix. If you’re outputting the components to a vector, the name that you specify is the name of the vector column.
12. (Optional) Select Keep input columns. We don’t recommend selecting this option if you plan on only using the principal components to train your model.

Encode Categorical

Categorical data is usually composed of a finite number of categories, where each category is represented with a string. For example, if you have a table of customer data, a column that indicates the country a person lives in is categorical. The categories would be Afghanistan, Albania, Algeria, and so on. Categorical data can be nominal or ordinal. Ordinal categories have an inherent order, and nominal categories do not. The highest degree obtained (High school, Bachelors, Masters, and so on) is an example of ordinal categories.

Encoding categorical data is the process of creating a numerical representation for categories. For example, if your categories are Dog and Cat, you may encode this information into two vectors, \([1, 0]\) to represent Dog, and \([0, 1]\) to represent Cat.
When you encode ordinal categories, you may need to translate the natural order of categories into your encoding. For example, you can represent the highest degree obtained with the following map: {"High school": 1, "Bachelors": 2, "Masters":3}.

Use categorical encoding to encode categorical data that is in string format into arrays of integers.

The Data Wrangler categorical encoders create encodings for all categories that exist in a column at the time the step is defined. If new categories have been added to a column when you start a Data Wrangler job to process your dataset at time $t$, and this column was the input for a Data Wrangler categorical encoding transform at time $t-1$, these new categories are considered missing in the Data Wrangler job.

The option you select for Invalid handling strategy is applied to these missing values. Examples of when this can occur are:

- When you use a .flow file to create a Data Wrangler job to process a dataset that was updated after the creation of the data flow. For example, you may use a data flow to regularly process sales data each month. If that sales data is updated weekly, new categories may be introduced into columns for which an encode categorical step is defined.
- When you select Sampling when you import your dataset, some categories may be left out of the sample.

In these situations, these new categories are considered missing values in the Data Wrangler job.

You can choose from and configure an ordinal and a one-hot encode. Use the following sections to learn more about these options.

Both transforms create a new column named Output column name. You specify the output format of this column with Output style:

- Select Vector to produce a single column with a sparse vector.
- Select Columns to create a column for every category with an indicator variable for whether the text in the original column contains a value that is equal to that category.

### Ordinal Encode

Select Ordinal encode to encode categories into an integer between 0 and the total number of categories in the Input column you select.

Invalid handling strategy: Select a method to handle invalid or missing values.

- Choose Skip if you want to omit the rows with missing values.
- Choose Keep to retain missing values as the last category.
- Choose Error if you want Data Wrangler to throw an error if missing values are encountered in the Input column.
- Choose Replace with NaN to replace missing with NaN. This option is recommended if your ML algorithm can handle missing values. Otherwise, the first three options in this list may produce better results.

### One-Hot Encode

Select One-hot encode for Transform to use one-hot encoding. Configure this transform using the following:

- Drop last category: If True, the last category does not have a corresponding index in the one-hot encoding. When missing values are possible, a missing category is always the last one and setting this to True means that a missing value results in an all zero vector.
• **Invalid handling strategy**: Select a method to handle invalid or missing values.
  • Choose **Skip** if you want to omit the rows with missing values.
  • Choose **Keep** to retain missing values as the last category.
  • Choose **Error** if you want Data Wrangler to throw an error if missing values are encountered in the Input column.

• **Is input ordinal encoded**: Select this option if the input vector contains ordinal encoded data. This option requires that input data contain non-negative integers. If **True**, input $i$ is encoded as a vector with a non-zero in the $i$th location.

**Similarity encode**

Use similarity encoding when you have the following:

• A large number of categorical variables
• Noisy data

The similarity encoder creates embeddings for columns with categorical data. An embedding is a mapping of discrete objects, such as words, to vectors of real numbers. It encodes similar strings to vectors containing similar values. For example, it creates very similar encodings for “California” and “Calfornia”.

Data Wrangler converts each category in your dataset into a set of tokens using a 3-gram tokenizer. It converts the tokens into an embedding using min-hash encoding.

The following example shows how the similarity encoder creates vectors from strings.
The similarity encodings that Data Wrangler creates:

- Have low dimensionality
- Are scalable to a large number of categories
- Are robust and resistant to noise

For the preceding reasons, similarity encoding is more versatile than one-hot encoding.

To add the similarity encoding transform to your dataset, use the following procedure.

To use similarity encoding, do the following.

1. Sign in to the Amazon SageMaker Console.
2. Choose Open Studio.
3. Choose Launch app.
4. Choose Studio.
5. Specify your data flow.
6. Choose a step with a transformation.
7. Choose Add step.
8. Choose Encode categorical.
9. Specify the following:
   
   - **Transform** – Similarity encode
   - **Input column** – The column containing the categorical data that you're encoding.
   - **Target dimension** – (Optional) The dimension of the categorical embedding vector. The default value is 30. We recommend using a larger target dimension if you have a large dataset with many categories.
   - **Output style** – Choose Vector for a single vector with all of the encoded values. Choose Column to have the encoded values in separate columns.
   - **Output column** – (Optional) The name of the output column for a vector encoded output. For a column-encoded output, this is the prefix of the column names followed by listed number.

**Featurize Text**

Use the **Featurize Text** transform group to inspect string-typed columns and use text embedding to featurize these columns.
This feature group contains two features, Character statistics and Vectorize. Use the following sections to learn more about these transforms. For both options, the input column must contain text data (string type).

Character Statistics

Use Character statistics to generate statistics for each row in a column containing text data.

This transform computes the following ratios and counts for each row, and creates a new column to report the result. The new column is named using the input column name as a prefix and a suffix that is specific to the ratio or count.

- **Number of words**: The total number of words in that row. The suffix for this output column is -stats_word_count.
- **Number of characters**: The total number of characters in that row. The suffix for this output column is -stats_char_count.
- **Ratio of upper**: The number of uppercase characters, from A to Z, divided by all characters in the column. The suffix for this output column is -stats_capital_ratio.
- **Ratio of lower**: The number of lowercase characters, from a to z, divided by all characters in the column. The suffix for this output column is -stats_lower_ratio.
- **Ratio of digits**: The ratio of digits in a single row over the sum of digits in the input column. The suffix for this output column is -stats_digit_ratio.
- **Special characters ratio**: The ratio of non-alphanumeric (characters like #$&%:@) characters to over the sum of all characters in the input column. The suffix for this output column is -stats_special_ratio.

Vectorize

Text embedding involves mapping words or phrases from a vocabulary to vectors of real numbers. Use the Data Wrangler text embedding transform to tokenize and vectorize text data into term frequency-inverse document frequency (TF-IDF) vectors.

When TF-IDF is calculated for a column of text data, each word in each sentence is converted to a real number that represents its semantic importance. Higher numbers are associated with less frequent words, which tend to be more meaningful.

When you define a Vectorize transform step, Data Wrangler uses the data in your dataset to define the count vectorizer and TF-IDF methods. Running a Data Wrangler job uses these same methods.

You configure this transform using the following:

- **Output column name**: This transform creates a new column with the text embedding. Use this field to specify a name for this output column.
- **Tokenizer**: A tokenizer converts the sentence into a list of words, or tokens.
  
  Choose **Standard** to use a tokenizer that splits by white space and converts each word to lowercase. For example, "Good dog" is tokenized to ["good", "dog"].
  
  Choose **Custom** to use a customized tokenizer. If you choose Custom, you can use the following fields to configure the tokenizer:
  
  - **Minimum token length**: The minimum length, in characters, for a token to be valid. Defaults to 1. For example, if you specify 3 for minimum token length, words like a, at, in are dropped from the tokenized sentence.
  - **Should regex split on gaps**: If selected, regex splits on gaps. Otherwise, it matches tokens. Defaults to True.
• **Regex pattern**: Regex pattern that defines the tokenization process. Defaults to `' \s+`.

• **To lowercase**: If chosen, Data Wrangler converts all characters to lowercase before tokenization. Defaults to `True`.

To learn more, see the Spark documentation on [Tokenizer](#).

• **Vectorizer**: The vectorizer converts the list of tokens into a sparse numeric vector. Each token corresponds to an index in the vector and a non-zero indicates the existence of the token in the input sentence. You can choose from two vectorizer options, `Count` and `Hashing`.

• **Count vectorize** allows customizations that filter infrequent or too common tokens. **Count vectorize parameters** include the following:
  
  • **Minimum term frequency**: In each row, terms (tokens) with smaller frequency are filtered. If you specify an integer, this is an absolute threshold (inclusive). If you specify a fraction between 0 (inclusive) and 1, the threshold is relative to the total term count. Defaults to 1.
  
  • **Minimum document frequency**: Minimum number of rows in which a term (token) must appear to be included. If you specify an integer, this is an absolute threshold (inclusive). If you specify a fraction between 0 (inclusive) and 1, the threshold is relative to the total term count. Defaults to 1.
  
  • **Maximum document frequency**: Maximum number of documents (rows) in which a term (token) can appear to be included. If you specify an integer, this is an absolute threshold (inclusive). If you specify a fraction between 0 (inclusive) and 1, the threshold is relative to the total term count. Defaults to 0.999.
  
  • **Maximum vocabulary size**: Maximum size of the vocabulary. The vocabulary is made up of all terms (tokens) in all rows of the column. Defaults to 262144.
  
  • **Binary outputs**: If selected, the vector outputs do not include the number of appearances of a term in a document, but rather are a binary indicator of its appearance. Defaults to `False`.

To learn more about this option, see the Spark documentation on [CountVectorizer](#).

• **Hashing** is computationally faster. **Hash vectorize parameters** includes the following:

  • **Number of features during hashing**: A hash vectorizer maps tokens to a vector index according to their hash value. This feature determines the number of possible hash values. Large values result in fewer collisions between hash values but a higher dimension output vector.

To learn more about this option, see the Spark documentation on [FeatureHasher](#).

• **IDF** applies an IDF transformation, which multiplies the term frequency with the standard inverse document frequency used for TF-IDF embedding. **IDF parameters** include the following:

  • **Minimum document frequency**: Minimum number of documents (rows) in which a term (token) must appear to be included. If `count_vectorize` is the chosen vectorizer, we recommend that you keep the default value and only modify the `min_doc_freq` field in **Count vectorize parameters**. Defaults to 5.

  • **Output format**: The output format of each row.

    • Select **Vector** to produce a single column with a sparse vector.

    • Select **Flattened** to create a column for every category with an indicator variable for whether the text in the original column contains a value that is equal to that category. You can only choose flattened when **Vectorizer** is set as **Count vectorizer**.

### Transform Time Series

In Data Wrangler, you can transform time series data. The values in a time series dataset are indexed to specific time. For example, a dataset that shows the number of customers in a store for each hour in a day is a time series dataset. The following table shows an example of a time series dataset.
Hourly number of customers in a store

<table>
<thead>
<tr>
<th>Number of customers</th>
<th>Time (hour)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>09:00</td>
</tr>
<tr>
<td>10</td>
<td>10:00</td>
</tr>
<tr>
<td>14</td>
<td>11:00</td>
</tr>
<tr>
<td>25</td>
<td>12:00</td>
</tr>
<tr>
<td>20</td>
<td>13:00</td>
</tr>
<tr>
<td>18</td>
<td>14:00</td>
</tr>
</tbody>
</table>

For the preceding table, the Number of Customers column contains the time series data. The time series data is indexed on the hourly data in the Time (hour) column.

You might need to perform a series of transformations on your data to get it in a format that you can use for your analysis. Use the Time series transform group to transform your time series data. For more information about the transformations that you can perform, see the following sections.

Topics

- Group by a Time Series (p. 909)
- Resample Time Series Data (p. 910)
- Handle Missing Time Series Data (p. 912)
- Validate the Timestamp of Your Time Series Data (p. 913)
- Standardizing the Length of the Time Series (p. 914)
- Extract Features from Your Time Series Data (p. 915)
- Use Lagged Features from Your Time Series Data (p. 916)
- Create a Datetime Range In Your Time Series (p. 916)
- Use a Rolling Window In Your Time Series (p. 917)

Group by a Time Series

You can use the group by operation to group time series data for specific values in a column.

For example, you have the following table that tracks the average daily electricity usage in a household.

Average daily household electricity usage

<table>
<thead>
<tr>
<th>Household ID</th>
<th>Daily timestamp</th>
<th>Electricity usage (kWh)</th>
<th>Number of household occupants</th>
</tr>
</thead>
<tbody>
<tr>
<td>household_0</td>
<td>1/1/2020</td>
<td>30</td>
<td>2</td>
</tr>
<tr>
<td>household_0</td>
<td>1/2/2020</td>
<td>40</td>
<td>2</td>
</tr>
<tr>
<td>household_0</td>
<td>1/4/2020</td>
<td>35</td>
<td>3</td>
</tr>
<tr>
<td>household_1</td>
<td>1/2/2020</td>
<td>45</td>
<td>3</td>
</tr>
<tr>
<td>household_1</td>
<td>1/3/2020</td>
<td>55</td>
<td>4</td>
</tr>
</tbody>
</table>
If you choose to group by ID, you get the following table.

**Electricity usage grouped by household ID**

<table>
<thead>
<tr>
<th>Household ID</th>
<th>Electricity usage series (kWh)</th>
<th>Number of household occupants series</th>
</tr>
</thead>
<tbody>
<tr>
<td>household_0</td>
<td>[30, 40, 35]</td>
<td>[2, 2, 3]</td>
</tr>
<tr>
<td>household_1</td>
<td>[45, 55]</td>
<td>[3, 4]</td>
</tr>
</tbody>
</table>

Each entry in the time series sequence is ordered by the corresponding timestamp. The first element of the sequence corresponds to the first timestamp of the series. For household_0, 30 is the first value of the **Electricity Usage Series**. The value of 30 corresponds to the first timestamp of 1/1/2020.

You can include the starting timestamp and ending timestamp. The following table shows how that information appears.

**Electricity usage grouped by household ID**

<table>
<thead>
<tr>
<th>Household ID</th>
<th>Electricity usage series (kWh)</th>
<th>Number of household occupants series</th>
<th>Start_time</th>
<th>End_time</th>
</tr>
</thead>
<tbody>
<tr>
<td>household_0</td>
<td>[30, 40, 35]</td>
<td>[2, 2, 3]</td>
<td>1/1/2020</td>
<td>1/4/2020</td>
</tr>
<tr>
<td>household_1</td>
<td>[45, 55]</td>
<td>[3, 4]</td>
<td>1/2/2020</td>
<td>1/3/2020</td>
</tr>
</tbody>
</table>

You can use the following procedure to group by a time series column.

1. Open your Data Wrangler data flow.
2. If you haven't imported your dataset, import it under the Import data tab.
3. In your data flow, under Data types, choose the +, and select Add transform.
4. Choose **Add step**.
5. Choose **Time Series**.
6. Under Transform, choose **Group by**.
7. Specify a column in **Group by this column**.
8. For **Apply to columns**, specify a value.
9. Choose **Preview** to generate a preview of the transform.
10. Choose **Add** to add the transform to the Data Wrangler data flow.

**Resample Time Series Data**

Time series data usually has observations that aren't taken at regular intervals. For example, a dataset could have some observations that are recorded hourly and other observations that are recorded every two hours.

Many analyses, such as forecasting algorithms, require the observations to be taken at regular intervals. Resampling gives you the ability to establish regular intervals for the observations in your dataset.

You can either upsample or downsample a time series. Downsampling increases the interval between observations in the dataset. For example, if you downsample observations that are taken either every hour or every two hours, each observation in your dataset is taken every two hours. The hourly
observations are aggregated into a single value using an aggregation method such as the mean or median.

Upsampling reduces the interval between observations in the dataset. For example, if you upsample observations that are taken every two hours into hourly observations, you can use an interpolation method to infer hourly observations from the ones that have been taken every two hours. For information on interpolation methods, see pandas.DataFrame.interpolate.

You can resample both numeric and non-numeric data.

Use the Resample operation to resample your time series data. If you have multiple time series in your dataset, Data Wrangler standardizes the time interval for each time series.

The following table shows an example of downsampling time series data by using the mean as the aggregation method. The data is downsamped from every two hours to every hour.

### Hourly temperature readings over a day before downsampling

<table>
<thead>
<tr>
<th>Timestamp</th>
<th>Temperature (Celsius)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12:00</td>
<td>30</td>
</tr>
<tr>
<td>1:00</td>
<td>32</td>
</tr>
<tr>
<td>2:00</td>
<td>35</td>
</tr>
<tr>
<td>3:00</td>
<td>32</td>
</tr>
<tr>
<td>4:00</td>
<td>30</td>
</tr>
</tbody>
</table>

### Temperature readings downsampled to every two hours

<table>
<thead>
<tr>
<th>Timestamp</th>
<th>Temperature (Celsius)</th>
</tr>
</thead>
<tbody>
<tr>
<td>12:00</td>
<td>30</td>
</tr>
<tr>
<td>2:00</td>
<td>33.5</td>
</tr>
<tr>
<td>2:00</td>
<td>35</td>
</tr>
<tr>
<td>4:00</td>
<td>32.5</td>
</tr>
</tbody>
</table>

You can use the following procedure to resample time series data.

1. Open your Data Wrangler data flow.
2. If you haven't imported your dataset, import it under the Import data tab.
3. In your data flow, under Data types, choose the +, and select Add transform.
5. Choose Resample.
6. For Timestamp, choose the timestamp column.
7. For Frequency unit, specify the frequency that you're resampling.
8. (Optional) Specify a value for Frequency quantity.
9. Configure the transform by specifying the remaining fields.
10. Choose Preview to generate a preview of the transform.
11. Choose Add to add the transform to the Data Wrangler data flow.
Handle Missing Time Series Data

If you have missing values in your dataset, you can do one of the following:

- For datasets that have multiple time series, drop the time series that have missing values that are greater than a threshold that you specify.
- Impute the missing values in a time series by using other values in the time series.

Imputing a missing value involves replacing the data by either specifying a value or by using an inferential method. The following are the methods that you can use for imputation:

- Constant value – Replace all the missing data in your dataset with a value that you specify.
- Most common value – Replace all the missing data with the value that has the highest frequency in the dataset.
- Forward fill – Use a forward fill to replace the missing values with the non-missing value that precedes the missing values. For the sequence: [2, 4, 7, NaN, NaN, NaN, 8], all of the missing values are replaced with 7. The sequence that results from using a forward fill is [2, 4, 7, 7, 7, 7, 8].
- Backward fill – Use a backward fill to replace the missing values with the non-missing value that follows the missing values. For the sequence: [2, 4, 7, NaN, NaN, NaN, 8], all of the missing values are replaced with 8. The sequence that results from using a backward fill is [2, 4, 7, 8, 8, 8, 8].
- Interpolate – Uses an interpolation function to impute the missing values. For more information on the functions that you can use for interpolation, see pandas.DataFrame.interpolate.

Some of the imputation methods might not be able to impute of all the missing value in your dataset. For example, a Forward fill can't impute a missing value that appears at the beginning of the time series. You can impute the values by using either a forward fill or a backward fill.

You can either impute missing values within a cell or within a column.

The following example shows how values are imputed within a cell.

**Electricity usage with missing values**

<table>
<thead>
<tr>
<th>Household ID</th>
<th>Electricity usage series (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>household_0</td>
<td>[30, 40, 35, NaN, NaN]</td>
</tr>
<tr>
<td>household_1</td>
<td>[45, NaN, 55]</td>
</tr>
</tbody>
</table>

**Electricity usage with values imputed using a forward fill**

<table>
<thead>
<tr>
<th>Household ID</th>
<th>Electricity usage series (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>household_0</td>
<td>[30, 40, 35, 35, 35]</td>
</tr>
<tr>
<td>household_1</td>
<td>[45, 45, 55]</td>
</tr>
</tbody>
</table>

The following example shows how values are imputed within a column.

**Average daily household electricity usage with missing values**

<table>
<thead>
<tr>
<th>Household ID</th>
<th>Electricity usage (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>household_0</td>
<td>30</td>
</tr>
</tbody>
</table>
Transform Data

### Average daily household electricity usage with values imputed using a forward fill

<table>
<thead>
<tr>
<th>Household ID</th>
<th>Electricity usage (kWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>household_0</td>
<td>30</td>
</tr>
<tr>
<td>household_0</td>
<td>40</td>
</tr>
<tr>
<td>household_0</td>
<td>40</td>
</tr>
<tr>
<td>household_1</td>
<td>40</td>
</tr>
<tr>
<td>household_1</td>
<td>40</td>
</tr>
</tbody>
</table>

You can use the following procedure to handle missing values.

1. Open your Data Wrangler data flow.
2. If you haven't imported your dataset, import it under the **Import data** tab.
3. In your data flow, under **Data types**, choose the +, and select **Add transform**.
4. Choose **Add step**.
5. Choose **Handle missing**.
6. For **Time series input type**, choose whether you want to handle missing values inside of a cell or along a column.
7. For **Impute missing values for this column**, specify the column that has the missing values.
8. For **Method for imputing values**, select a method.
9. Configure the transform by specifying the remaining fields.
10. Choose **Preview** to generate a preview of the transform.
11. If you have missing values, you can specify a method for imputing them under **Method for imputing values**.
12. Choose **Add** to add the transform to the Data Wrangler data flow.

### Validate the Timestamp of Your Time Series Data

You might have time stamp data that is invalid. You can use the **Validate time stamp** function to determine whether the timestamps in your dataset are valid. Your timestamp can be invalid for one or more of the following reasons:

- Your timestamp column has missing values.
- The values in your timestamp column are not formatted correctly.

If you have invalid timestamps in your dataset, you can't perform your analysis successfully. You can use Data Wrangler to identify invalid timestamps and understand where you need to clean your data.
The time series validation works in one of the two ways:

You can configure Data Wrangler to do one of the following if it encounters missing values in your dataset:

- Drop the rows that have the missing or invalid values.
- Identify the rows that have the missing or invalid values.
- Throw an error if it finds any missing or invalid values in your dataset.

You can validate the timestamps on columns that either have the timestamp type or the string type. If the column has the string type, Data Wrangler converts the type of the column to timestamp and performs the validation.

You can use the following procedure to validate the timestamps in your dataset.

1. Open your Data Wrangler data flow.
2. If you haven't imported your dataset, import it under the Import data tab.
3. In your data flow, under Data types, choose the +, and select Add transform.
5. Choose Validate timestamps.
6. For Timestamp Column, choose the timestamp column.
7. For Policy, choose whether you want to handle missing timestamps.
8. (Optional) For Output column, specify a name for the output column.
9. If the date time column is formatted for the string type, choose Cast to datetime.
10. Choose Preview to generate a preview of the transform.
11. Choose Add to add the transform to the Data Wrangler data flow.

Standardizing the Length of the Time Series

If you have time series data stored as arrays, you can standardize each time series to the same length. Standardizing the length of the time series array might make it easier for you to perform your analysis on the data.

You can standardize your time series for data transformations that require the length of your data to be fixed.

Many ML algorithms require you to flatten your time series data before you use them. Flattening time series data is separating each value of the time series into its own column in a dataset. The number of columns in a dataset can't change, so the lengths of the time series need to be standardized between you flatten each array into a set of features.

Each time series is set to the length that you specify as a quantile or percentile of the time series set. For example, you can have three sequences that have the following lengths:

- 3
- 4
- 5

You can set the length of all of the sequences as the length of the sequence that has the 50th percentile length.
Time series arrays that are shorter than the length you've specified have missing values added. The following is an example format of standardizing the time series to a longer length: [2, 4, 5, NaN, NaN, NaN].

You can use different approaches to handle the missing values. For information on those approaches, see Handle Missing Time Series Data (p. 912).

The time series arrays that are longer than the length that you specify are truncated.

You can use the following procedure to standardize the length of the time series.

1. Open your Data Wrangler data flow.
2. If you haven't imported your dataset, import it under the Import data tab.
3. In your data flow, under Data types, choose the +, and select Add transform.
5. Choose Standardize length.
6. For Standardize the time series length for the column, choose a column.
7. (Optional) For Output column, specify a name for the output column. If you don't specify a name, the transform is done in place.
8. If the datetime column is formatted for the string type, choose Cast to datetime.
9. Choose Cutoff quantile and specify a quantile to set the length of the sequence.
10. Choose Flatten the output to output the values of the time series into separate columns.
11. Choose Preview to generate a preview of the transform.
12. Choose Add to add the transform to the Data Wrangler data flow.

Extract Features from Your Time Series Data

If you're running a classification or a regression algorithm on your time series data, we recommend extracting features from the time series before running the algorithm. Extracting features might improve the performance of your algorithm.

Use the following options to choose how you want to extract features from your data:

- Use Minimal subset to specify extracting 8 features that you know are useful in downstream analyses. You can use a minimal subset when you need to perform computations quickly. You can also use it when your ML algorithm has a high risk of overfitting and you want to provide it with fewer features.
- Use Efficient subset to specify extracting the most features possible without extracting features that are computationally intensive in your analyses.
- Use All features to specify extracting all features from the time series.
- Use Manual subset to choose a list of features that you think explain the variation in your data well.

Use the following the procedure to extract features from your time series data.

1. Open your Data Wrangler data flow.
2. If you haven't imported your dataset, import it under the Import data tab.
3. In your data flow, under Data types, choose the +, and select Add transform.
5. Choose Extract features.
6. For Extract features for this column, choose a column.
7. (Optional) Select Flatten to output the features into separate columns.
8. For **Strategy**, choose a strategy to extract the features.
9. Choose **Preview** to generate a preview of the transform.
10. Choose **Add** to add the transform to the Data Wrangler data flow.

**Use Lagged Features from Your Time Series Data**

For many use cases, the best way to predict the future behavior of your time series is to use its most recent behavior.

The most common uses of lagged features are the following:

- Collecting a handful of past values. For example, for time, \( t + 1 \), you collect \( t, t - 1, t - 2, \) and \( t - 3 \).
- Collecting values that correspond to seasonal behavior in the data. For example, to predict the occupancy in a restaurant at 1:00 PM, you might want to use the features from 1:00 PM on the previous day. Using the features from 12:00 PM or 11:00 AM on the same day might not be as predictive as using the features from previous days.

1. Open your Data Wrangler data flow.
2. If you haven’t imported your dataset, import it under the **Import data** tab.
3. In your data flow, under **Data types**, choose the +, and select **Add transform**.
4. Choose **Add step**.
5. Choose **Lag features**.
6. For **Generate lag features for this column**, choose a column.
7. For **Timestamp Column**, choose the column containing the timestamps.
8. For **Lag**, specify the duration of the lag.
9. (Optional) Configure the output using one of the following options:
   - **Include the entire lag window**
   - **Flatten the output**
   - **Drop rows without history**
10. Choose **Preview** to generate a preview of the transform.
11. Choose **Add** to add the transform to the Data Wrangler data flow.

**Create a Datetime Range In Your Time Series**

You might have time series data that don’t have timestamps. If you know that the observations were taken at regular intervals, you can generate timestamps for the time series in a separate column. To generate timestamps, you specify the value for the start timestamp and the frequency of the timestamps.

For example, you might have the following time series data for the number of customers at a restaurant.

**Time series data on the number of customers at a restaurant**

<table>
<thead>
<tr>
<th>Number of customers</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
</tr>
<tr>
<td>14</td>
</tr>
<tr>
<td>24</td>
</tr>
</tbody>
</table>
If you know that the restaurant opened at 5:00 PM and that the observations are taken hourly, you can add a timestamp column that corresponds to the time series data. You can see the timestamp column in the following table.

<table>
<thead>
<tr>
<th>Number of customers</th>
<th>Timestamp</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1:00 PM</td>
</tr>
<tr>
<td>14</td>
<td>2:00 PM</td>
</tr>
<tr>
<td>24</td>
<td>3:00 PM</td>
</tr>
<tr>
<td>40</td>
<td>4:00 PM</td>
</tr>
<tr>
<td>30</td>
<td>5:00 PM</td>
</tr>
<tr>
<td>20</td>
<td>6:00 PM</td>
</tr>
</tbody>
</table>

Use the following procedure to add a datetime range to your data.

1. Open your Data Wrangler data flow.
2. If you haven't imported your dataset, import it under the Import data tab.
3. In your data flow, under Data types, choose the +, and select Add transform.
5. Choose Datetime range.
6. For Frequency type, choose the unit used to measure the frequency of the timestamps.
7. For Starting timestamp, specify the start timestamp.
8. For Output column, specify a name for the output column.
9. (Optional) Configure the output using the remaining fields.
10. Choose Preview to generate a preview of the transform.
11. Choose Add to add the transform to the Data Wrangler data flow.

**Use a Rolling Window In Your Time Series**

You can extract features over a time period. For example, for time, $t$, and a time window length of 3, and for the row that indicates the $t$th timestamp, we append the features that are extracted from the time series at times $t - 3$, $t - 2$, and $t - 1$. For information on extracting features, see Extract Features from Your Time Series Data (p. 915).

You can use the following procedure to extract features over a time period.

1. Open your Data Wrangler data flow.
2. If you haven't imported your dataset, import it under the Import data tab.
3. In your data flow, under Data types, choose the +, and select Add transform.
5. Choose Rolling window features.
6. For Generate rolling window features for this column, choose a column.
7. For Timestamp Column, choose the column containing the timestamps.
8. (Optional) For Output Column, specify the name of the output column.
9. For Window size, specify the window size.
10. For Strategy, choose the extraction strategy.
11. Choose Preview to generate a preview of the transform.
12. Choose Add to add the transform to the Data Wrangler data flow.

Featurize Datetime

Use Featurize date/time to create a vector embedding representing a datetime field. To use this transform, your datetime data must be in one of the following formats:

- Strings describing datetime: For example, "January 1st, 2020, 12:44pm".
- A Unix timestamp: A Unix timestamp describes the number of seconds, milliseconds, microseconds, or nanoseconds from 1/1/1970.

You can choose to Infer datetime format and provide a Datetime format. If you provide a datetime format, you must use the codes described in the Python documentation. The options you select for these two configurations have implications for the speed of the operation and the final results.

- The most manual and computationally fastest option is to specify a Datetime format and select No for Infer datetime format.
- To reduce manual labor, you can choose Infer datetime format and not specify a datetime format. It is also a computationally fast operation; however, the first datetime format encountered in the input column is assumed to be the format for the entire column. If there are other formats in the column, these values are NaN in the final output. Inferring the datetime format can give you unparsed strings.
- If you don't specify a format and select No for Infer datetime format, you get the most robust results. All the valid datetime strings are parsed. However, this operation can be an order of magnitude slower than the first two options in this list.

When you use this transform, you specify an Input column which contains datetime data in one of the formats listed above. The transform creates an output column named Output column name. The format of the output column depends on your configuration using the following:

- Vector: Outputs a single column as a vector.
- Columns: Creates a new column for every feature. For example, if the output contains a year, month, and day, three separate columns are created for year, month, and day.

Additionally, you must choose an Embedding mode. For linear models and deep networks, we recommend choosing cyclic. For tree-based algorithms, we recommend choosing ordinal.

Format String

The Format string transforms contain standard string formatting operations. For example, you can use these operations to remove special characters, normalize string lengths, and update string casing.
This feature group contains the following transforms. All transforms return copies of the strings in the **Input column** and add the result to a new, output column.

<table>
<thead>
<tr>
<th>Name</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Left pad</td>
<td>Left-pad the string with a given Fill character to the given width. If the string is longer than width, the return value is shortened to width characters.</td>
</tr>
<tr>
<td>Right pad</td>
<td>Right-pad the string with a given Fill character to the given width. If the string is longer than width, the return value is shortened to width characters.</td>
</tr>
<tr>
<td>Center (pad on either side)</td>
<td>Center-pad the string (add padding on both sides of the string) with a given Fill character to the given width. If the string is longer than width, the return value is shortened to width characters.</td>
</tr>
<tr>
<td>Prepend zeros</td>
<td>Left-fill a numeric string with zeros, up to a given width. If the string is longer than width, the return value is shortened to width characters.</td>
</tr>
<tr>
<td>Strip left and right</td>
<td>Returns a copy of the string with the leading and trailing characters removed.</td>
</tr>
<tr>
<td>Strip characters from left</td>
<td>Returns a copy of the string with leading characters removed.</td>
</tr>
<tr>
<td>Strip characters from right</td>
<td>Returns a copy of the string with trailing characters removed.</td>
</tr>
<tr>
<td>Lower case</td>
<td>Convert all letters in text to lowercase.</td>
</tr>
<tr>
<td>Upper case</td>
<td>Convert all letters in text to uppercase.</td>
</tr>
<tr>
<td>Capitalize</td>
<td>Capitalize the first letter in each sentence.</td>
</tr>
<tr>
<td>Swap case</td>
<td>Converts all uppercase characters to lowercase and all lowercase characters to uppercase characters of the given string, and returns it.</td>
</tr>
<tr>
<td>Add prefix or suffix</td>
<td>Adds a prefix and a suffix the string column. You must specify at least one of Prefix and Suffix.</td>
</tr>
<tr>
<td>Remove symbols</td>
<td>Removes given symbols from a string. All listed characters are removed. Defaults to white space.</td>
</tr>
</tbody>
</table>

### Handle Outliers

Machine learning models are sensitive to the distribution and range of your feature values. Outliers, or rare values, can negatively impact model accuracy and lead to longer training times. Use this feature group to detect and update outliers in your dataset.

When you define a Handle outliers transform step, the statistics used to detect outliers are generated on the data available in Data Wrangler when defining this step. These same statistics are used when running a Data Wrangler job.

Use the following sections to learn more about the transforms this group contains. You specify an **Output name** and each of these transforms produces an output column with the resulting data.
Robust standard deviation numeric outliers

This transform detects and fixes outliers in numeric features using statistics that are robust to outliers.

You must define an Upper quantile and a Lower quantile for the statistics used to calculate outliers. You must also specify the number of Standard deviations from which a value must vary from the mean to be considered an outlier. For example, if you specify 3 for Standard deviations, a value must fall more than 3 standard deviations from the mean to be considered an outlier.

The Fix method is the method used to handle outliers when they are detected. You can choose from the following:

- **Clip**: Use this option to clip the outliers to the corresponding outlier detection bound.
- **Remove**: Use this option to remove rows with outliers from the dataframe.
- **Invalidate**: Use this option to replace outliers with invalid values.

Standard Deviation Numeric Outliers

This transform detects and fixes outliers in numeric features using the mean and standard deviation.

You specify the number of Standard deviations a value must vary from the mean to be considered an outlier. For example, if you specify 3 for Standard deviations, a value must fall more than 3 standard deviations from the mean to be considered an outlier.

The Fix method is the method used to handle outliers when they are detected. You can choose from the following:

- **Clip**: Use this option to clip the outliers to the corresponding outlier detection bound.
- **Remove**: Use this option to remove rows with outliers from the dataframe.
- **Invalidate**: Use this option to replace outliers with invalid values.

Quantile Numeric Outliers

Use this transform to detect and fix outliers in numeric features using quantiles. You can define an Upper quantile and a Lower quantile. All values that fall above the upper quantile or below the lower quantile are considered outliers.

The Fix method is the method used to handle outliers when they are detected. You can choose from the following:

- **Clip**: Use this option to clip the outliers to the corresponding outlier detection bound.
- **Remove**: Use this option to remove rows with outliers from the dataframe.
- **Invalidate**: Use this option to replace outliers with invalid values.

Min-Max Numeric Outliers

This transform detects and fixes outliers in numeric features using upper and lower thresholds. Use this method if you know threshold values that demark outliers.

You specify a Upper threshold and a Lower threshold, and if values fall above or below those thresholds respectively, they are considered outliers.

The Fix method is the method used to handle outliers when they are detected. You can choose from the following:
Transform Data

- **Clip**: Use this option to clip the outliers to the corresponding outlier detection bound.
- **Remove**: Use this option to remove rows with outliers from the dataframe.
- **Invalidate**: Use this option to replace outliers with invalid values.

**Replace Rare**

When you use the **Replace rare** transform, you specify a threshold and Data Wrangler finds all values that meet that threshold and replaces them with a string that you specify. For example, you may want to use this transform to categorize all outliers in a column into an "Others" category.

- **Replacement string**: The string with which to replace outliers.
- **Absolute threshold**: A category is rare if the number of instances is less than or equal to this absolute threshold.
- **Fraction threshold**: A category is rare if the number of instances is less than or equal to this fraction threshold multiplied by the number of rows.
- **Max common categories**: Maximum not-rare categories that remain after the operation. If the threshold does not filter enough categories, those with the top number of appearances are classified as not rare. If set to 0 (default), there is no hard limit to the number of categories.

**Handle Missing Values**

Missing values are a common occurrence in machine learning datasets. In some situations, it is appropriate to impute missing data with a calculated value, such as an average or categorically common value. You can process missing values using the **Handle missing values** transform group. This group contains the following transforms.

**Fill Missing**

Use the **Fill missing** transform to replace missing values with a **Fill value** you define.

**Impute Missing**

Use the **Impute missing** transform to create a new column that contains imputed values where missing values were found in input categorical and numerical data. The configuration depends on your data type.

For numeric data, choose an imputing strategy, the strategy used to determine the new value to impute. You can choose to impute the mean or the median over the values that are present in your dataset. Data Wrangler uses the value that it computes to impute the missing values.

For categorical data, Data Wrangler imputes missing values using the most frequent value in the column. To impute a custom string, use the **Fill missing** transform instead.

**Add Indicator for Missing**

Use the **Add indicator for missing** transform to create a new indicator column, which contains a Boolean "false" if a row contains a value, and "true" if a row contains a missing value.

**Drop Missing**

Use the **Drop missing** option to drop rows that contain missing values from the **Input column**.

**Manage Columns**

You can use the following transforms to quickly update and manage columns in your dataset:
Transform Data

<table>
<thead>
<tr>
<th>Name</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Drop Column</td>
<td>Delete a column.</td>
</tr>
<tr>
<td>Duplicate Column</td>
<td>Duplicate a column.</td>
</tr>
<tr>
<td>Rename Column</td>
<td>Rename a column.</td>
</tr>
<tr>
<td>Move Column</td>
<td>Move a column's location in the dataset. Choose to move your column to the start or end of the dataset, before or after a reference column, or to a specific index.</td>
</tr>
</tbody>
</table>

**Manage Rows**

Use this transform group to quickly perform sort and shuffle operations on rows. This group contains the following:

- **Sort**: Sort the entire dataframe by a given column. Select the check box next to *Ascending order* for this option; otherwise, deselect the check box and descending order is used for the sort.
- **Shuffle**: Randomly shuffle all rows in the dataset.

**Manage Vectors**

Use this transform group to combine or flatten vector columns. This group contains the following transforms.

- **Assemble**: Use this transform to combine Spark vectors and numeric data into a single column. For example, you can combine three columns: two containing numeric data and one containing vectors. Add all the columns you want to combine in *Input columns* and specify a *Output column name* for the combined data.
- **Flatten**: Use this transform to flatten a single column containing vector data. The input column must contain PySpark vectors or array-like objects. You can control the number of columns created by specifying a *Method to detect number of outputs*. For example, if you select *Length of first vector*, the number of elements in the first valid vector or array found in the column determines the number of output columns that are created. All other input vectors with too many items are truncated. Inputs with too few items are filled with NaNs.
  
  You also specify an *Output prefix*, which is used as the prefix for each output column.

**Process Numeric**

Use the **Process Numeric** feature group to process numeric data. Each scalar in this group is defined using the Spark library. The following scalars are supported:

- **Standard Scaler**: Standardize the input column by subtracting the mean from each value and scaling to unit variance. To learn more, see the Spark documentation for `StandardScaler`.
- **Robust Scaler**: Scale the input column using statistics that are robust to outliers. To learn more, see the Spark documentation for `RobustScaler`.
- **Min Max Scaler**: Transform the input column by scaling each feature to a given range. To learn more, see the Spark documentation for `MinMaxScaler`.
- **Max Absolute Scaler**: Scale the input column by dividing each value by the maximum absolute value. To learn more, see the Spark documentation for `MaxAbsScaler`.
Sampling

After you've imported your data, you can use the Sampling transformer to take one or more samples of it. When you use the sampling transformer, Data Wrangler samples your original dataset.

You can choose one of the following sample methods:

- **Limit**: Samples the dataset starting from the first row up to the limit that you specify.
- **Randomized**: Takes a random sample of a size that you specify.
- **Stratified**: Takes a stratified random sample.

You can stratify a randomized sample to make sure that it represents the original distribution of the dataset.

You might be performing data preparation for multiple use cases. For each use case, you can take a different sample and apply a different set of transformations.

The following procedure describes the process of creating a random sample.

To take a random sample from your data.

1. Choose the + to the right of the dataset that you've imported. The name of your dataset is located below the +.
2. Choose Add transform.
3. Choose Sampling.
4. For Sampling method, choose the sampling method.
5. For Approximate sample size, choose the approximate number of observations that you want in your sample.
6. (Optional) Specify an integer for Random seed to create a reproducible sample.

The following procedure describes the process of creating a stratified sample.

To take a stratified sample from your data.

1. Choose the + to the right of the dataset that you've imported. The name of your dataset is located below the +.
2. Choose Add transform.
3. Choose Sampling.
4. For Sampling method, choose the sampling method.
5. For Approximate sample size, choose the approximate number of observations that you want in your sample.
6. For Stratify column, specify the name of the column that you want to stratify on.
7. (Optional) Specify an integer for Random seed to create a reproducible sample.

Search and Edit

Use this section to search for and edit specific patterns within strings. For example, you can find and update strings within sentences or documents, split strings by delimiters, and find occurrences of specific strings.

The following transforms are supported under Search and edit. All transforms return copies of the strings in the Input column and add the result to a new output column.
<table>
<thead>
<tr>
<th>Name</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Find substring</td>
<td>Returns the index of the first occurrence of the <strong>Substring</strong> for which you searched <strong>Substring</strong> for which you searched. You can start and end the search at <strong>Start</strong> and <strong>End</strong> respectively.</td>
</tr>
<tr>
<td>Find substring (from right)</td>
<td>Returns the index of the last occurrence of the <strong>Substring</strong> for which you searched. You can start and end the search at <strong>Start</strong> and <strong>End</strong> respectively.</td>
</tr>
<tr>
<td>Matches prefix</td>
<td>Returns a Boolean value if the string contains a given <strong>Pattern</strong>. A pattern can be a character sequence or regular expression. Optionally, you can make the pattern case sensitive.</td>
</tr>
<tr>
<td>Find all occurrences</td>
<td>Returns an array with all occurrences of a given pattern. A pattern can be a character sequence or regular expression.</td>
</tr>
<tr>
<td>Extract using regex</td>
<td>Returns a string that matches a given Regex pattern.</td>
</tr>
<tr>
<td>Extract between delimiters</td>
<td>Returns a string with all characters found between <strong>Left delimiter</strong> and <strong>Right delimiter</strong>.</td>
</tr>
<tr>
<td>Extract from position</td>
<td>Returns a string, starting from <strong>Start position</strong> in the input string, that contains all characters up to the start position plus <strong>Length</strong>.</td>
</tr>
<tr>
<td>Find and replace substring</td>
<td>Returns a string with all matches of a given <strong>Pattern</strong> (regular expression) replaced by <strong>Replacement string</strong>.</td>
</tr>
<tr>
<td>Replace between delimiters</td>
<td>Returns a string with the substring found between the first appearance of a <strong>Left delimiter</strong> and the last appearance of a <strong>Right delimiter</strong> replaced by <strong>Replacement string</strong>. If no match is found, nothing is replaced.</td>
</tr>
<tr>
<td>Replace from position</td>
<td>Returns a string with the substring between <strong>Start position</strong> and <strong>Start position</strong> plus <strong>Length</strong> replaced by <strong>Replacement string</strong>. If <strong>Start position</strong> plus <strong>Length</strong> is greater than the length of the replacement string, the output contains <strong>....</strong>.</td>
</tr>
<tr>
<td>Convert regex to missing</td>
<td>Converts a string to None if invalid and returns the result. Validity is defined with a regular expression in <strong>Pattern</strong>.</td>
</tr>
<tr>
<td>Split string by delimiter</td>
<td>Returns an array of strings from the input string, split by <strong>Delimiter</strong>, with up to <strong>Max number of splits</strong> (optional). The delimiter defaults to white space.</td>
</tr>
</tbody>
</table>

**Split data**

Use the **Split data** transform to split your dataset into two or three datasets. For example, you can split your dataset into a dataset used to train your model and a dataset used to test it. You can determine the
proportion of the dataset that goes into each split. For example, if you’re splitting one dataset into two
datasets, the training dataset can have 80% of the data while the testing dataset has 20%.

Splitting your data into three datasets gives you the ability to create training, validation, and test
datasets. You can see how well the model performs on the test dataset by dropping the target column.

Your use case determines how much of the original dataset each of your datasets get and the method
you use to split the data. For example, you might want to use a stratified split to make sure that the
distribution of the observations in the target column are the same across datasets. You can use the
following split transforms:

- Randomized split — Each split is a random, non-overlapping sample of the original dataset. For larger
datasets, using a randomized split might be computationally expensive and take longer than an
ordered split.

- Ordered split – Splits the dataset based on the sequential order of the observations. For example, for
an 80/20 train-test split, the first observations that make up 80% of the dataset go to the training
data set. The last 20% of the observations go to the testing dataset. Ordered splits are effective in
keeping the existing order of the data between splits.

- Stratified split – Splits the dataset to make sure that the number of observations in the input column
have proportional representation. For an input column that has the observations 1, 1, 1, 1, 1, 2, 2, 2,
2, 2, 2, 2, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, an 80/20 split on the column would mean that approximately 80% of the
1s, 80% of the 2s, and 80% of the 3s go to the training set. About 20% of each type of observation go
to the testing set.

- Split by key – Avoids data with the same key occurring in more than one split. For example, if you have
a dataset with the column ‘customer_id’ and you’re using it as a key, no customer id is in more than
one split.

After you split the data, you can apply additional transformations to each dataset. For most use cases,
they aren’t necessary.

Data Wrangler calculates the proportions of the splits for performance. You can choose an error
threshold to set the accuracy of the splits. Lower error thresholds more accurately reflect the proportions
that you specify for the splits. If you set a higher error threshold, you get better performance, but lower
accuracy.

For perfectly split data, set the error threshold to 0. You can specify a threshold between 0 and 1 for
better performance. If you specify a value greater than 1, Data Wrangler interprets that value as 1.

If you have 10000 rows in your dataset and you specify an 80/20 split with an error of 0.001, you would
get observations approximating one of the following results:

- 8010 observations in the training set and 1990 in the testing set
- 7990 observations in the training set and 2010 in the testing set

The number of observations for the testing set in the preceding example is in the interval between 8010
and 7990.

By default, Data Wrangler uses a random seed to make the splits reproducible. You can specify a
different value for the seed to create a different reproducible split.

Randomized split

Use the following procedure to perform a randomized split on your dataset.

To split your dataset randomly, do the following

1. Choose the + next to the node containing the dataset that you’re splitting.
2. Choose **Add transform**.
3. Choose **Split data**.
4. (Optional) For **Splits**, specify the names and proportions of each split. The proportions must sum to 1.
5. (Optional) Choose the + to create an additional split.
   - Specify the names and proportions of all the splits. The proportions must sum to 1.
6. (Optional) Specify a value for **Error threshold** other than the default value.
7. (Optional) Specify a value for **Random seed**.
8. Choose **Preview**.
9. Choose **Add**.

**Ordered split**

Use the following procedure to perform an ordered split on your dataset.

To make an ordered split in your dataset, do the following.

1. Choose the + next to the node containing the dataset that you're splitting.
2. Choose **Add transform**.
3. For **Transform**, choose **Ordered split**.
4. Choose **Split data**.
5. (Optional) For **Splits**, specify the names and proportions of each split. The proportions must sum to 1.
6. (Optional) Choose the + to create an additional split.
   - Specify the names and proportions of all the splits. The proportions must sum to 1.
7. (Optional) Specify a value for **Error threshold** other than the default value.
8. (Optional) For **Input column**, specify a column with numeric values. Uses the values of the columns to infer which records are in each split. The smaller values are in one split with the larger values in the other splits.
9. (Optional) Select **Handle duplicates** to add noise to duplicate values and create a dataset of entirely unique values.
10. (Optional) Specify a value for **Random seed**.
11. Choose **Preview**.
12. Choose **Add**.

**Stratified split**

Use the following procedure to perform a stratified split on your dataset.

To make a stratified split in your dataset, do the following.

1. Choose the + next to the node containing the dataset that you're splitting.
2. Choose **Add transform**.
3. Choose **Split data**.
4. For **Transform**, choose **Stratified split**.
5. (Optional) For **Splits**, specify the names and proportions of each split. The proportions must sum to 1.
6. (Optional) Choose the + to create an additional split.
   - Specify the names and proportions of all the splits. The proportions must sum to 1.
7. For **Input column**, specify a column with up to 100 unique values. Data Wrangler can’t stratify a column with more than 100 unique values.
8. (Optional) Specify a value for **Error threshold** other than the default value.
9. (Optional) Specify a value for **Random seed** to specify a different seed.
10. Choose **Preview**.
11. Choose **Add**.

**Split by column keys**

Use the following procedure to split by the column keys in your dataset.

To split by the column keys in your dataset, do the following.

1. Choose the + next to the node containing the dataset that you're splitting.
2. Choose **Add transform**.
3. Choose **Split data**.
4. For **Transform**, choose **Split by key**.
5. (Optional) For **Splits**, specify the names and proportions of each split. The proportions must sum to 1.
6. (Optional) Choose the + to create an additional split.
   - Specify the names and proportions of all the splits. The proportions must sum to 1.
7. For **Key columns**, specify the columns with values that you don't want to appear in both datasets.
8. (Optional) Specify a value for **Error threshold** other than the default value.
9. Choose **Preview**.
10. Choose **Add**.

**Parse Value as Type**

Use this transform to cast a column to a new type. The supported Data Wrangler data types are:

- Long
- Float
- Boolean
- Date, in the format dd-MM-yyyy, representing day, month, and year respectively.
- String

**Validate String**

Use the **Validate string** transforms to create a new column that indicates that a row of text data meets a specified condition. For example, you can use a **Validate string** transform to verify that a string only contains lowercase characters. The following transforms are supported under **Validate string**.

The following transforms are included in this transform group. If a transform outputs a Boolean value, **True** is represented with a 1 and **False** is represented with a 0.
<table>
<thead>
<tr>
<th>Name</th>
<th>Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>String length</td>
<td>Returns True if a string length equals specified length. Otherwise, returns False.</td>
</tr>
<tr>
<td>Starts with</td>
<td>Returns True if a string starts will a specified prefix. Otherwise, returns False.</td>
</tr>
<tr>
<td>Ends with</td>
<td>Returns True if a string length equals specified length. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is alphanumeric</td>
<td>Returns True if a string only contains numbers and letters. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is alpha (letters)</td>
<td>Returns True if a string only contains letters. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is digit</td>
<td>Returns True if a string only contains digits. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is space</td>
<td>Returns True if a string only contains numbers and letters. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is title</td>
<td>Returns True if a string contains any white spaces. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is lowercase</td>
<td>Returns True if a string only contains lower case letters. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is uppercase</td>
<td>Returns True if a string only contains upper case letters. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is numeric</td>
<td>Returns True if a string only contains numbers. Otherwise, returns False.</td>
</tr>
<tr>
<td>Is decimal</td>
<td>Returns True if a string only contains decimal numbers. Otherwise, returns False.</td>
</tr>
</tbody>
</table>

**Unnest JSON Data**

If you have a .csv file, you might have values in your dataset that are JSON strings. Similarly, you might have nested data in columns of either a Parquet file or a JSON document.

Use the **Flatten structured** operator to separate the first level keys into separate columns. A first level key is a key that isn't nested within a value.

For example, you might have a dataset that has a `person` column with demographic information on each person stored as JSON strings. A JSON string might look like the following.

```
{"seq": 1,"name": {"first": "Nathaniel","last": "Ferguson"},"age": 59,"city": "Posbotno","state": "WV"}
```

The **Flatten structured** operator converts the following first level keys into additional columns in your dataset:

- `seq`
• name
• age
• city
• state

Data Wrangler puts the values of the keys as values under the columns. The following shows the column names and values of the JSON.

<table>
<thead>
<tr>
<th>seq</th>
<th>name</th>
<th>age</th>
<th>city</th>
<th>state</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{&quot;first&quot;: &quot;Nathaniel&quot;,&quot;last&quot;: &quot;Ferguson&quot;}, 59, Posbotno, WV</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For each value in your dataset containing JSON, the Flatten structured operator creates columns for the first-level keys. To create columns for nested keys, call the operator again. For the preceding example, calling the operator creates the columns:

• name_first
• name_last

The following example shows the dataset that results from calling the operation again.

<table>
<thead>
<tr>
<th>seq</th>
<th>name</th>
<th>age</th>
<th>city</th>
<th>state</th>
<th>name_first</th>
<th>name_last</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>{&quot;first&quot;: &quot;Nathaniel&quot;,&quot;last&quot;: &quot;Ferguson&quot;}, 59, Posbotno, WV, Nathaniel, Ferguson</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Choose Keys to flatten on to specify the first-level keys that want to extract as separate columns. If you don't specify any keys, Data Wrangler extracts all the keys by default.

**Explode Array**

Use Explode array to expand the values of the array into separate output rows. For example, the operation can take each value in the array, [[1, 2, 3], [4, 5, 6], [7, 8, 9]] and create a new column with the following rows:

[1, 2, 3]
[4, 5, 6]
[7, 8, 9]

Data Wrangler names the new column, input_column_name_flatten.

You can call the Explode array operation multiple times to get the nested values of the array into separate output columns. The following example shows the result of calling the operation multiple times on a dataset with a nested array.

**Putting the values of a nested array into separate columns**

<table>
<thead>
<tr>
<th>id</th>
<th>array</th>
<th>id</th>
<th>array_items</th>
<th>id</th>
<th>array_items_items</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>[[cat, dog], [bat, frog]]</td>
<td>1</td>
<td>[cat, dog]</td>
<td>1</td>
<td>cat</td>
</tr>
</tbody>
</table>
Analyze and Visualize

Amazon SageMaker Data Wrangler includes built-in analyses that help you generate visualizations and data analyses in a few clicks. You can also create custom analyses using your own code.

You add an analysis to a dataframe by selecting a step in your data flow, and then choosing Add analysis. To access an analysis you’ve created, select the step that contains the analysis, and select the analysis.

All analyses are generated using 100,000 rows of your dataset.

You can add the following analysis to a dataframe:

- Data visualizations, including histograms and scatter plots.
- A quick summary of your dataset, including number of entries, minimum and maximum values (for numeric data), and most and least frequent categories (for categorical data).
- A quick model of the dataset, which can be used to generate an importance score for each feature.
- A target leakage report, which you can use to determine if one or more features are strongly correlated with your target feature.
- A custom visualization using your own code.

Use the following sections to learn more about these options.

Histogram

Use histograms to see the counts of feature values for a specific feature. You can inspect the relationships between features using the Color by option. For example, the following histogram charts the distribution of user ratings of the best-selling books on Amazon from 2009–2019, colored by genre.
You can use the **Facet by** feature to create histograms of one column, for each value in another column. For example, the following diagram shows histograms of user reviews of best-selling books on Amazon if faceted by year.

### Scatter Plot

Use the **Scatter Plot** feature to inspect the relationship between features. To create a scatter plot, select a feature to plot on the **X axis** and the **Y axis**. Both of these columns must be numeric typed columns.

You can color scatter plots by an additional column. For example, the following example shows a scatter plot comparing the number of reviews against user ratings of top-selling books on Amazon between 2009 and 2019. The scatter plot is colored by book genre.
Additionally, you can facet scatter plots by features. For example, the following image shows an example of the same review versus user rating scatter plot, faceted by year.

Table Summary

Use the Table Summary analysis to quickly summarize your data.

For columns with numerical data, including log and float data, a table summary reports the number of entries (count), minimum (min), maximum (max), mean, and standard deviation (stddev) for each column.

For columns with non-numerical data, including columns with string, Boolean, or date/time data, a table summary reports the number of entries (count), least frequent value (min), and most frequent value (max).
Quick Model

Use the Quick Model visualization to quickly evaluate your data and produce importance scores for each feature. A feature importance score indicates how useful a feature is at predicting a target label. The feature importance score is between \([0, 1]\) and a higher number indicates that the feature is more important to the whole dataset. On the top of the quick model chart, there is a model score. A classification problem shows an F1 score. A regression problem has a mean squared error (MSE) score.

When you create a quick model chart, you select a dataset you want evaluated, and a target label against which you want feature importance to be compared. Data Wrangler does the following:

- Infers the data types for the target label and each feature in the dataset selected.
- Determines the problem type. Based on the number of distinct values in the label column, Data Wrangler determines if this is a regression or classification problem type. Data Wrangler sets a categorical threshold to 100. If there are more than 100 distinct values in the label column, Data Wrangler classifies it as a regression problem; otherwise, it is classified as a classification problem.
- Pre-processes features and label data for training. The algorithm used requires encoding features to vector type and encoding labels to double type.
- Trains a random forest algorithm with 70% of data. Spark’s RandomForestRegressor is used to train a model for regression problems. The RandomForestClassifier is used to train a model for classification problems.
- Evaluates a random forest model with the remaining 30% of data. Data Wrangler evaluates classification models using an F1 score and evaluates regression models using an MSE score.
- Calculates feature importance for each feature using the Gini importance method.

The following image shows the user interface for the quick model feature.

Target Leakage

Target leakage occurs when there is data in a machine learning training dataset that is strongly correlated with the target label, but is not available in real-world data. For example, you may have a column in your dataset that serves as a proxy for the column you want to predict with your model.

When you use the Target Leakage analysis, you specify the following:

- **Target**: This is the feature about which you want your ML model to be able to make predictions.
• **Problem type**: This is the ML problem type on which you are working. Problem type can either be *classification* or *regression*.

• *(Optional) Max features*: This is the maximum number of features to present in the visualization, which shows features ranked by their risk of being target leakage.

For classification, the target leakage analysis uses the area under the receiver operating characteristic, or AUC - ROC curve for each column, up to *Max features*. For regression, it uses a coefficient of determination, or R2 metric.

The AUC - ROC curve provides a predictive metric, computed individually for each column using cross-validation, on a sample of up to around 1000 rows. A score of 1 indicates perfect predictive abilities, which often indicates target leakage. A score of 0.5 or lower indicates that the information on the column could not provide, on its own, any useful information towards predicting the target. Although it can happen that a column is uninformative on its own but is useful in predicting the target when used in tandem with other features, a low score could indicate the feature is redundant.

For example, the following image shows a target leakage report for a diabetes classification problem, that is, predicting if a person has diabetes or not. An AUC - ROC curve is used to calculate the predictive ability of five features, and all are determined to be safe from target leakage.

**Multicollinearity**

Multicollinearity is a circumstance where two or more predictor variables are related to each other. The predictor variables are the features in your dataset that you’re using to predict a target variable. When you have multicollinearity, the predictor variables are not only predictive of the target variable, but also predictive of each other.

You can use the **Variance Inflation Factor (VIF)**, **Principal Component Analysis (PCA)**, or **Lasso feature selection** as measures for the multicollinearity in your data. For more information, see the following.

**Variance Inflation Factor (VIF)**

The Variance Inflation Factor (VIF) is a measure of collinearity among variable pairs. Data Wrangler returns a VIF score as a measure of how closely the variables are related to each other. A VIF score is a positive number that is greater than or equal to 1.

A score of 1 means that the variable is uncorrelated with the other variables. Scores greater than 1 indicate higher correlation.
Theoretically, you can have a VIF score with a value of infinity. Data Wrangler clips high scores to 50. If you have a VIF score greater than 50, Data Wrangler sets the score to 50.

You can use the following guidelines to interpret your VIF scores:

- A VIF score less than or equal to 5 indicates that the variables are moderately correlated with the other variables.
- A VIF score greater than or equal to 5 indicates that the variables are highly correlated with the other variables.

**Principle Component Analysis (PCA)**

Principal Component Analysis (PCA) measures the variance of the data along different directions in the feature space. The feature space consists of all the predictor variables that you use to predict the target variable in your dataset.

For example, if you're trying to predict who survived on the *RMS Titanic* after it hit an iceberg, your feature space can include the passengers' age, gender, and the fare that they paid.

From the feature space, PCA generates an ordered list of variances. These variances are also known as singular values. The values in the list of variances are greater than or equal to 0. We can use them to determine how much multicollinearity there is in our data.

When the numbers are roughly uniform, the data has very few instances of multicollinearity. When there is a lot of variability among the values, we have many instances of multicollinearity. Before it performs PCA, Data Wrangler normalizes each feature to have a mean of 0 and a standard deviation of 1.

*Note*

PCA in this circumstance can also be referred to as Singular Value Decomposition (SVD).

**Lasso feature selection**

Lasso feature selection uses the L1 regularization technique to only include the most predictive features in your dataset.

For both classification and regression, the regularization technique generates a coefficient for each feature. The absolute value of the coefficient provides an importance score for the feature. A higher importance score indicates that it is more predictive of the target variable. A common feature selection method is to use all the features that have a non-zero lasso coefficient.

**Detect Anomalies In Time Series Data**

You can use the anomaly detection visualization to see outliers in your time series data. To understand what determines an anomaly, you need to understand that we decompose the time series into a predicted term and an error term. We treat the seasonality and trend of the time series as the predicted term. We treat the residuals as the error term.

For the error term, you specify a threshold as the number of standard of deviations the residual can be away from the mean for it to be considered an anomaly. For example, you can specify a threshold as being 3 standard deviations. Any residual greater than 3 standard deviations away from the mean is an anomaly.

You can use the following procedure to perform an **Anomaly detection** analysis.

1. Open your Data Wrangler data flow.
2. In your data flow, under **Data types**, choose the +, and select **Add analysis**.
3. For **Analysis type**, choose **Time Series**.
4. For **Visualization**, choose **Anomaly detection**.
5. For **Anomaly threshold**, choose the threshold that a value is considered an anomaly.
6. Choose **Preview** to generate a preview of the analysis.
7. Choose **Add** to add the transform to the Data Wrangler data flow.

### Seasonal Trend Decomposition In Time Series Data

You can determine whether there's seasonality in your time series data by using the Seasonal Trend Decomposition visualization. We use the STL (Seasonal Trend decomposition using LOESS) method to perform the decomposition. We decompose the time series into its seasonal, trend, and residual components. The trend reflects the long term progression of the series. The seasonal component is a signal that recurs in a time period. After removing the trend and the seasonal components from the time series, you have the residual.

You can use the following procedure to perform a **Seasonal-Trend decomposition** analysis.

1. Open your Data Wrangler data flow.
2. In your data flow, under **Data types**, choose the +, and select **Add analysis**.
3. For **Analysis type**, choose **Time Series**.
4. For **Visualization**, choose **Seasonal-Trend decomposition**.
5. For **Anomaly threshold**, choose the threshold that a value is considered an anomaly.
6. Choose **Preview** to generate a preview of the analysis.
7. Choose **Add** to add the transform to the Data Wrangler data flow.

### Bias Report

You can use the bias report in Data Wrangler to uncover potential biases in your data. To generate a bias report, you must specify the target column, or **Label**, that you want to predict and a **Facet**, or the column that you want to inspect for biases.

**Label**: The feature about which you want a model to make predictions. For example, if you are predicting customer conversion, you may select a column containing data on whether or not a customer has placed an order. You must also specify whether this feature is a label or a threshold. If you specify a label, you must specify what a **positive outcome** looks like in your data. In the customer conversion example, a positive outcome may be a 1 in the orders column, representing the positive outcome of a customer placing an order within the last three months. If you specify a threshold, you must specify a lower bound defining a positive outcome. For example, if your customer orders columns contains the number of orders placed in the last year, you may want to specify 1.

**Facet**: The column that you want to inspect for biases. For example, if you are trying to predict customer conversion, your facet may be the age of the customer. You may choose this facet because you believe that your data is biased toward a certain age group. You must identify whether the facet is measured as a value or threshold. For example, if you wanted to inspect one or more specific ages, you select **Value** and specify those ages. If you want to look at an age group, you select **Threshold** and specify the threshold of ages you want to inspect.

After you select your feature and label, you select the types of bias metrics you want to calculate.

To learn more, see **Generate reports for bias in pre-training data**.

### Create Custom Visualizations

You can add an analysis to your Data Wrangler flow to create a custom visualization. Your dataset, with all the transformations you've applied, is available as a **Pandas DataFrame**. Data Wrangler uses the df variable to store the dataframe. You access the dataframe by calling the variable.
You must provide the output variable, chart, to store an Altair output chart. For example, you can use the following code block to create a custom histogram using the Titanic dataset.

```python
import altair as alt
df = df.iloc[:30]
df = df.rename(columns={"Age": "value"})
df = df.assign(count=df.groupby('value').value.transform('count'))
df = df["value", "count"]
base = alt.Chart(df)
bar = base.mark_bar().encode(x=alt.X('value', bin=True, axis=None), y=alt.Y('count'))
rule = base.mark_rule(color='red').encode(
    x='mean(value):Q',
    size=alt.value(5))
chart = bar + rule
```

To create a custom visualization:

1. Next to the node containing the transformation that you'd like to visualize, choose the +.
2. Choose Add analysis.
3. For Analysis type, choose Custom Visualization.
4. For Analysis name, specify a name.
5. Enter your code in the code box.
6. Choose Preview to preview your visualization.
7. Choose Save to add your visualization.

If you don’t know how to use the Altair visualization package in Python, you can use custom code snippets to help you get started.

Data Wrangler has a searchable collection of visualization snippets. To use a visualization snippet, choose Search example snippets and specify a query in the search bar.
The following example uses the Binned scatterplot code snippet. It plots a histogram for 2 dimensions. The snippets have comments to help you understand the changes that you need to make to the code. You usually need to specify the column names of your dataset in the code.

```python
import altair as alt

# Specify the number of top rows for plotting
rows_number = 1000
df = df.head(rows_number)
# You can also choose bottom rows or randomly sampled rows
# df = df.tail(rows_number)
# df = df.sample(rows_number)

chart = (alt.Chart(df)
    .mark_circle()
    .encode(
        # Specify the column names for binning and number of bins for X and Y axis
        x=alt.X("col1:Q", bin=alt.Bin(maxbins=20)),
        y=alt.Y("col2:Q", bin=alt.Bin(maxbins=20)),
        size="count()",
    )
)
```

Note: :Q specifies that label column has quantitative type.
For more details on Altair typing refer to https://altair-viz.github.io/user_guide/encoding.html#encoding-data-types

Reusing Data Flows for Different Datasets

For Amazon Simple Storage Service (Amazon S3) data sources, you can create and use parameters. A parameter is a variable that you've saved in your Data Wrangler flow. Its value can be any portion of the data source's Amazon S3 path. Use parameters to quickly change the data that you're importing into a Data Wrangler flow or exporting to a processing job.

After you created a Data Wrangler flow, you might have trained a model on the data that you've transformed. For datasets that have the same schema, you can use parameters to apply the same transformations on a different dataset and train a different model. You can use the new datasets to perform inference with your model or you could be using them to retrain your model.

In general, parameters have the following attributes:

- **Name** – The name you specify for the parameter
- **Type** – The type of value that the parameter represents
- **Default value** – The value of the parameter when you don't specify a new value

**Note**

Datet ime parameters have a time range attribute that they use as the default value.

Data Wrangler uses curly braces, {{}}, to indicate that a parameter is being used in the Amazon S3 path. For example, you can have a URL such as s3://{DOC-EXAMPLE-BUCKET1}{{example_parameter_name}}/example-dataset.csv.

You create a parameter when you're editing the Amazon S3 data source that you've imported. You can set any portion of the file path to a parameter value. You can set the parameter value to either a value or a pattern. The following are the available parameter value types in the Data Wrangler flow:
• Number
• String
• Pattern
• Datetime

**Note**
You can't create a pattern parameter or a datetime parameter for the name of the bucket in the Amazon S3 path.

You must set a number as the default value of a number parameter. You can change the value of the parameter to a different number when you're editing a parameter or when you're launching a processing job. For example, in the S3 path, `s3://DOC-EXAMPLE-BUCKET/example-prefix/example-file-1.csv`, you can create a number parameter named `number_parameter` in the place of `1`. Your S3 path now appears as `s3://DOC-EXAMPLE-BUCKET/example-prefix/example-file-{{number_parameter}}.csv`. The path continues to point to the example-file-1.csv dataset until you change the value of the parameter. If you change the value of `number_parameter` to 2, the path is now `s3://DOC-EXAMPLE-BUCKET/example-prefix/example-file-2.csv`. You can import `example-file-2.csv` into Data Wrangler if you've uploaded the file to that Amazon S3 location.

A string parameter stores a string as its default value. For example, in the S3 path, `s3://DOC-EXAMPLE-BUCKET/example-prefix/example-file-1.csv`, you can create a string parameter named `string_parameter` in the place of the filename, `example-file-1.csv`. The path now appears as `s3://DOC-EXAMPLE-BUCKET/example-prefix/{{string_parameter}}`. It continues to match `s3://DOC-EXAMPLE-BUCKET/example-prefix/example-file-1.csv`, until you change the value of the parameter.

Instead of specifying the filename as a string parameter, you can create a string parameter using the entire Amazon S3 path. You can specify a dataset from any Amazon S3 location in the string parameter.

A pattern parameter stores a regular expression (Python REGEX) string as its default value. You can use a pattern parameter to import multiple data files at the same time. To import more than one object at a time, specify a parameter value that matches the Amazon S3 objects that you're importing.

You can also create a pattern parameter for the following datasets:

- `s3://DOC-EXAMPLE-BUCKET1/example-prefix/example-file-1.csv`
- `s3://DOC-EXAMPLE-BUCKET1/example-prefix/example-file-2.csv`
- `s3://DOC-EXAMPLE-BUCKET1/example-prefix/example-file-10.csv`
- `s3://DOC-EXAMPLE-BUCKET/example-prefix/example-file-0123.csv`

For `s3://DOC-EXAMPLE-BUCKET1/example-prefix/example-file-1.csv`, you can create a pattern parameter in the place of `1`, and set the default value of the parameter to `\d+`. The `\d+` REGEX string matches any one or more decimal digits. If you create a pattern parameter named `pattern_parameter`, your S3 path appears as `s3://DOC-EXAMPLE-BUCKET1/example-prefix/example-file-{{pattern_parameter}}.csv`.

You can also use pattern parameters to match all CSV objects within your bucket. To match all objects in a bucket, create a pattern parameter with the default value of `.*` and set the path to `s3://DOC-EXAMPLE-BUCKET/{{pattern_parameter}}.csv`. The `.*` character matches any string character in the path.

The `s3://DOC-EXAMPLE-BUCKET/{{pattern_parameter}}.csv` path can match the following datasets:

- `example-file-1.csv`
A datetime parameter stores the format with the following information:

- A format for parsing strings inside an Amazon S3 path.
- A relative time range to limit the datetime values that match

For example, in the Amazon S3 file path, `s3://DOC-EXAMPLE-BUCKET/2020/01/01/example-dataset.csv`, 2020/01/01 represents a datetime in the format of `year/month/day`. You can set the parameter's time range to an interval such as 1 year or 24 hours. An interval of 1 year matches all S3 paths with datetimes that fall between the current time and the time exactly a year before the current time. The current time is the time when you start exporting the transformations that you've made to the data. For more information about exporting data, see Export (p. 945). If the current date is 2022/01/01 and the time range is 1 year, the S3 path matches datasets such as the following:

- `s3://DOC-EXAMPLE-BUCKET/2021/01/01/example-dataset.csv`
- `s3://DOC-EXAMPLE-BUCKET/2021/06/30/example-dataset.csv`
- `s3://DOC-EXAMPLE-BUCKET/2021/12/31/example-dataset.csv`

The datetime values within a relative time range change as time passes. The S3 paths that fall within the relative time range might also differ.

For the Amazon S3 file path, `s3://DOC-EXAMPLE-BUCKET/20200101/example-dataset.csv`, 20220101 is an example of a path that can become a datetime parameter.

To view a table of all parameters that you've created in Data Wrangler flow, choose the `{}` to the right of the text box containing the Amazon S3 path. If you no longer need a parameter that you've created, you can edit or delete. To edit or delete a parameter, choose icons to the right of the parameter.

**Important**
Before you delete a parameter, make sure that you haven't used it anywhere in your Data Wrangler flow. Deleted parameters that are still within the flow cause errors.

You can create parameters for any step of your Data Wrangler flow. You can edit or delete any parameter that you create. If the parameter has transformations that are no longer relevant to your use case, you can modify them.

The following sections provide additional examples and general guidance on using parameters. You can use the sections to understand the parameters that work best for you.

**Note**
The following sections contain procedures that use the Data Wrangler interface to override the parameters and create a processing job.
You can also override the parameters by using the following procedures.

To export your Data Wrangler flow and override the value of a parameter, do the following.

1. Choose the + next to the node that you want to export.
2. Choose Export to.
3. Choose the location where you're exporting the data.
4. Under parameter_overrides, specify different values for the parameters that you've created.
5. Run the Jupyter Notebook.
Applying a Data Wrangler flow to files using patterns

You can use parameters to apply transformations in your Data Wrangler flow to different files that match a pattern in the Amazon S3 URI path. This helps you specify the files in your S3 bucket that you want to transform with high specificity. For example, you might have a dataset with the path s3://DOC-EXAMPLE-BUCKET1/example-prefix-0/example-prefix-1/example-prefix-2/example-dataset.csv. Different datasets named example-dataset.csv are stored under many different example prefixes. The prefixes might also be numbered sequentially. You can create patterns for the numbers in the Amazon S3 URI. Pattern parameters use REGEX to select any number of files that match the pattern of the expression. The following are REGEX patterns that might be useful:

- .* – Matches zero or more of any character, except newline characters
- .+ – Matches one or more of any character, excluding newline characters
- \d+ – Matches one or more of any decimal digit
- \w+ – Matches one or more of any alphanumeric character
- [abc-\_]{2,4} – Matches a string two, three, or four characters composed of the set of characters provided within a set of brackets
- abc|def – Matches one string or another. For example, the operation matches either abc or def

You can replace each number in the following paths with a single parameter that has a value of \d+.

- s3://DOC-EXAMPLE-BUCKET1/example-prefix-3/example-prefix-4/example-prefix-5/example-dataset.csv
- s3://DOC-EXAMPLE-BUCKET1/example-prefix-8/example-prefix-12/example-prefix-13/example-dataset.csv
- s3://DOC-EXAMPLE-BUCKET1/example-prefix-4/example-prefix-9/example-prefix-137/example-dataset.csv

The following procedure creates a pattern parameter for a dataset with the path s3://DOC-EXAMPLE-BUCKET1/example-prefix-0/example-prefix-1/example-prefix-2/example-dataset.csv.

To create a pattern parameter, do the following.

1. Next to the dataset that you've imported, choose Edit dataset.
2. Highlight the 0 in example-prefix-0.
3. Specify values for the following fields:
   - Name – A name for parameter
   - Type – Pattern
   - Value – \d+ a regular expression that corresponds to one or more digits
4. Choose Create.
5. Replace the 1 and the 2 in S3 URI path with the parameter. The path should have the following format: s3://DOC-EXAMPLE-BUCKET1/example-prefix-{{example_parameter_name}}/example-prefix-{{example_parameter_name}}/example-prefix-{{example_parameter_name}}/example-dataset.csv

The following is a general procedure for creating a pattern parameter.

1. Navigate to your Data Wrangler flow.
2. Next to the dataset that you've imported, choose Edit dataset.
3. Highlight the portion of the URI that you're using as the value of the pattern parameter.
4. Choose Create custom parameter.
5. Specify values for the following fields:
   - **Name** – A name for parameter
   - **Type** – Pattern
   - **Value** – A regular expression containing the pattern that you'd like to store.
6. Choose Create.

### Applying a Data Wrangler flow to files using numeric values

You can use parameters to apply transformations in your Data Wrangler flow to different files that have similar paths. For example, you might have a dataset with the path `s3://DOC-EXAMPLE-BUCKET1/example-prefix-0/example-prefix-1/example-prefix-2/example-dataset.csv`.

You might have the transformations from your Data Wrangler flow that you've applied to datasets under `example-prefix-1`. You might want to apply the same transformations to `example-dataset.csv` that falls under `example-prefix-10` or `example-prefix-20`.

You can create a parameter that stores the value 1. If you want to apply the transformations to different datasets, you can create processing jobs that replace the value of the parameter with a different value. The parameter acts as a placeholder for you to change when you want to apply the transformations from your Data Wrangler flow to new data. You can override the value of the parameter when you create a Data Wrangler processing job to apply the transformations in your Data Wrangler flow to different datasets.

Use the following procedure to create numeric parameters for `s3://DOC-EXAMPLE-BUCKET1/example-prefix-0/example-prefix-1/example-prefix-2/example-dataset.csv`.

To create parameters for the preceding S3 URI path, do the following.

1. Navigate to your Data Wrangler flow.
2. Next to the dataset that you've imported, choose **Edit dataset**.
3. Highlight the number in an example prefix of **example-prefix-number**.
4. Choose **Create custom parameter**.
5. For **Name**, specify a name for the parameter.
6. For **Type**, choose **Integer**.
7. For **Value**, specify the number.
8. Create parameters for the remaining numbers by repeating the procedure.

After you've created the parameters, apply the transforms to your dataset and create a destination node for them. For more information about destination nodes, see Export (p. 945).

Use the following procedure to apply the transformations from your Data Wrangler flow to a different time range. It assumes that you've created a destination node for the transformations in your flow.

To change the value of a numeric parameter in a Data Wrangler processing job, do the following.

1. From your Data Wrangler flow, choose **Create job**.
2. Select only the destination node that contains the transformations to the dataset containing the datetime parameters.
3. Choose **Configure job**.
4. Choose **Parameters**.
5. Choose the name of a parameter that you've created.
6. Change the value of the parameter.
7. Repeat the procedure for the other parameters.
Applying a Data Wrangler flow to files using strings

You can use parameters to apply transformations in your Data Wrangler flow to different files that have similar paths. For example, you might have a dataset with the path `s3://DOC-EXAMPLE-BUCKET1/example-prefix/example-dataset.csv`.

You might have transformations from your Data Wrangler flow that you've applied to datasets under `example-prefix`. You might want to apply the same transformations to `example-dataset.csv` under another `example-prefix` or `example-prefix-20`.

You can create a parameter that stores the value `example-prefix`. If you want to apply the transformations to different datasets, you can create processing jobs that replace the value of the parameter with a different value. The parameter acts as a placeholder for you to change when you want to apply the transformations from your Data Wrangler flow to new data. You can override the value of the parameter when you create a Data Wrangler processing job to apply the transformations in your Data Wrangler flow to different datasets.

Use the following procedure to create a string parameter for `s3://DOC-EXAMPLE-BUCKET1/example-prefix/example-dataset.csv`.

To create a parameter for the preceding S3 URI path, do the following.

1. Navigate to your Data Wrangler flow.
2. Next to the dataset that you've imported, choose **Edit dataset**.
3. Highlight the example prefix, `example-prefix`.
4. Choose **Create custom parameter**.
5. For **Name**, specify a name for the parameter.
6. For **Type**, choose **String**.
7. For **Value**, specify the prefix.

After you've created the parameter, apply the transforms to your dataset and create a destination node for them. For more information about destination nodes, see Export (p. 945).

Use the following procedure to apply the transformations from your Data Wrangler flow to a different time range. It assumes that you've created a destination node for the transformations in your flow.

To change the value of a numeric parameter in a Data Wrangler processing job, do the following:

1. From your Data Wrangler flow, choose **Create job**
2. Select only the destination node that contains the transformations to the dataset containing the datetime parameters.
3. Choose **Configure job**.
4. Choose **Parameters**.
5. Choose the name of a parameter that you've created.
6. Change the value of the parameter.
7. Repeat the procedure for the other parameters.
8. Choose **Run**.

Applying a Data Wrangler flow to different datetime ranges

Use datetime parameters to apply transformations in your Data Wrangler flow to different time ranges. Highlight the portion of the Amazon S3 URI that has a timestamp and create a parameter for it.
When you create a parameter, you specify a time range from the current time to a time in the past. For example, you might have an Amazon S3 URI that looks like the following: s3://DOC-EXAMPLE-BUCKET1/example-prefix/2022/05/15/example-dataset.csv. You can save 2022/05/15 as a datetime parameter. If you specify a year as the time range, the time range includes the moment that you run the processing job containing the datetime parameter and the time exactly one year ago. If the moment you're running the processing job is September 6th, 2022 or 2022/09/06, the time ranges can include the following:

- s3://DOC-EXAMPLE-BUCKET1/example-prefix/2022/03/15/example-dataset.csv
- s3://DOC-EXAMPLE-BUCKET1/example-prefix/2022/01/08/example-dataset.csv
- s3://DOC-EXAMPLE-BUCKET1/example-prefix/2022/07/31/example-dataset.csv
- s3://DOC-EXAMPLE-BUCKET1/example-prefix/2021/09/07/example-dataset.csv

The transformations in the Data Wrangler flow apply to all of the preceding prefixes. Changing the value of the parameter in the processing job doesn't change the value of the parameter in the Data Wrangler flow. To apply the transformations to datasets within a different time range, do the following:

1. Create a destination node containing all the transformations that you'd like to use.
2. Create a Data Wrangler job.
3. Configure the job to use a different time range for the parameter. Changing the value of the parameter in the processing job doesn't change the value of the parameter in the Data Wrangler flow.

For more information about destination nodes and Data Wrangler jobs, see Export (p. 945).

The following procedure creates a datetime parameter for the Amazon S3 path: s3://DOC-EXAMPLE-BUCKET1/example-prefix/2022/05/15/example-dataset.csv.

To create a datetime parameter for the preceding S3 URI path, do the following.

1. Navigate to your Data Wrangler flow.
2. Next to the dataset that you've imported, choose Edit dataset.
3. Highlight the portion of the URI that you're using as the value of the datetime parameter.
4. Choose Create custom parameter.
5. For Name, specify a name for the parameter.
6. For Type, choose Datetime.

**Note**
By default, Data Wrangler selects Predefined, which provides a dropdown menu for you to select a date format. However, the timestamp format that you're using might not be available. Instead of using Predefined as the default option, you can choose Custom and specify the timestamp format manually.

7. For Date format, open the dropdown menu following Predefined and choose yyyy/MM/dd. The format, yyyy/MM/dd, corresponds to the year/month/day of the timestamp.
8. For Timezone, choose a time zone.

**Note**
The data that you're analyzing might have time stamps taken in a different time zone from your time zone. Make sure that the time zone that you select matches the time zone of the data.

9. For Time range, specify the time range for the parameter.
10. (Optional) Enter a description to describe how you're using the parameter.
11. Choose Create.
After you’ve created the datetime parameters, apply the transforms to your dataset and create a destination node for them. For more information about destination nodes, see Export (p. 945).

Use the following procedure to apply the transformations from your Data Wrangler flow to a different time range. It assumes that you’ve created a destination node for the transformations in your flow.

To change the value of a datetime parameter in a Data Wrangler processing job, do the following:

1. From your Data Wrangler flow, choose **Create job**
2. Select only the destination node that contains the transformations to the dataset containing the datetime parameters.
3. Choose **Configure job**.
4. Choose **Parameters**.
5. Choose the name of the datetime parameter that you’ve created.
6. For **Time range**, change the time range for the datasets.
7. Choose **Run**.

## Export

In your Data Wrangler flow, you can export some or all of the transformations that you’ve made to your data processing pipelines.

A **Data Wrangler flow** is the series of data preparation steps that you’ve performed on your data. In your data preparation, you perform one or more transformations to your data. Each transformation is done using a transform step. The flow has a series of nodes that represent the import of your data and the transformations that you’ve performed. For an example of nodes, see the following image.

The preceding image shows a Data Wrangler flow with two nodes. The **Source - sampled** node shows the data source from which you’ve imported your data. The **Data types** node indicates that Data Wrangler has performed a transformation to convert the dataset into a usable format.
Each transformation that you add to the Data Wrangler flow appears as an additional node. For information on the transforms that you can add, see Transform Data (p. 889). The following image shows a Data Wrangler flow that has a Rename-column node to change the name of a column in a dataset.

You can export your data transformations to the following:

- Amazon S3
- SageMaker Pipelines
- Amazon SageMaker Feature Store
- Python Code

**Important**

We recommend that you use the IAM AmazonSageMakerFullAccess managed policy to grant AWS permission to use Data Wrangler. If you don't use the managed policy, you can use an IAM policy that gives Data Wrangler access to an Amazon S3 bucket. For more information on the policy, see Security and Permissions (p. 966).

When you export your data flow, you're charged for the AWS resources that you use. You can use cost allocation tags to organize and manage the costs of those resources. You create these tags for your user-profile and Data Wrangler automatically applies them to the resources used to export the data flow. For more information, see Using Cost Allocation Tags.

**Export to Amazon S3**

Data Wrangler gives you the ability to export your data to a location within an Amazon S3 bucket. You can specify the location using one of the following methods:

- Destination node – Where Data Wrangler stores the data after it has processed it.
- Export to – Exports the data resulting from a transformation to Amazon S3.
- Export data – For small datasets, can quickly export the data that you've transformed.

Use the following sections to learn more about each of these methods.

**Destination Node**

If you want to output a series of data processing steps that you've performed to Amazon S3, you create a destination node. A destination node tells Data Wrangler where to store the data after you've processed it. After you create a destination node, you create a processing job to output the data. A processing job is an Amazon SageMaker processing job. When you're using a destination node, it runs the computational resources needed to output the data that you've transformed to Amazon S3.

You can use a destination node to export some of the transformations or all of the transformations that you've made in your Data Wrangler flow.

You can use multiple destination nodes to export different transformations or sets of transformations. The following example shows two destination nodes in a single Data Wrangler flow.
You can use the following procedure to create destination nodes and export them to an Amazon S3 bucket.

To export your data flow, you create destination nodes and a Data Wrangler job to export the data. Creating a Data Wrangler job starts a SageMaker processing job to export your flow. You can choose the destination nodes that you want to export after you've created them.

Use the following procedure to create destination nodes.

1. Choose the + next to the nodes that represent the transformations that you want to export.
2. Choose **Add destination**.
3. Choose Amazon S3.

4. Specify the fields shown in the following image.
5. Choose **Add destination**.

Use the following procedure to create a Data Wrangler job.

Create a job from the **Data flow** page and choose the destination nodes that you want to export.

1. Choose **Create job**. The following image shows the pane that appears after you select **Create job**.
2. For **Job name**, specify the name of the export job.
3. Choose the destination nodes that you want to export.
4. (Optional) Specify an AWS KMS key ARN. An AWS KMS key is a cryptographic key that you can use to protect your data. For more information about AWS KMS keys, see [AWS Key Management Service](#).
5. (Optional) Under **Trained parameters**, choose **Refit** if you’ve done the following:
   - Sampled your dataset
   - Applied a transform that uses your data to create a new column in the dataset

For more information about refitting the transformations you’ve made to an entire dataset, see [Refit Transforms to The Entire Dataset and Export Them](#) (p. 960).
6. Choose **Configure job**. The following image shows the **Configure job** page.

7. (Optional) Configure the Data Wrangler job.
8. Choose **Run**.
Export to

As an alternative to using a destination node, you can use the Export to option to export your Data Wrangler flow to Amazon S3 using a Jupyter Notebook. You can choose any data node in your Data Wrangler flow and export it. Exporting the data node exports the transformation that the node represents and the transformations that precede it.

Use the following procedure to generate a Jupyter Notebook and run it to export your Data Wrangler flow to Amazon S3.

1. Choose the + next to the node that you want to export.
2. Choose Export to.
3. Choose Amazon S3 (via Jupyter Notebook).
4. Run the Jupyter Notebook.

When you run the notebook, it exports your data flow (.flow file) in the same AWS Region as the Data Wrangler flow.

The notebook provides options that you can use to configure the processing job and the data that it outputs.

**Important**

We provide you with job configurations to configure the output of your data. For the partitioning and driver memory options, we strongly recommend that you don't specify a configuration unless you already have knowledge about them.

Under **Job Configurations**, you can configure the following:

- **output_content_type** – The content type of the output file. Uses CSV as the default format, but you can specify Parquet.
- **delimiter** – The character used to separate values in the dataset when writing to a CSV file.
- **compression** – If set, compresses the output file. Uses gzip as the default compression format.
- **num_partitions** – The number of partitions or files that Data Wrangler writes as the output.
- **partition_by** – The names of the columns that you use to partition the output.
To change the output file format from CSV to Parquet, change the value from "CSV" to "Parquet". For the rest of the preceding fields, uncomment the lines containing the fields that you want to specify.

Under **(Optional) Configure Spark Cluster Driver Memory** you can configure Spark properties for the job, such as the Spark driver memory, in the config dictionary.

The following shows the config dictionary.

```json
cfg = json.dumps({
    "Classification": "spark-defaults",
    "Properties": {
        "spark.driver.memory": f"{driver_memory_in_mb}m",
    }
})
```

To apply the configuration to the processing job, uncomment the following lines:

```python
# data_sources.append(ProcessingInput(
#     source=config_s3_uri,
#     destination="/opt/ml/processing/input/conf",
#     input_name="spark-config",
#     s3_data_type="S3Prefix",
#     s3_data_distribution_type="FullyReplicated"
# ))
```

Export data

If you have a transformation on a small dataset that you want to export quickly, you can use the Export data method. When you start choose Export data, Data Wrangler works synchronously to export the data that you've transformed to Amazon S3. You can't use Data Wrangler until either it finishes exporting your data or you cancel the operation.

For information on using the Export data method in your Data Wrangler flow, see the following procedure.

To use the Export data method.

1. Choose a node in your Data Wrangler flow by double-clicking on it.
2. Configure how you want to export the data.
3. Choose Export data.

When you export your data flow to an Amazon S3 bucket, Data Wrangler stores a copy of the flow file in the S3 bucket. It stores the flow file under the `data_wrangler_flows` prefix. If you use the default Amazon S3 bucket to store your flow files, they use the following naming convention: `sagemaker-region-account number`. For example, if your account number is 111122223333 and you are using Studio in us-east-1, your imported datasets are stored in `sagemaker-us-east-1-111122223333`. In this example, your .flow files created in us-east-1 are stored in `s3://sagemaker-region-account number/data_wrangler_flows/`.

Export to SageMaker Pipelines

When you want to build and deploy large-scale machine learning (ML) workflows, you can use SageMaker Pipelines to create end-to-end workflows that manage and deploy SageMaker jobs. SageMaker Pipelines gives you the ability to build workflows that manage your SageMaker data preparation, model training, and model deployment jobs. You can use the first-party algorithms that SageMaker offers by using SageMaker Pipelines. For more information on SageMaker Pipelines, see SageMaker Pipelines.

When you export one or more steps from your data flow to SageMaker Pipelines, Data Wrangler creates a Jupyter Notebook that you can use to define, instantiate, run, and manage a pipeline.

Use a Jupyter Notebook to Create a Pipeline

Use the following procedure to create a Jupyter Notebook to export your Data Wrangler flow to SageMaker Pipelines.

Use the following procedure to generate a Jupyter Notebook and run it to export your Data Wrangler flow to SageMaker Pipelines.

1. Choose the + next to the node that you want to export.
2. Choose Export to.
4. Run the Jupyter notebook.
The Jupyter Notebook that Data Wrangler produces can be used to define a pipeline. The pipeline includes the data processing steps that are defined by your Data Wrangler flow.

You can add additional steps to your pipeline by adding steps to the steps list in the following code in the notebook:

```python
pipeline = Pipeline(
    name=pipeline_name,
    parameters=[instance_type, instance_count],
    steps=[step_process],  # Add more steps to this list to run in your Pipeline
)
```

For more information on defining pipelines, see Define SageMaker Pipeline.

**Export to Python Code**

To export all steps in your data flow to a Python file that you can manually integrate into any data processing workflow, use the following procedure.

Use the following procedure to generate a Jupyter Notebook and run it to export your Data Wrangler flow to Python Code.

1. Choose the + next to the node that you want to export.
2. Choose Export to.
4. Run the Jupyter Notebook.
You might need to configure the Python script to make it run in your pipeline. For example, if you're running a Spark environment, make sure that you are running the script from an environment that has permission to access AWS resources.

### Export to Amazon SageMaker Feature Store

You can use Data Wrangler to export features you've created to Amazon SageMaker Feature Store. A feature is a column in your dataset. Feature Store is a centralized store for features and their associated metadata. You can use Feature Store to create, share, and manage curated data for machine learning (ML) development. Centralized stores make your data more discoverable and reusable. For more information about Feature Store, see [Amazon SageMaker Feature Store](#).

A core concept in Feature Store is a feature group. A feature group is a collection of features, their records (observations), and associated metadata. It's similar to a table in a database.

You can use Data Wrangler to do one of the following:

- Update an existing feature group with new records. A record is an observation in the dataset.
- Create a new feature group from a node in your Data Wrangler flow. Data Wrangler adds the observations from your datasets as records in your feature group.

If you're updating an existing feature group, your dataset's schema must match the schema of the feature group. All the records in the feature group are replaced with the observations in your dataset.

You can use either a Jupyter Notebook or a destination node to update your feature group with the observations in the dataset.

#### Destination Node

If you want to output a series of data processing steps that you've performed to a feature group, you can create a destination node. When you create and run a destination node, Data Wrangler updates a feature group with your data. You can also create a new feature group from the destination node UI. After you create a destination node, you create a processing job to output the data. A processing job is an Amazon SageMaker processing job. When you're using a destination node, it runs the computational resources needed to output the data that you've transformed to the feature group.
You can use a destination node to export some of the transformations or all of the transformations that you've made in your Data Wrangler flow.

Use the following procedure to create a destination node to update a feature group with the observations from your dataset.

To update a feature group using a destination node, do the following.
1. Choose the + symbol next to the node containing the dataset that you'd like to export.
2. Under **Add destination**, choose **SageMaker Feature Store**.
3. Double click on the feature group. Data Wrangler checks whether the schema of the feature group matches the schema of the data that you're using to update the feature group.
4. (Optional) Select **Export to offline store only** for feature groups that have both an online store and an offline store. This option only updates the offline store with observations from your dataset.
5. After Data Wrangler validates the schema of your dataset, choose **Add**.

Use the following procedure to create a new feature group with data from your dataset.

You can have the following options for how you want to store your feature group:

- **Online** – Low latency, high availability cache for a feature group that enables real-time lookup of records. The online store allows quick access to the latest value for a record in a feature group.
- **Offline** – Stores data for your feature group in an Amazon S3 bucket. You can store your data offline when you don't need low latency (sub-second) reads. You can use an offline store for features used in data exploration, model training, and batch inference.
- **Both online and offline** – Stores your data in both an online store and an offline store.

To create a feature group using a destination node, do the following.
1. Choose the + symbol next to the node containing the dataset that you'd like to export.
2. Under **Add destination**, choose **SageMaker Feature Store**.
3. Choose **Create Feature Group**.
4. In the following dialog box, if your dataset doesn't have an event time column, select **Create "EventTime" column**.
5. Choose **Next**.
6. Choose **Copy JSON Schema**. When you create a feature group, you paste the schema into the feature definitions.

7. Choose **Create**.

8. For **Feature group name**, specify a name for your feature group.

9. For **Description (optional)**, specify a description to make your feature group more discoverable.

10. To create a feature group for an online store, do the following.
   a. Select **Enable storage online**.
   b. For **Online store encryption key**, specify an AWS managed encryption key or an encryption key of your own.

11. To create a feature group for an offline store, do the following.
   a. Select **Enable storage offline**.
   b. Specify values for the following fields:
      - **S3 bucket name** – The name of the bucket storing the feature group.
      - **(Optional) Dataset directory name** – The Amazon S3 prefix that you're using to store the feature group.
      - **IAM Role ARN** – The IAM role that has access to feature store.
      - **Offline store encryption key** – By default, Feature Store uses an AWS managed key, but you can use the field to specify a key of your own.

12. Choose **Continue**.

13. Choose **JSON**.

14. Remove the placeholder brackets in the window.

15. Paste the JSON text from Step 6.

16. Choose **Continue**.

17. For **RECORD IDENTIFIER FEATURE NAME**, choose the column in your dataset that has unique identifiers for each record in your dataset.

18. For **EVENT TIME FEATURE NAME**, choose the column with the timestamp values.

19. Choose **Continue**.

20. (Optional) Add tags to make your feature group more discoverable.

21. Choose **Continue**.

22. Choose **Create feature group**.

23. Navigate back to your Data Wrangler flow and choose the refresh icon next to the **Feature Group** search bar.

**Note**
If you've already created a destination node for a feature group within a flow, you can't create another destination node for the same feature group. If you want to create another destination node for the same feature group, you must create another flow file.

Use the following procedure to create a Data Wrangler job.

Create a job from the **Data flow** page and choose the destination nodes that you want to export.

1. Choose **Create job**. The following image shows the pane that appears after you select **Create job**.

2. For **Job name**, specify the name of the export job.

3. Choose the destination nodes that you want to export.
4. (Optional) For **Output KMS Key**, specify an ARN, ID, or alias of an AWS KMS key. A KMS key is a cryptographic key. You can use the key to encrypt the output data from the job. For more information about AWS KMS keys, see *AWS Key Management Service*.

5. The following image shows the **Configure job** page with the **Job configuration** tab open.

![Configure job page](image_url)

(Optional) Under **Trained parameters**, choose **Refit** if you've done the following:

- Sampled your dataset
- Applied a transform that uses your data to create a new column in the dataset

For more information about refitting the transformations you've made to an entire dataset, see *Refit Transforms to The Entire Dataset and Export Them* (p. 960).

6. Choose **Configure job**. The following image shows the **Configure job** page.

7. (Optional) Configure the Data Wrangler job. The following are examples of optional configurations.

   a. For **Flow file S3 location**, specify the Amazon S3 location where you'd like to save the flow file.

   b. For **Flow file KMS key**, specify the AWS KMS key, ARN, or alias that you're using to encrypt the flow file.

Jupyter Notebook

Use the following procedure to a Jupyter Notebook to export to Amazon SageMaker Feature Store.

Use the following procedure to generate a Jupyter Notebook and run it to export your Data Wrangler flow to Feature Store.

1. Choose the + next to the node that you want to export.
2. Choose Export to.
4. Run the Jupyter Notebook.

Running a Jupyter Notebook runs a Data Wrangler job. Running a Data Wrangler job starts a SageMaker processing job. The processing job ingests the flow into an online and offline feature store.

**Important**

The IAM role you use to run this notebook must have the following AWS managed policies attached: AmazonSageMakerFullAccess and AmazonSageMakerFeatureStoreAccess.

You only need to enable one online or offline feature store when you create a feature group. You can also enable both. To disable online store creation, set `EnableOnlineStore` to `False`:

```python
# Online Store Configuration
online_store_config = {
    "EnableOnlineStore": False
}
```

The notebook uses the column names and types of the dataframe you export to create a feature group schema, which is used to create a feature group. A feature group is a group of features defined in the feature store to describe a record. The feature group defines the schema and features contained in the feature group. A feature group definition is composed of a list of features, a record
identifier feature name, an event time feature name, and configurations for its online store and offline store.

Each feature in a feature group can have one of the following types: String, Fractional, or Integral. If a column in your exported dataframe is not one of these types, it defaults to String.

The following is an example of a feature group schema.

```python
column_schema = [
    {
        "name": "Height",
        "type": "long"
    },
    {
        "name": "Input",
        "type": "string"
    },
    {
        "name": "Output",
        "type": "string"
    },
    {
        "name": "Sum",
        "type": "string"
    },
    {
        "name": "Time",
        "type": "string"
    }
]
```

Additionally, you must specify a record identifier name and event time feature name:

- The **record identifier name** is the name of the feature whose value uniquely identifies a record defined in the feature store. Only the latest record per identifier value is stored in the online store. The record identifier feature name must be one of feature definitions’ names.

- The **event time feature name** is the name of the feature that stores the EventTime of a record in a feature group. An EventTime is a point in time when a new event occurs that corresponds to the creation or update of a record in a feature. All records in the feature group must have a corresponding EventTime.

The notebook uses these configurations to create a feature group, process your data at scale, and then ingest the processed data into your online and offline feature stores. To learn more, see Data Sources and Ingestion.

The notebook uses these configurations to create a feature group, process your data at scale, and then ingest the processed data into your online and offline feature stores. To learn more, see Data Sources and Ingestion.

**Refit Transforms to The Entire Dataset and Export Them**

When you import data, Data Wrangler uses a sample of the data to apply the encodings. By default, Data Wrangler uses the first 50,000 rows as a sample, but you can import the entire dataset or use a different sampling method. For more information, see Import (p. 827).

The following transformations use your data to create a column in the dataset:

- **Encode Categorical (p. 903)**
• Featurize Text (p. 906)
• Handle Outliers (p. 919)
• Handle Missing Values (p. 921)

If you used sampling to import your data, the preceding transforms only use the data from the sample to create the column. The transform might not have used all of the relevant data. For example, if you use the **Encode Categorical** transform, there might have been a category in the entire dataset that wasn't present in the sample.

You can either use a destination node or a Jupyter notebook to refit the transformations to the entire dataset. When Data Wrangler exports the transformations in the flow, it creates a SageMaker processing job. When the processing job finishes, Data Wrangler saves the following files in either the default Amazon S3 location or an S3 location that you specify:

- The Data Wrangler flow file that specifies the transformations that are refit to the dataset
- The dataset with the refit transformations applied to it

You can open a Data Wrangler flow file within Data Wrangler and apply the transformations to a different dataset. For example, if you've applied the transformations to a training dataset, you can open and use the Data Wrangler flow file to apply the transformations to a dataset used for inference.

For a information about using destination nodes to refit transforms and export see the following pages:

- Export to Amazon S3 (p. 946)
- Export to Amazon SageMaker Feature Store (p. 955)

Use the following procedure to run a Jupyter notebook to refit the transformations and export the data.

To run a Jupyter Notebook and to refit the transformations and export your Data Wrangler flow, do the following.

1. Choose the + next to the node that you want to export.
2. Choose **Export to**.
3. Choose the location where you're exporting the data.
4. For the `refit_trained_params` object, set `refit` to `True`.
5. For the `output_flow` field, specify the name of the output flow file with the refit transformations.
6. Run the Jupyter Notebook.

**Create a Schedule to Automatically Process New Data**

If you're processing data periodically, you can create a schedule to run the processing job automatically. For example, you can create a schedule that runs a processing job automatically when you get new data. For more information about processing jobs, see Export to Amazon S3 (p. 946) and Export to Amazon SageMaker Feature Store (p. 955).

When you create a job you must specify an IAM role that has permissions to create the job. By default, the IAM role that you use to access Data Wrangler is the **SageMakerExecutionRole**.

The following permissions enable Data Wrangler to access EventBridge and allow EventBridge to run processing jobs:

- Add the following AWS Managed policy to the Amazon SageMaker Studio execution role that provides Data Wrangler with permissions to use EventBridge:
arn:aws:iam::aws:policy/AmazonEventBridgeFullAccess

For more information about the policy, see AWS managed policies for EventBridge.

- Add the following policy to the IAM role that you specify when you create a job in Data Wrangler:

```
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": "sagemaker:StartPipelineExecution",
        }
    ]
}
```

If you’re using the default IAM role, you add the preceding policy to the Amazon SageMaker Studio execution role.

Add the following trust policy to the role to allow EventBridge to assume it.

```
{
    "Effect": "Allow",
    "Principal": {
        "Service": "events.amazonaws.com"
    },
    "Action": "sts:AssumeRole"
}
```

**Important**
When you create a schedule, Data Wrangler creates an eventRule in EventBridge. You incur charges for both the event rules that you create and the instances used to run the processing job.

For information about EventBridge pricing, see Amazon EventBridge pricing. For information about processing job pricing, see Amazon SageMaker Pricing.

You can set a schedule using one of the following methods:

- **CRON expressions**
  
  **Note**
  Data Wrangler doesn't support the following expressions:
  
  - LW#
  - Abbreviations for days
  - Abbreviations for months

- **RATE expressions**
  
  Recurring – Set an hourly or daily interval to run the job.
  Specific time – Set specific days and times to run the job.
The following sections provide procedures on creating jobs.

CRON

Use the following procedure to create a schedule with a CRON expression.

To specify a schedule with a CRON expression, do the following.

1. Open your Data Wrangler flow.
2. Choose Create job.
3. (Optional) For Output KMS key, specify an AWS KMS key to configure the output of the job.
5. Select Associate Schedules.
6. Choose Create a new schedule.
7. For Schedule Name, specify the name of the schedule.
8. For Run Frequency, choose CRON.
9. Specify a valid CRON expression.
10. Choose Create.
11. (Optional) Choose Add another schedule to run the job on an additional schedule.

Note
You can associate a maximum of two schedules. The schedules are independent and don't affect each other unless the times overlap.

12. Choose one of the following:

- **Schedule and run now** – Data Wrangler the job runs immediately and subsequently runs on the schedules.
- **Schedule only** – Data Wrangler the job only runs on the schedules that you specify.

13. Choose Run

RATE

Use the following procedure to create a schedule with a RATE expression.

To specify a schedule with a RATE expression, do the following.

1. Open your Data Wrangler flow.
2. Choose Create job.
3. (Optional) For Output KMS key, specify an AWS KMS key to configure the output of the job.
5. Select Associate Schedules.
6. Choose Create a new schedule.
7. For Schedule Name, specify the name of the schedule.
8. For Run Frequency, choose Rate.
9. For Value, specify an integer.
10. For Unit, select one of the following:

- Minutes
- Hours
- Days

11. Choose Create.
12. (Optional) Choose Add another schedule to run the job on an additional schedule.

   Note
   You can associate a maximum of two schedules. The schedules are independent and
don't affect each other unless the times overlap.

13. Choose one of the following:
   • Schedule and run now – Data Wrangler the job runs immediately and subsequently runs on
     the schedules.
   • Schedule only – Data Wrangler the job only runs on the schedules that you specify.

14. Choose Run

Recurring

Use the following procedure to create a schedule that runs a job on a recurring basis.

To specify a schedule with a CRON expression, do the following.

1. Open your Data Wrangler flow.
2. Choose Create job.
3. (Optional) For Output KMS key, specify an AWS KMS key to configure the output of the job.
5. Select Associate Schedules.
6. Choose Create a new schedule.
7. For Schedule Name, specify the name of the schedule.
8. For Run Frequency, make sure Recurring is selected by default.
9. For Every x hours, specify the hourly frequency that the job runs during the day. Valid values are
   integers in the inclusive range of 1 and 23.
10. For On days, select one of the following options:
   • Every Day
   • Weekends
   • Weekdays
   • Select Days

   • (Optional) If you’ve selected Select Days, choose the days of the week to run the job.

   Note
   The schedule resets every day. If you schedule a job to run every five hours, it runs at
   the following times during the day:
   • 00:00
   • 05:00
   • 10:00
   • 15:00
   • 20:00

11. Choose Create.
12. (Optional) Choose Add another schedule to run the job on an additional schedule.

    Note
    You can associate a maximum of two schedules. The schedules are independent and
don't affect each other unless the times overlap.
13. Choose one of the following:
   - **Schedule and run now** – Data Wrangler the job runs immediately and subsequently runs on the schedules.
   - **Schedule only** – Data Wrangler the job only runs on the schedules that you specify.

14. Choose **Run**

**Specific time**

Use the following procedure to create a schedule that runs a job at specific times.

To specify a schedule with a CRON expression, do the following.

1. Open your Data Wrangler flow.
2. Choose **Create job**.
3. (Optional) For **Output KMS key**, specify an AWS KMS key to configure the output of the job.
4. Choose **Next, 2. Configure job**.
5. Select **Associate Schedules**.
6. Choose **Create a new schedule**.
7. For **Schedule Name**, specify the name of the schedule.
8. Choose **Create**.
9. (Optional) Choose **Add another schedule** to run the job on an additional schedule.

   **Note**
   You can associate a maximum of two schedules. The schedules are independent and don’t affect each other unless the times overlap.

10. Choose one of the following:
    - **Schedule and run now** – Data Wrangler the job runs immediately and subsequently runs on the schedules.
    - **Schedule only** – Data Wrangler the job only runs on the schedules that you specify.

11. Choose **Run**

You can use Amazon SageMaker Studio to view the jobs that are scheduled to run. Your processing jobs run within SageMaker Pipelines. Each processing job has its own pipeline. It runs as a processing step within the pipeline. You can view the schedules that you’ve created within a pipeline. For information about viewing a pipeline, see **View a Pipeline** (p. 3266).

Use the following procedure to view the jobs that you’ve scheduled.

To view the jobs you’ve scheduled, do the following.

1. Open Amazon SageMaker Studio.
2. Open SageMaker Pipelines
3. View the pipelines for the jobs that you’ve created.

   The pipeline running the job uses the job name as a prefix. For example, if you’ve created a job named housing-data-feature-engineering, the name of the pipeline is data-wrangler-housing-data-feature-engineering.
4. Choose the pipeline containing your job.
5. View the status of the pipelines. Pipelines with a **Status** of **Succeeded** have run the processing job successfully.
To stop the processing job from running, do the following:

To stop a processing job from running, delete the event rule that specifies the schedule. Deleting an event rule stops all the jobs associated with the schedule from running. For information about deleting a rule, see Disabling or deleting an Amazon EventBridge rule.

You can stop and delete the pipelines associated with the schedules as well. For information about stopping a pipeline, see StopPipelineExecution. For information about deleting a pipeline, see DeletePipeline.

Security and Permissions

When you query data from Athena or Amazon Redshift, the queried dataset is automatically stored in the default SageMaker S3 bucket for the AWS Region in which you are using Studio. Additionally, when you export a Jupyter Notebook from Amazon SageMaker Data Wrangler and run it, your data flows, or .flow files, are saved to the same default bucket, under the prefix data_wrangler_flows.

For high-level security needs, you can configure a bucket policy that restricts the AWS roles that have access to this default SageMaker S3 bucket. Use the following section to add this type of policy to an S3 bucket. To follow the instructions on this page, use the AWS Command Line Interface (AWS CLI). To learn how, see Configuring the AWS CLI in the IAM User Guide.

Additionally, you need to grant each IAM role that uses Data Wrangler permissions to access required resources. If you do not require granular permissions for the IAM role you use to access Data Wrangler, you can add the IAM managed policy, AmazonSageMakerFullAccess, to an IAM role that you use to create your Studio user. This policy grants you full permission to use Data Wrangler. If you require more granular permissions, refer to the section, Grant an IAM Role Permission to Use Data Wrangler (p. 967).

Add a Bucket Policy To Restrict Access to Datasets Imported to Data Wrangler

You can add a policy to the S3 bucket that contains your Data Wrangler resources using an Amazon S3 bucket policy. Resources that Data Wrangler uploads to your default SageMaker S3 bucket in the AWS Region you are using Studio in include the following:

- Queried Amazon Redshift results. These are stored under the redshift/ prefix.
- Queried Athena results. These are stored under the athena/ prefix.
- The .flow files uploaded to Amazon S3 when you run an exported Jupyter Notebook Data Wrangler produces. These are stored under the data_wrangler_flows/ prefix.

Use the following procedure to create an S3 bucket policy that you can add to restrict IAM role access to that bucket. To learn how to add a policy to an S3 bucket, see How do I add an S3 Bucket policy?.

To set up a bucket policy on the S3 bucket that stores your Data Wrangler resources:

1. Configure one or more IAM roles that you want to be able to access Data Wrangler.
2. Open a command prompt or shell. For each role that you create, replace role-name with the name of the role and run the following:

   $ aws iam get-role --role-name role-name

   In the response, you see a RoleId string which begins with AROA. Copy this string.
3. Add the following policy to the SageMaker default bucket in the AWS Region in which you are using Data Wrangler. Replace region with the AWS Region in which the bucket is located, and account-id with your AWS account ID. Replace userIds starting with AROAEXAMPLEID with the IDs of an AWS roles to which you want to grant permission to use Data Wrangler.
Grant an IAM Role Permission to Use Data Wrangler

You can grant an IAM role permission to use Data Wrangler with the general IAM managed policy, `AmazonSageMakerFullAccess`. This is a general policy that includes permissions required to use all SageMaker services. This policy grants an IAM role full access to Data Wrangler. You should be aware of the following when using `AmazonSageMakerFullAccess` to grant access to Data Wrangler:

- If you import data from Amazon Redshift, the **Database User** name must have the prefix `sagemaker_access`.
- This managed policy only grants permission to access buckets with one of the following in the name: SageMaker, SageMaker, sagemaker, or aws-glue. If want to use Data Wrangler to import from an S3 bucket without these phrases in the name, refer to the last section on this page to learn how to grant permission to an IAM entity to access your S3 buckets.

If you have high-security needs, you can attach the policies in this section to an IAM entity to grant permissions required to use Data Wrangler.

If you have datasets in Amazon Redshift or Athena that an IAM role needs to import from Data Wrangler, you must add a policy to that entity to access these resources. The following policies are the most restrictive policies you can use to give an IAM role permission to import data from Amazon Redshift and Athena.

To learn how to attach a custom policy to an IAM role, refer to Managing IAM policies in the IAM User Guide.

**Policy example to grant access to an Athena dataset import**

The following policy assumes that the IAM role has permission to access the underlying S3 bucket where data is stored through a separate IAM policy.
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "athena:ListDataCatalogs",
        "athena:ListDatabases",
        "athena:ListTableMetadata",
        "athena:GetQueryExecution",
        "athena:GetQueryResults",
        "athena:StartQueryExecution",
        "athena:StopQueryExecution"
      ],
      "Resource": [
        "*
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "glue:CreateTable"
      ],
      "Resource": [
        "arn:aws:glue::*:table/*/sagemaker_tmp_*",
        "arn:aws:glue::*:table/sagemaker_featurestore/**",
        "arn:aws:glue::*:catalog",
        "arn:aws:glue::*:database/*
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "glue:DeleteTable"
      ],
      "Resource": [
        "arn:aws:glue::*:table/*/sagemaker_tmp_*",
        "arn:aws:glue::*:catalog",
        "arn:aws:glue::*:database/*
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "glue:GetDatabases",
        "glue:GetTable",
        "glue:GetTables"
      ],
      "Resource": [
        "arn:aws:glue::*:table/**",
        "arn:aws:glue::*:catalog",
        "arn:aws:glue::*:database/*
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "glue:CreateDatabase",
        "glue:GetDatabase"
      ],
      "Resource": [
        "arn:aws:glue::*:catalog",
        "arn:aws:glue::*:database/sagemaker_featurestore",
        "arn:aws:glue::*:database/sagemaker_processing",
        "arn:aws:glue::*:database/default",
        "arn:aws:glue::*:table/sagemaker_featurestore/**"
      ]
    }
  ]
}
Policy example to grant access to an Amazon Redshift dataset import

The following policy grants permission to set up an Amazon Redshift connection to Data Wrangler using database users that have the prefix `sagemaker_access` in the name. To grant permission to connect using additional database users, add additional entries under "Resources" in the following policy. The following policy assumes that the IAM role has permission to access the underlying S3 bucket where data is stored through a separate IAM policy, if applicable.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [
                "redshift-data:ExecuteStatement",
                "redshift-data:DescribeStatement",
                "redshift-data:CancelStatement",
                "redshift-data:GetStatementResult",
                "redshift-data:ListSchemas",
                "redshift-data:ListTables"
            ],
            "Resource": ["*"]
        },
        {
            "Effect": "Allow",
            "Action": ["redshift:GetClusterCredentials"],
            "Resource": ["arn:aws:redshift:*:*:dbuser:*/sagemaker_access*", "arn:aws:redshift:*:*:dbname:*"]
        }
    ]
}
```

Policy to grant access to an S3 bucket

If your dataset is stored in Amazon S3, you can grant an IAM role permission to access this bucket with a policy similar to the following. This example grants programmatic read-write access to the bucket named `test`.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": ["s3:ListBucket"],
            "Resource": ["arn:aws:s3:::test"]
        },
        {
            "Effect": "Allow",
            "Action": ["s3:PutObject", "s3:GetObject"]
        }
    ]
}
```
To import data from Athena and Amazon Redshift, you must grant an IAM role permission to access the following prefixes under the default Amazon S3 bucket in the AWS Region Data Wrangler in which is being used: athena/, redshift/. If a default Amazon S3 bucket does not already exist in the AWS Region, you must also give the IAM role permission to create a bucket in this region.

Additionally, if you want the IAM role to be able to use the Amazon SageMaker Feature Store, SageMaker Pipelines, and Data Wrangler job export options, you must grant access to the prefix data_wrangler_flows/ in this bucket.

Data Wrangler uses the athena/ and redshift/ prefixes to store preview files and imported datasets. To learn more, see Imported Data Storage (p. 863).

Data Wrangler uses the data_wrangler_flows/ prefix to store .flow files when you run a Jupyter Notebook exported from Data Wrangler. To learn more, see Export (p. 945).

Use a policy similar to the following to grant the permissions described in the preceding paragraphs.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": ["s3:GetObject", "s3:PutObject"],
        },
        {
            "Effect": "Allow",
            "Action": ["s3:CreateBucket", "s3:ListBucket"],
            "Resource": "arn:aws:s3:::sagemaker-region-account-id"
        },
        {
            "Effect": "Allow",
            "Action": ["s3:ListAllMyBuckets", "s3:GetBucketLocation"],
            "Resource": "*"
        }
    ]
}
```

You can also access data in your Amazon S3 bucket from another AWS account by specifying the Amazon S3 bucket URI. To do this, the IAM policy that grants access to the Amazon S3 bucket in the other
account should use a policy similar to the following example, where BucketFolder is the specific directory in the user's bucket UserBucket. This policy should be added to the user granting access to their bucket for another user.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [
                "s3:GetObject",
                "s3:PutObject",
                "s3:PutObjectAcl"
            ],
            "Resource": "arn:aws:s3:::UserBucket/BucketFolder/*"
        },
        {
            "Effect": "Allow",
            "Action": [
                "s3:ListBucket"
            ],
            "Resource": "arn:aws:s3:::UserBucket",
            "Condition": {
                "StringLike": {
                    "s3:prefix": [
                        "BucketFolder/*"
                    ]
                }
            }
        }
    ]
}
```

The user that is accessing the bucket (not the bucket owner) must add a policy similar to the following example to their user. Note that AccountX and TestUser below refers to the bucket owner and their user respectively.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "AWS": "arn:aws:iam::AccountX:user/TestUser"
            },
            "Action": [
                "s3:GetObject",
                "s3:PutObject",
                "s3:PutObjectAcl"
            ],
            "Resource": ["arn:aws:s3:::UserBucket/BucketFolder/*"
        }
        ,
        {
            "Effect": "Allow",
            "Principal": {
                "AWS": "arn:aws:iam::AccountX:user/TestUser"
            },
            "Action": [
                "s3:ListBucket"
            ],
            "Resource": ["arn:aws:s3:::UserBucket/BucketFolder/*"
        }
    ]
}
```

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Policy example to grant access to use SageMaker Studio

Use a policy like the following to create an IAM execution role that can be used to set up a Studio instance.

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "sagemaker:CreatePresignedDomainUrl",
        "sagemaker:DescribeDomain",
        "sagemaker:ListDomains",
        "sagemaker:DescribeUserProfile",
        "sagemaker:ListUserProfiles",
        "sagemaker:*App",
        "sagemaker:ListApps"
      ],
      "Resource": "*"
    }
  ]
}
```

Snowflake and Data Wrangler

All permissions for AWS resources are managed via your IAM role attached to your Studio instance. The Snowflake administrator manages Snowflake-specific permissions, as they can grant granular permissions and privileges to each Snowflake user. This includes databases, schemas, tables, warehouses, and storage integration objects. You must ensure that the correct permissions are set up outside of Data Wrangler.

Note that the Snowflake COPY INTO Amazon S3 command moves data from Snowflake to Amazon S3 over the public internet by default, but data in transit is secured using SSL. Data at rest in Amazon S3 is encrypted with SSE-KMS using the default AWS KMS key.

With respect to Snowflake credentials storage, Data Wrangler does not store customer credentials. Data Wrangler uses Secrets Manager to store the credentials in a secret and rotates secrets as part of a best practice security plan. The Snowflake or Studio administrator needs to ensure that the data scientist’s Studio execution role is granted permission to perform GetSecretValue on the secret storing the credentials. If already attached to the Studio execution role, the AmazonSageMakerFullAccess policy has the necessary permissions to read secrets created by Data Wrangler and secrets created by following the naming and tagging convention in the instructions above. Secrets that do not follow the conventions must be separately granted access. We recommend using Secrets Manager to prevent sharing credentials over unsecured channels; however, note that a logged-in user can retrieve the plain-text password by launching a terminal or Python notebook in Studio and then invoking API calls from the Secrets Manager API.

Data Encryption with AWS KMS

Within Data Wrangler, you can decrypt encrypted files and add them to your Data Wrangler flow. You can also encrypt the output of the transforms using either a default AWS KMS key or one that you provide.
You can import files if they have the following:

- server-side encryption
- SSE-KMS as the encryption type

To decrypt the file and import to a Data Wrangler flow, you must add the SageMaker Studio user that you’re using as a key user.

The following screenshot shows a Studio user role added as a key user. See IAM Roles to access users under the left panel to make this change.

![Key users](image)

**Amazon S3 customer managed key setup for Data Wrangler imported data storage**

By default, Data Wrangler uses Amazon S3 buckets that have the following naming convention: `sagemaker-region-account number`. For example, if your account number is `111122223333` and you are using Studio in us-east-1, your imported datasets are stored with the following naming convention: `sagemaker-us-east-1-111122223333`.

The following instructions explain how to set up a customer managed key for your default Amazon S3 bucket.

1. To enable server-side encryption and setup a customer managed key for your default S3 bucket, see Using KMS Encryption.
2. After following step 1, navigate to AWS KMS in your AWS Management Console. Find the customer managed key you selected in step 1 of the previous step and add the Studio role as the key user. To do this, follow the instructions in Allows key users to use a customer managed key.

**Encrypting the Data That You Export**

You can encrypt the data that you export using one of the following methods:

- Specifying that your Amazon S3 bucket has object use SSE-KMS encryption.
- Specifying an AWS KMS key to encrypt the data that you export from Data Wrangler.

On the Export data page, specify a value for the AWS KMS key ID or ARN.

For more information on using AWS KMS keys, see Protecting Data Using Server-Side Encryption with AWS KMS keys Stored in AWS Key Management Service (SSE-KMS).
Using Lifecycle Configurations in Data Wrangler

You might have an Amazon EC2 instance that is configured to run Kernel Gateway applications, but not the Data Wrangler application. Kernel Gateway applications provide access to the environment and the kernels that you use to run Studio notebooks and terminals. The Data Wrangler application is the UI application that runs Data Wrangler. Amazon EC2 instances that aren't Data Wrangler instances require a modification to their lifecycle configurations to run Data Wrangler. Lifecycle configurations are shell scripts that automate the customization of your Amazon SageMaker Studio environment.

For more information about lifecycle configurations, see Use Lifecycle Configurations with Amazon SageMaker Studio (p. 167).

The default lifecycle configuration for your instance doesn't support using Data Wrangler. You can make the following modifications to the default configuration to use Data Wrangler with your instance.

```bash
#!/bin/bash
set -eux
STATUS=$(python3 -c "import sagemaker_dataprep; echo $?"
if [ "$STATUS" -eq 0 ]; then
  echo 'Instance is of Type Data Wrangler'
else
  echo 'Instance is not of Type Data Wrangler'

# Replace this with the URL of your git repository
export REPOSITORY_URL="https://github.com/aws-samples/sagemaker-studio-lifecycle-config-examples.git"
git -C /root clone $REPOSITORY_URL
fi
```

You can save the script as lifecycle_configuration.sh.

You attach the lifecycle configuration to your Studio domain or user profile. For more information about creating and attaching a lifecycle configuration, see Creating and Associating a Lifecycle Configuration (p. 168).

The following instructions show you how to attach a lifecycle configuration to a Studio domain or user profile.

You might run into errors when you’re creating or attaching a lifecycle configuration. For information about debugging lifecycle configuration errors, KernelGateway App failure (p. 174).

Release Notes

Data Wrangler is regularly updated with new features and bug fixes. To upgrade the version of Data Wrangler you are using in Studio, follow the instructions in Shut down and Update Studio Apps (p. 180).

<table>
<thead>
<tr>
<th>Release Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>10/12/2022</td>
</tr>
</tbody>
</table>

New functionality:
**Release Notes**

You can now reuse data flows for different data sets. For more information, see [Reusing Data Flows for Different Datasets](p. 938).

**10/05/2022**

New functionality:

You can now use Principal Component Analysis (PCA) as a transform. For more information, see [Reduce Dimensionality within a Dataset](p. 902).

**10/05/2022**

New functionality:

You can now refit parameters in your Data Wrangler flow. For more information, see [Export](p. 945).

**10/03/2022**

New functionality:

You can now deploy models from your Data Wrangler flow. For more information, see [Automatically Train Models on Your Data Flow](p. 888).

**9/20/2022**

New functionality:

You can now set data retention periods in Athena. For more information, see [Import data from Athena](p. 832).

**6/9/2022**

New functionality:

You can now use Amazon SageMaker Autopilot to train a model directly from your Data Wrangler flow. For more information, see [Automatically Train Models on Your Data Flow](p. 888).

**5/6/2022**

New functionality:

You can now use additional m5 and r5 instances. For more information, see [Instances](p. 864).

**4/27/2022**

New functionalities:

- You can now get a data quality report. For more information, see [Get Insights On Data and Data Quality](p. 875)
- You can now perform random sampling and stratified sampling. For more information, see [Sampling](p. 923).

**4/1/2022**

New functionality:

You can now use Databricks as a data source. For more information, see [Import data from Databricks (JDBC)](p. 839).
### Release Notes

**2/2/2022**

New functionalities:

- You can now export using destination nodes. For more information, see [Export](#).
- You can import ORC and JSON files. For more information about file types, see [Import](#).
- Data Wrangler now supports using the SMOTE transform. For more information, see [Balance Data](#).
- Data Wrangler now supports similarity encoding for categorical data. For more information, see [Similarity encode](#).
- Data Wrangler now supports unnesting JSON data. For more information, see [Unnest JSON Data](#).
- Data Wrangler now supports expanding the values of an array into separate columns. For more information, see [Explode Array](#).
- Data Wrangler now supports reaching out to the service team when you're having issues. For more information, see [Troubleshoot](#).
- Data Wrangler now supports editing and deleting steps in your data flow. For more information, see [Delete a Step from Your Data Flow](#) and [Edit a Step in Your Data Wrangler Flow](#).
- You can now perform transformations on multiple columns. For more information, see [Transform Data](#).
- Data Wrangler now supports cost allocation tags. For more information, see [Using Cost Allocation Tags](#).

**10/16/2021**

New functionality:

Data Wrangler now supports Athena workgroups. For more information, see [Import data from Athena](#).

**10/6/2021**

New functionality:

Data Wrangler now supports transforming time series data. For more information, see [Transform Time Series](#).

**7/15/2021**

New functionalities:

- [Snowflake and Data Wrangler](#) is now supported. You can use Snowflake as a data source in Data Wrangler.
- Added support for custom field delimiter in CSV. Now comma, colon, semicolon, pipe (|) and Tab are supported.
- Now you can export results directly to Amazon S3.
- Added a few new multicollinearity analyzers: Variance Inflation Factors, Principal Component Analysis and Lasso feature selection.

Enhancements:

- The analyze charts can no longer be could be packed with overlapping labels.
## Release Notes

### Bug Fixes:
- One-hot encoder handles empty string gracefully.
- Fixed crashes that occurred when a dataframe column name contained dots.

### 4/26/2021

### Enhancements:
- Added support for distributed processing Jobs. You can use multiple instances when running a processing job.
- Data Wrangler Processing job now automatically coalesces small outputs when estimated result size is less than 1 gigabytes.
- Data Wrangler Processing jobs now use 1.x as the authoritative container tag for future releases.

### Bug Fixes:
- Fixed rendering issues for faceted histogram.
- Fixed **Export to Processing Job** to support vector type columns.
- Fixed **Extract using regex** operator to return the first captured group if one or more exists in the regular expression or regex.

### 2/8/2021

### New Functionalities:
- Data Wrangler Flows supports multiple instances.
- Updated Export to Data Wrangler Job Notebook to use SageMaker SDK 2.20.0.
- Updated Export to Pipeline Notebook to use SageMaker SDK 2.20.0.
- Updated Export to Pipeline Notebook to add XGBoost training example as an optional step.

### Enhancements:
- To improve performance, importing CSV files that contain multiple lines in a single field is no longer supported.

### Bug Fixes:
- Fixed type inference issue in Quick model.
- Fixed the bias metric bug in bias reports.
- Fixed the Featurize text transform to work with columns with missing values.
- Fixed Histogram and Scatter plot built-in visualizations to work with datasets that contain array-like columns.
- Athena query now re-runs if the query execution ID has expired.
Troubleshoot

If an issue arises when using Amazon SageMaker Data Wrangler, we recommend you do the following:

- If an error message is provided, read the message and resolve the issue it reports if possible.
- Make sure the IAM role of your Studio user has the required permissions to perform the action. For more information, see Security and Permissions (p. 966).
- If the issue occurs when you are trying to import from another AWS service, such as Amazon Redshift or Athena, make sure that you have configured the necessary permissions and resources to perform the data import. For more information, see Import (p. 827).
- If you're still having issues, choose Get help at the top right of your screen to reach out to the Data Wrangler team. For more information, see the following images.
As a last resort, you can try restarting the kernel on which Data Wrangler is running.

1. Save and exit the .flow file for which you want to restart the kernel.
2. Select the Running Terminals and Kernels icon, as shown in the following image.

3. Select the Stop icon to the right of the .flow file for which you want to terminate the kernel, as shown in the following image.
Increase Amazon EC2 Instance Limit

You might see the following error message when you're using Data Wrangler: The following instance type is not available: ml.m5.4xlarge. Try selecting a different instance below.

The message can indicate that you need to select a different instance type, but it can also indicate that you don’t have enough Amazon EC2 instances to successfully run Data Wrangler on your workflow. You can increase the number of instances by using the following procedure.

To increase the number of instances, do the following.

1. Open the AWS Management Console.
2. In the search bar, specify Services Quotas.
3. Choose Service Quotas.
Update Data Wrangler

To update Data Wrangler to the latest release, first shut down the corresponding KernelGateway app from the Amazon SageMaker Studio control panel. After the KernelGateway app is shut down, restart it by opening a new or existing Data Wrangler flow in Studio. When you open a new or existing Data Wrangler flow, the kernel that starts contains the latest version of Data Wrangler.

Update your Studio and Data Wrangler instance

1. Navigate to your SageMaker Console.
2. Choose SageMaker and then Studio.
3. Choose your user name.
4. Under Apps, in the row displaying the App name, choose Delete app for the app that starts with sagemaker-data-wrangler, and for the JupyterServer app.
5. Choose Yes, delete app.
6. Type delete in the confirmation box.
7. Choose Delete.
8. Reopen your Studio instance. When you begin to create a Data Wrangler flow, your instance now uses the latest version of Data Wrangler.

Alternatively, if you are using a Data Wrangler application version that is not the latest version, and you have an existing Data Wrangler flow open, you are prompted to update your Data Wrangler application version in the Studio UI. The following screenshot shows this prompt.

Important
This updates the Data Wrangler kernel gateway app only. You still need to shut down the JupyterServer app in your user account. To do this, follow the preceding steps.
You can also choose Remind me later, in which case an Update button appears in the top-right corner of the screen.

**Shut Down Data Wrangler**

When you are not using Data Wrangler, it is important to shut down the instance on which it runs to avoid incurring additional fees.

To avoid losing work, save your data flow before shutting Data Wrangler down. To save your data flow in Studio, choose File and then choose Save Data Wrangler Flow. Data Wrangler automatically saves your data flow every 60 seconds.
Prepare Data at Scale with Studio Notebooks

Amazon SageMaker Studio gives data scientists, machine learning (ML) engineers, and general practitioners tools to perform data analytics and data preparation at scale. Analyzing, transforming, and preparing large amounts of data is a foundational step of any data science and ML workflow. SageMaker Studio comes with built-in integration of Amazon EMR and AWS Glue Interactive Sessions to handle your large-scale interactive data preparation and machine learning workflows, all within your Studio notebook.

Amazon EMR is a managed big data platform with resources to help you run petabyte-scale distributed data processing jobs using open-source analytics frameworks on AWS such as Apache Spark, Apache Hive, Presto, HBase, Flink, and Hudi among others. Data engineers and data scientists use Amazon
EMR for a wide variety of use cases, including big data analytics, what-if analyses, real time analytics, and data preparation for machine learning. Studio integration with Amazon EMR allows you to easily create, browse, discover, and connect to EMR clusters without leaving your Studio notebook. You can even monitor and debug your Spark workloads with one-click access to the Spark UI from within the notebook. You should consider EMR for your data preparation workloads if you want maximum control over hardware and software versions, containers, and big data processing applications.

AWS Glue Interactive Sessions is a serverless service that you can enlist to collect, transform, cleanse, and prepare data for storage in your data lakes and data pipelines. Glue Interactive Sessions provides an on-demand, serverless Apache Spark runtime environment that you can initialize in seconds on a dedicated Data Processing Unit (DPU) without having to worry about provisioning and managing complex compute cluster infrastructure. After initialization, you can quickly browse the Glue data catalog, run large queries, access data governed by AWS Lake Formation, and interactively analyze and prepare data using Spark, right in your Studio notebook. You can then use the prepared data to build, train, tune and deploy models using the purpose-built ML tools within SageMaker Studio. You should consider Glue Interactive Sessions for your data preparation workloads when you want a serverless Spark service with moderate control of configurability and flexibility.

Prepare Data using Amazon EMR

Data scientists and data engineers use Apache Spark, Hive, and Presto on Amazon EMR for fast data preparation. Studio comes with built-in integration of Amazon EMR, enabling you to perform petabyte-scale interactive data preparation and machine learning right in your Studio notebook. Within your notebook, you can visually browse, discover, and connect to Amazon EMR. After you connect, you can interactively explore, visualize, and prepare petabyte-scale data for machine learning (ML) using Apache Spark, Hive, and Presto. Amazon EMR can handle your ETL jobs, run large-scale model training, perform analyses, and handle reporting, among many other capabilities.

For guided instructions about how to connect to an Amazon EMR cluster from SageMaker Studio, see Create and manage Amazon EMR Clusters from SageMaker Studio to run interactive Spark and ML workloads.

Prerequisites

• You will need access to SageMaker Studio that is set up to use Amazon Virtual Private Cloud (Amazon VPC) mode.
  • To connect to Amazon EMR, Studio must be configured as Amazon VPC only mode. For more information, see Connect SageMaker Studio Notebooks to Resources in a Amazon VPC. For more information on how to onboard, see Onboard to SageMaker Domain.
  • All subnets used by SageMaker Studio must be private subnets.
  • If you use the sm-analytics utility to configure the SparkMagic kernel, follow one of these two prerequisites:
    • Make sure that the Amazon VPC interface endpoint is attached to all of the subnets used by SageMaker Studio.
    • Ensure that all of the subnets used by SageMaker Studio are routed to use a NAT gateway. For more information, see NAT gateways.
  • If either one of the following points apply to you, you must have Spark and Livy installed when using Amazon EMR.
    • Your Amazon EMR cluster is in the same Amazon VPC as Studio.
    • Your cluster is in a Amazon VPC that's connected to the Amazon VPC in Studio.
    • The security groups for both Amazon SageMaker Studio and Amazon EMR must allow access to and from each other.
    • Your Amazon EMR security group must open port 8998, so that Amazon SageMaker Studio can communicate with the Spark cluster through Livy. For more information about setting up the security group, see Build SageMaker notebooks backed by Spark in Amazon EMR.
To connect to an Amazon EMR cluster from Studio, you must first access SageMaker Studio. If you have not set up SageMaker Studio, follow the Get Started guide.

If you created a new domain during Studio setup, then discovering an Amazon EMR cluster from Studio should be available to you.

If you are reusing an existing domain, you must update both Studio and Studio applications. For detailed instructions, see Update Studio and Update Studio applications.

SageMaker Studio comes with built-in support to connect to EMR clusters in the following images and kernels:

- **Images:** Data Science, Data Science 2.0, SparkMagic, SparkAnalytics 1.0, PyTorch 1.8, TensorFlow 2.6
- **Kernel:** PySpark and Spark kernels for the SparkMagic image, Python 3 (IPython) for the Data Science, Data Science 2.0, PyTorch 1.8, TensorFlow 2.6 images.

If you want to connect to EMR clusters using another built-in image or your own image, follow instructions in Bring your own image (p. 985).

### Bring your own image

If you want to bring your own image, first install the following dependencies to your kernel. The following list shows `pip` commands with the library name that you will install.

```
pip install sparkmagic
pip install sagemaker-studio-sparkmagic-lib
pip install sagemaker-studio-analytics-extension
```

You can update the libraries from the previous list manually, if they are not the latest version.

If you want to connect to Amazon EMR with Kerberos authentication, you must install the kinit client. Depending on your OS, the command to install the kinit client can vary. To bring an Ubuntu (Debian based) image, use the `apt-get install -y -qq krb5-user` command.

### Topics

- Discover Amazon EMR Clusters from Studio (p. 985)
- Connect to an Amazon EMR Cluster from Studio (p. 988)
- Troubleshoot and Monitor Workloads in Amazon EMR (p. 999)
- Manage Amazon EMR Clusters from Studio (p. 1000)
- Required Permissions (p. 1016)

### Discover Amazon EMR Clusters from Studio

From within Studio, data scientists and data engineers can easily discover, connect to, and manage Amazon EMR clusters. Your Amazon EMR clusters may be in the same AWS account as SageMaker Studio or they may be in a different AWS account. This section explains how to discover an Amazon EMR cluster that exists in the same account as SageMaker Studio. For information about discovering Amazon EMR clusters in a different AWS account, see Discover Amazon EMR Clusters Across Accounts (p. 988).

Before you can activate discovering functionality, you must add a required policy to your Studio execution role. After you add this policy, you can connect to an Amazon EMR cluster in Studio.

#### To add the required policy to your Studio execution role

1. Open the IAM console.
2. Select Roles in the left-side panel.
3. Find the Studio execution role that you will be using and select it.
4. Under the Permissions tab, select Attach policies.
5. Select Create policy.
6. Select JSON.
7. Copy and paste in the following policy. For more information on required permissions, see Required Permissions (p. 1016).

```json
{
   "Statement": [
      {
         "Action": [
            "elasticmapreduce:DescribeCluster",
            "elasticmapreduce:ListInstanceGroups"
         ],
         "Effect": "Allow",
         "Resource": [
            "arn:aws:elasticmapreduce:*:*:cluster/**"
         ]
      },
      {
         "Action": [
            "elasticmapreduce:ListClusters"
         ],
         "Effect": "Allow",
         "Resource": "*"
      }
   ],
   "Version": "2012-10-17"
}
```

8. Select Next: Tags.
9. Select Next: Review.
10. Enter a Name, Description, and Select Create policy.
Now you can log in to Studio. If this is your first time logging in, follow the instructions in Log in to Studio.
Discover Amazon EMR Clusters Across Accounts

If you want to discover Amazon EMR clusters in a different AWS account than the SageMaker Studio is in, you must specify the IAM role ARN in the remote account. This IAM role ARN must be assumed to list and describe Amazon EMR clusters. Specify this remote role in a file that’s named emr-discovery-iam-role-arns-DO_NOT_DELETE.json, and in a directory named .cross-account-configuration-DO_NOT_DELETE. You will find this in your home directory, located in the Amazon EFS Storage volume used by SageMaker Studio. You can automate this process by using Lifecycle Configuration (LCC) scripts. You can attach the LCC to your Studio domain or user profile. You have the option to set your LCC script to run by default when your Jupyter server starts.

The LCC script that you use must be a JupyterServer configuration. For more information on how to create and use your LCC script and how to attach it at the Domain and UserProfile level, see Use Lifecycle Configurations with Studio. For more information on required permissions, see Required Permissions (p. 1016).

1. The following is an example LCC script that you can use. To modify the script, populate the script with the following details. Make sure that you replace ASSUMABLE-ROLE and 123456789012 with your role name and account ID, respectively. There is a limit of one role name and account ID combination.

```bash
#!/bin/bash
set -eux
FILE_DIRECTORY="/home/sagemaker-user/.cross-account-configuration-DO_NOT_DELETE"
FILE_NAME="emr-discovery-iam-role-arns-DO_NOT_DELETE.json"
FILE="$FILE_DIRECTORY/$FILE_NAME"
mkdir -p $FILE_DIRECTORY
cat > "$FILE" <<- "EOF"
{
  "123456789012": "arn:aws:iam::123456789012:role/ASSUMABLE-ROLE"
}
EOF
```

Connect to an Amazon EMR Cluster from Studio

This guide explains how you can connect to an Amazon EMR cluster from SageMaker Studio with the PySpark kernel selected.

To connect Amazon EMR cluster with PySpark kernel selected

1. After you connect to Studio, if you have an existing Studio notebook instance, open that. Otherwise, to create a new notebook instance, select File, and then select New.
2. After you have an open Studio notebook instance, choose a kernel and instance.

   Note
   Only a subset of kernels can connect to an Amazon EMR cluster. The supported images are Data Science and SparkMagic. The supported kernels are PySpark from the SparkMagic image and Python3 (IPython) from the Data Science image. Studio supports both PySpark and Scala kernels.
To switch your kernel, select in the top right of the UI the currently selected kernel where a pop-up window appears. Then select a kernel of your choice from the kernel drop-down menu. Lastly, select the **Select** button to make your changes.
3. After you have selected your kernel of choice, select **Cluster**.
4. A **Connect to cluster** UI screen will appear. Choose a cluster and select **Connect**. Not all Amazon EMR clusters can be connected to Studio. For more information, see [Perform interactive data processing using Spark in Studio Notebooks](#).

When you connect to a cluster, it adds a code block to an active cell to establish the connection.
5. If the cluster that you're connecting to does not use Kerberos or Lightweight Directory Access Protocol (LDAP) connection, you will be prompted to select the credential type. You can choose **HTTP basic authentication** or **No credential**.
6. An active cell will populate. This will contain the connection information that you need for connecting to the Amazon EMR cluster that you selected.

- When the authentication type is Kerberos and HTTP Basic Auth, a widget will be created in an active cell for you to provide your **Username** and **Password**.
- If the cluster that you are connecting to does not use Kerberos or LDAP, and you selected No credentials, you will automatically connect to an Amazon EMR cluster.

7. This step is optional. If you want to change the Amazon EMR cluster that the Studio notebook is connected to, select **Cluster** at the top-right of your notebook. After selecting **Cluster**, browse the list of clusters and select a different cluster.

For more information on required permissions, see Required Permissions (p. 1016).

**Connect Amazon EMR Clusters Across Accounts**

If you have set up cross-account discoverability and connectivity, when you select **Cluster**, all clusters from both Studio and remote accounts will show. After you select **Connect**, Studio will initiate and establish a connection to the Amazon EMR cluster in the remote account. The following screenshot shows this connection.
Create and manage Amazon EMR Clusters from here. Use "View Clusters" to see a list of Amazon EMR clusters visible to you. Use "Create Cluster" to create an EMR cluster based on a template provided by your administrator.

Manage Amazon EMR Clusters from Studio

Prepare data at scale with Studio Notebooks

View clusters
Create cluster
Troubleshoot and Monitor Workloads in Amazon EMR

The following sections give instructions for accessing the Spark UI from SageMaker Studio notebooks. The Spark UI allows you to monitor and debug your Spark Jobs submitted to run on Amazon EMR from Studio notebooks. SSH tunneling and presigned URLs are two ways for accessing the Spark UI.

Set up SSH tunneling for Spark UI access

To set up SSH tunneling to access the Spark UI, follow one of the two options in this section. Note that the screenshot in Step 6b of Connect to an Amazon EMR Cluster from Studio (p. 988) shows links under Spark UI and Driver log. These links will activate only after you complete the SSH tunneling setup.

Options for setting up SSH tunneling:

- Option 1: Set up an SSH tunnel to the master node using local port forwarding
- Option 2, part 1: Set up an SSH tunnel to the master node using dynamic port forwarding
  - Option 2, part 2: Configure proxy settings to view websites hosted on the master node

For information about viewing web interfaces hosted on Amazon EMR clusters, see View web interfaces hosted on Amazon EMR Clusters. You can also visit your Amazon EMR console to get access to the Spark UI.

Note
You can set up an SSH tunnel even if presigned URLs are not available to you.

Presigned URLs

To create one-click URLs that can access Spark UI on Amazon EMR from SageMaker Studio notebooks, you must enable the following IAM permissions. Choose the option that applies to you:

- For Amazon EMR clusters that are in the same account as the SageMaker Studio notebook: Add the following permissions to the SageMaker Studio IAM execution role.
- For Amazon EMR clusters that are in a different account (not SageMaker Studio notebook): Add the following permissions to the cross-account role that you created for Discover Amazon EMR Clusters from Studio (p. 985).

Note
You can access presigned URLs from the console in the following regions:

- US East (N. Virginia) Region
- US West (N. California) Region
- Canada (Central) Region
- Europe (Frankfurt) Region
- Europe (Stockholm) Region
- Europe (Ireland) Region
- Europe (London) Region
- Europe (Paris) Region
- Asia Pacific (Tokyo) Region
- Asia Pacific (Seoul) Region
- Asia Pacific (Sydney) Region
- Asia Pacific (Mumbai) Region
• Asia Pacific (Singapore) Region
• South America (São Paulo)

The following policy gives access to presigned URLs for your execution role.

```json
{
    "Sid": "AllowPresignedUrl",
    "Effect": "Allow",
    "Action": [
        "elasticmapreduce:DescribeCluster",
        "elasticmapreduce:ListInstanceGroups",
        "elasticmapreduce:CreatePersistentAppUI",
        "elasticmapreduce:DescribePersistentAppUI",
        "elasticmapreduce:GetPersistentAppUIPresignedURL",
        "elasticmapreduce:GetOnClusterAppUIPresignedURL"
    ],
    "Resource": [
        "arn:aws:elasticmapreduce:<region>:<account-id>:cluster/*"
    ]
}
```

For more information about required permissions, see Required Permissions (p. 1016).

**Manage Amazon EMR Clusters from Studio**

Administrators can use AWS Service Catalog to define templates. These templates allow you to create Amazon EMR clusters and make them available to selected users. Using AWS Service Catalog, administrators can fully control the organizational, security, and networking in Amazon EMR clusters. Administrators can view, select, and customize templates for their specific workloads. If they choose, admins can limit exposure to selected configuration parameters, such as only to specific data workers. Admins can create on-demand Amazon EMR clusters within SageMaker Studio. This can be done without manually setting up complex configurations. Users can also terminate Amazon EMR clusters after use, directly from SageMaker Studio.

The topics in this guide provide more details about setting up and using AWS Service Catalog templates, and creating and terminating Amazon EMR clusters.

**Topics**

- Configure AWS Service Catalog Products (p. 1000)
- Provision Amazon EMR Clusters from Studio (p. 1004)

**Configure AWS Service Catalog Products**

In this guide, you get parameters for configuring AWS Service Catalog products so you can discover CloudFormation (CFN) templates. CFN templates are used to create and manage Amazon EMR clusters. The AWS Service Catalog product can associate with an AWS Service Catalog portfolio that is shared with the Studio execution role IAM entity.

To enable Amazon EMR cluster management from Studio, you need a CloudFormation (CFN) template with Amazon EMR cluster details and configurable parameters. For information about how you can use CloudFormation, see Getting started with CloudFormation. For more information about AWS Service Catalog products, see Step 4: Create an AWS Service Catalog Product.

The AWS Service Catalog product with the Amazon EMR resource must have the following tags:

```plaintext
sagemaker:studio-visibility:emr true
```
The CFN templates in the AWS Service Catalog product must have the following mandatory stack parameters:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>SageMakerProjectName</td>
<td>String</td>
<td>Name of the project</td>
</tr>
<tr>
<td>SageMakerProjectId</td>
<td>String</td>
<td>Service generated Id of the project</td>
</tr>
</tbody>
</table>

For more information about creating AWS Service Catalog portfolios and products, see Step 3: Create an AWS Service Catalog Portfolio and its subsequent sections.

Optional template parameters

When creating Amazon EMR templates from within SageMaker Studio, you can include additional options in the parameters section of your template. This section lets users input or select custom values for a cluster. The following example parameters define additional input parameters that you can use when creating an Amazon EMR template from within Studio.

```json
"Parameters": {
    "EmrClusterName": {
        "Type": "String",
        "Description": "EMR cluster Name."
    },
    "MasterInstanceType": {
        "Type": "String",
        "Description": "Instance type of the EMR master node.",&quot;
        "Default": "m5.xlarge",
        "AllowedValues": [
            "m5.xlarge",
            "m5.2xlarge",
            "m5.4xlarge"
        ]
    },
    "CoreInstanceType": {
        "Type": "String",
        "Description": "Instance type of the EMR core nodes.",&quot;
        "Default": "m5.xlarge",
        "AllowedValues": [
            "m5.xlarge",
            "m5.2xlarge",
            "m5.4xlarge",
            "m3.medium",
            "m3.large",
            "m3.xlarge",
            "m3.2xlarge"
        ]
    },
    "CoreInstanceCount": {
        "Type": "String",
        "Description": "Number of core instances in the EMR cluster.",&quot;
        "Default": "2",
        "AllowedValues": [
            "2",
            "5",
            "10"
        ]
    },
    "EmrReleaseVersion": {
        "Type": "String",
        "Description": "The release version of EMR to launch."
    }
}
```
"Default": "emr-5.33.1",
"AllowedValues": [
  "emr-5.33.1",
  "emr-6.4.0"
]
}

The following image shows how the Studio UI will look when you create an Amazon EMR cluster from Studio.
Provision Amazon EMR Clusters from Studio

This section provides guided instructions with screenshots from Studio that show how to create a cluster, view a list of available clusters, and terminate a cluster.

If you configured cross-account discovery, you will see a consolidated list of clusters in Studio, and in the remote account.

To start, add the following permissions to the IAM execution role that will be accessing Studio. For more information about required permissions, see Required Permissions (p. 1016).

```json
{
    "Sid": "AllowSagemakerProjectManagement",
    "Effect": "Allow",
    "Action": [
        "sagemaker:CreateProject",
        "sagemaker:DeleteProject"
    ],
    "Resource": "arn:aws:sagemaker:<region>:<account-id>:project/*"
}
```

After you’ve added the previous permissions, you can connect to Studio. If you have an existing Studio notebook instance, you can open it. Otherwise, if you want to create a new notebook instance, select File, and then select New.

- To open the cluster management page, select Clusters from the left-side panel.
Amazon SageMaker Studio

SageMaker resources
Select the resource to

Clusters

Data wrangler

Feature Store

Pipelines
The following screenshot shows the cluster management page. From here, you can create and manage your Amazon EMR clusters.
A cluster can be in different statuses. To filter clusters by status, select the dropdown arrow icon. A cluster can only be in one status at a time.

Status options include Starting, Bootstrapping, Running/Walking, Terminating, Terminated, and Terminated with error. The following screenshot shows the cluster status options in the status dropdown.
Amazon SageMaker Developer Guide
Prepare Data using Amazon EMR

SageMaker resources
Select the resource to:

Clusters
Create and manage
"View Clusters" to see what's available to you. Use "Create Cluster" to create a new cluster with this.
The following procedure shows how to create a cluster using a template from Studio.

**To create a cluster from a template:**

1. Navigate to the cluster management page by selecting the **Clusters** from the left-side panel. Then, select **Create cluster**.
Amazon SageMaker Developer Guide
Prepare Data using Amazon EMR

Amazon SageMaker Studio

SageMaker resources
Select the resource to view.

Clusters
Create and manage Amazon EMR clusters. Use "View Clusters" to see a list of available clusters and select one for you. Use "Create Cluster" to create a new cluster using the template provided by your administrator.

Manage Amazon EMR Clusters

Prepare data at scale with Studio
2. Enter your SageMaker Studio subnet ID, Amazon EMR cluster name, Amazon VPC ID, and SageMaker Studio security group ID.
Create and manage Amazon EMR Clusters from "View Clusters" to see a list of Amazon EMR clusters assigned to you. Use "Create Cluster" to create an EMR cluster from a template provided by your administrator.

Manage Amazon EMR Clusters from Studio

Prepare data at scale with Studio Notebooks

View clusters
3. After entering the information from the previous step, select **Create cluster**.

The following procedure shows how to terminate a cluster.

**To terminate a cluster**

1. Navigate to the cluster management page by selecting the **Clusters** from the left-side panel.

   Select the cluster that you want to terminate, then choose **Terminate** next to **Create cluster** in the UI.

2. A window will appear advising that any pending work or data on your cluster will be lost after termination, and termination is irreversible. Select **Terminate**.
Required Permissions

This guide shows you how to apply an example IAM policy to your execution role. The examples in this guide provide you with various permissions and monitoring capabilities. At the end of this guide, you will find a comprehensive IAM policy role that includes all required permissions. These permissions provide access to Amazon EMR clusters from within Studio, and allow discoverability of clusters from within Studio (for presigned URLs). Access the IAM console to add the policy to your role.

To discover and connect to Amazon EMR clusters from within Studio, ensure that your execution role has the following permissions:

```json
{
    "Sid": "AllowClusterDetailsDiscovery",
    "Effect": "Allow",
    "Action": ["elasticmapreduce:DescribeCluster", "elasticmapreduce:ListInstanceGroups"],
},
{
    "Sid": "AllowClusterDiscovery",
    "Effect": "Allow",
    "Action": ["elasticmapreduce:ListClusters"],
    "Resource": "*"
}
```

To enhance monitoring capabilities, attach the following permissions to your Studio execution role:

```json
{
    "Sid": "AllowPresignedUrl",
    "Effect": "Allow",
}
```

To allow users to create Amazon EMR clusters, add the following permission to your Studio execution role:

```json
{
    "Sid": "AllowSagemakerProjectManagement",
    "Effect": "Allow",
    "Action": ["sagemaker:CreateProject", "sagemaker:DeleteProject"],
    "Resource": "arn:aws:sagemaker:<region>:<account-id>:project/*"
}
```
If you have provided Studio with a cross-account discovery and connectivity role, the role in the non-Studio account must allow "assume role" permissions to the Studio execution role. This can be done by attaching the following permissions to your Studio execution role:

**Note**
For all cross-account use cases, the Studio execution role must have the `sts:AssumeRole` permission added to allow Studio to assume a role in the remote account.

```json
{
    "Sid": "AllowRoleAssumptionForCrossAccountDiscovery",
    "Effect": "Allow",
    "Action": "sts:AssumeRole",
    "Resource": ["arn:aws:iam::<cross-account>:role/<studio-execution-role>"
}
```

To allow discoverability for Amazon EMR templates, attach the following permissions to your Studio execution role:

```json
{
    "Sid": "AllowEMRTemplateDiscovery",
    "Effect": "Allow",
    "Action": [ "servicecatalog:SearchProducts"
    ],
    "Resource": "*"
}
```

The following is a comprehensive example IAM policy that includes all of the previous permissions in this guide:

```json
{
    "Version": "2012-10-17",
    "Statement": [
    {
        "Sid": "AllowPresignedUrl",
        "Effect": "Allow",
        "Action": [ "elasticmapreduce:DescribeCluster",
                    "elasticmapreduce:ListInstanceGroups",
                    "elasticmapreduce:CreatePersistentAppUI",
                    "elasticmapreduce:DescribePersistentAppUI",
                    "elasticmapreduce:GetPersistentAppUIPresignedURL",
                    "elasticmapreduce:GetOnClusterAppUIPresignedURL"
        ],
        ]
    },
    {
        "Sid": "AllowClusterDetailsDiscovery",
        "Effect": "Allow",
        "Action": [ "elasticmapreduce:DescribeCluster",
                    "elasticmapreduce:ListInstanceGroups"
        ],
        ]
    },
    {
        "Sid": "AllowClusterDiscovery",
        "Effect": "Allow",
        "Action": [ "elasticmapreduce:DescribeCluster",
                    "elasticmapreduce:ListInstanceGroups"
        ],
        ]
    }
]
```
Prepare Data using AWS Glue Interactive Sessions

AWS Glue Interactive Sessions is a serverless service that equips you with the tools to collect, transform, cleanse, and prepare the data that will populate your data lakes and pipelines. Glue Interactive Sessions provides an on-demand, serverless Apache Spark runtime environment that data scientists and engineers can use to rapidly build, test, and run data preparation and analytics applications.

Starting a Glue interactive session from a SageMaker Studio notebook is simple. When you create your Studio notebook, choose the built-in Glue PySpark or Glue Spark kernel and start coding in your interactive, serverless Spark session in just seconds. You don't have worry about provisioning or managing complex compute cluster infrastructure. After initialization, you can quickly browse the Glue data catalog, run large queries, and interactively analyze and prepare data using Spark, all within your Studio notebook. You can then use the prepared data to build, train, tune, and deploy models using the purpose-built ML tools within SageMaker Studio.

Before you start your AWS Glue interactive session in SageMaker Studio, you need to set the appropriate roles and policies. You may also need access to additional resources, such as Amazon S3, which may require additional policies. For more information about required and additional IAM policies, see Permissions for Glue Interactive Sessions in SageMaker Studio (p. 1019).

SageMaker Studio provides a default configuration for your AWS Glue interactive session, but you can use Glue's full catalog of Jupyter magic commands to further customize your environment. For information about the default and additional Jupyter magics that you can use in your Glue interactive session, see Configure your Glue interactive session in SageMaker Studio (p. 1021).

The supported images and kernels for connecting to a Glue interactive session are as follows:

- Images: SparkAnalytics 1.0
- Kernel: PySpark and Spark
Prerequisites:

The SparkAnalytics image that you select to launch your Glue session in Studio is a combination of two frameworks - the SparkMagic framework (used with Amazon EMR), and AWS Glue. For this reason, the prerequisites for both frameworks apply. However, you do not have to set up the EMR cluster if you only plan to use Glue Interactive Sessions. Before you start your first Glue interactive session in Studio, complete the following:

- Complete the prerequisites required to use the SparkMagic image. For a list of the prerequisites, see the Prerequisites section in Prepare Data at Scale with Studio Notebooks.
- Create an execution role with permissions for both AWS Glue and SageMaker Studio. Add the managed policy AwsGlueSessionUserRestrictedServiceRole, and create a custom policy that includes permissions sts:GetCallerIdentity, iam:GetRole, and IAM:Passrole. For instructions about how to create the necessary permissions, see Permissions for Glue Interactive Sessions in SageMaker Studio (p. 1019).
- Create a SageMaker domain with the execution role you created. For instructions about how to create a domain, see Onboard to Amazon SageMaker Domain Using IAM (p. 40).

Get Started with AWS Glue Interactive Sessions

This guide will show you how set up the necessary permissions, launch your first Glue interactive session in Studio, and manage your environment with Jupyter magics.

Permissions for Glue Interactive Sessions in SageMaker Studio

This guide will show you how to obtain the required permissions to use Glue Interactive Sessions in Studio. You will attach two managed policies, then create and attach a custom policy, and lastly, modify the trust relationship.

To add the managed policies to your execution role

1. Open the IAM console.
2. Select Roles in the left-side panel.
3. Find the Studio execution role that you will use, and choose the role name to go to the role summary page.
4. Under the Permissions tab, select Attach policies from the Add Permissions dropdown menu.
5. Select the checkbox next to the managed policy AwsGlueSessionUserRestrictedServiceRole.
6. Choose Attach policies.

The summary page shows your newly-added managed policies.

To create the custom policy and attach it to your execution role

1. Select Create inline policy in the Add Permissions dropdown menu.
2. Select the JSON tab.
3. Copy and paste in the following policy.

```json

{  
   "Version": "2012-10-17",
   "Statement": [
      
      "Sid": "unique_statement_id",
      
```
5. Enter a Name and choose Create policy.

The summary page shows your newly-added custom policy.

To modify the trust relationship
1. Select the Trust relationships tab.
2. Choose Edit trust policy.
3. Copy and paste in the following policy.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Principal": {
        "Service": ["glue.amazonaws.com", "sagemaker.amazonaws.com"
      },
      "Action": "sts:AssumeRole"
    }
  ]
}
```
4. Choose Update policy.

You can add additional roles and policies if you need to access other AWS resources. For a description of the additional roles and policies you can include, see Interactive sessions with IAM in the AWS Glue documentation.

Launch your Glue interactive session on SageMaker Studio

After you create the roles, policies, and SageMaker domain, you can launch your Glue interactive session in SageMaker Studio.

To launch Glue in SageMaker Studio
1. Create a SageMaker domain. For instructions on how to create a new domain, see Onboard to Amazon SageMaker Domain (p. 35).
3. Select Control Panel in the left-side panel.
4. In the Launch App dropdown menu next to the user name, select Studio.
5. In the Jupyter view, choose File, then New, then Notebook.
6. In the Image dropdown menu, select SparkAnalytics 1.0. In the kernel dropdown menu, select Glue Spark or Glue PySpark. Choose Select.

7. (optional) Use Jupyter magics to customize your environment. For more information about Jupyter magics, see Configure your Glue interactive session in SageMaker Studio (p. 1021).

8. Start writing your Spark data processing scripts.

Configure your Glue interactive session in SageMaker Studio

You can use Jupyter magics in your AWS Glue interactive session to modify your session and configuration parameters. Magics are short commands prefixed with % at the start of Jupyter cells that provide a quick and easy way to help you control your environment. In your Glue interactive session, the following magics are set for you by default:

<table>
<thead>
<tr>
<th>Magic</th>
<th>Default value</th>
</tr>
</thead>
<tbody>
<tr>
<td>%glue_version</td>
<td>3.0</td>
</tr>
<tr>
<td>%iam_policy</td>
<td>execution role attached to your SageMaker domain</td>
</tr>
<tr>
<td>%region</td>
<td>your region</td>
</tr>
</tbody>
</table>

You can use magics to further customize your environment. For example, if you want to change the number of workers allocated to your job from the default five to 10, you can specify %number_of_workers 10. If you want to configure your session to stop after 10 minutes of idle time instead of the default 2880, you can specify %idle_timeout 10.

All of the Jupyter magics currently available in AWS Glue are also available in SageMaker Studio. For the complete list of AWS Glue magics available, see Configuring AWS Glue interactive sessions for Jupyter and AWS Glue Studio notebooks.

AWS Glue Interactive Session Pricing

When you use AWS Glue Interactive Sessions on SageMaker Studio notebooks, you are charged separately for resource usage on AWS Glue and Studio notebooks.

AWS charges for Glue Interactive Sessions based on how long the session is active and the number of Data Processing Units (DPU) used. You are charged an hourly rate for the number of DPUs used to run your workloads, billed in increments of one second. Glue Interactive Sessions assigns a default of five DPUs and requires a minimum of two DPUs. There is also a one-minute minimum billing duration for each interactive session. To see the AWS Glue rates and pricing examples, or to estimate your costs using the AWS Pricing Calculator, see AWS Glue pricing.

Your SageMaker Studio notebook runs on an Amazon EC2 instance and you are charged for the instance type you choose, based on the duration of use. Studio assigns you a default EC2 instance type of ml-t3-medium when you select the SparkAnalytics image and associated kernel. You can change the instance type for of your Studio notebook to suit your workload. For information about SageMaker Studio pricing, see Amazon SageMaker Pricing.
Process Data

To analyze data and evaluate machine learning models on Amazon SageMaker, use Amazon SageMaker Processing. With Processing, you can use a simplified, managed experience on SageMaker to run your data processing workloads, such as feature engineering, data validation, model evaluation, and model interpretation. You can also use the Amazon SageMaker Processing APIs during the experimentation phase and after the code is deployed in production to evaluate performance.

The preceding diagram shows how Amazon SageMaker spins up a Processing job. Amazon SageMaker takes your script, copies your data from Amazon Simple Storage Service (Amazon S3), and then pulls a processing container. The processing container image can either be an Amazon SageMaker built-in image or a custom image that you provide. The underlying infrastructure for a Processing job is fully managed by Amazon SageMaker. Cluster resources are provisioned for the duration of your job, and cleaned up when a job completes. The output of the Processing job is stored in the Amazon S3 bucket you specified.

**Note**
Your input data must be stored in an Amazon S3 bucket. Alternatively, you can use Amazon Athena or Amazon Redshift as input sources.

Use Amazon SageMaker Processing Sample Notebooks

We provide two sample Jupyter notebooks that show how to perform data preprocessing, model evaluation, or both.

For a sample notebook that shows how to run scikit-learn scripts to perform data preprocessing and model training and evaluation with the SageMaker Python SDK for Processing, see scikit-learn Processing. This notebook also shows how to use your own custom container to run processing workloads with your Python libraries and other specific dependencies.

For a sample notebook that shows how to use Amazon SageMaker Processing to perform distributed data preprocessing with Spark, see Distributed Processing (Spark). This notebook also shows how to train a regression model using XGBoost on the preprocessed dataset.

For instructions on how to create and access Jupyter notebook instances that you can use to run these samples in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have
Monitor Amazon SageMaker Processing Jobs with CloudWatch Logs and Metrics

Amazon SageMaker Processing provides Amazon CloudWatch logs and metrics to monitor processing jobs. CloudWatch provides CPU, GPU, memory, GPU memory, and disk metrics, and event logging. For more information, see Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663) and Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675).

Data Processing with Apache Spark

Apache Spark is a unified analytics engine for large-scale data processing. Amazon SageMaker provides prebuilt Docker images that include Apache Spark and other dependencies needed to run distributed data processing jobs. With the Amazon SageMaker Python SDK, you can easily apply data transformations and extract features (feature engineering) using the Spark framework. For information about using the SageMaker Python SDK to run Spark processing jobs, see Data Processing with Spark in the Amazon SageMaker Python SDK.

A code repository that contains the source code and Dockerfiles for the Spark images is available on GitHub.

Running a Spark Processing Job

You can use the `sagemaker.spark.PySparkProcessor` or `sagemaker.spark.SparkJarProcessor` class to run your Spark application inside of a processing job. Note you can set MaxRuntimeInSeconds to a maximum runtime limit of 5 days. With respect to execution time, and number of instances used, simple spark workloads see a near linear relationship between the number of instances vs. time to completion.

The following code example shows how to run a processing job that invokes your PySpark script `preprocess.py`.

```python
from sagemaker.spark.processing import PySparkProcessor

spark_processor = PySparkProcessor(
    base_job_name="spark-preprocessor",
    framework_version="2.4",
    role=role,
    instance_count=2,
    instance_type="ml.m5.xlarge",
    max_runtime_in_seconds=1200,
)

spark_processor.run(
    submit_app="preprocess.py",
    arguments=['s3_input_bucket', bucket,
              's3_input_key_prefix', input_prefix,
              's3_output_bucket', bucket,
              's3_output_key_prefix', output_prefix]
)
```
For an in-depth look, see the Distributed Data Processing with Apache Spark and SageMaker Processing example notebook.

If you are not using the Amazon SageMaker Python SDK and one of its Processor classes to retrieve the pre-built images, you can retrieve these images yourself. The SageMaker prebuilt Docker images are stored in Amazon Elastic Container Registry (Amazon ECR). For a complete list of the available pre-built Docker images, see the available images document.

To learn more about using the SageMaker Python SDK with Processing containers, see Amazon SageMaker Python SDK.

Data Processing with scikit-learn

For a sample notebook that shows how to run scikit-learn scripts using a Docker image provided and maintained by SageMaker to preprocess data and evaluate models, see scikit-learn Processing. To use this notebook, you need to install the SageMaker Python SDK for Processing.

This notebook runs a processing job using SKLearnProcessor class from the the SageMaker Python SDK to run a scikit-learn script that you provide. The script preprocesses data, trains a model using a SageMaker training job, and then runs a processing job to evaluate the trained model. The processing job estimates how the model is expected to perform in production.

To learn more about using the SageMaker Python SDK with Processing containers, see the SageMaker Python SDK. For a complete list of pre-built Docker images available for processing jobs, see Docker Registry Paths and Example Code (p. 1105) and choose your region.

The following code example shows how the notebook uses SKLearnProcessor to run your own scikit-learn script using a Docker image provided and maintained by SageMaker, instead of your own Docker image.

```python
from sagemaker.sklearn.processing import SKLearnProcessor
from sagemaker.processing import ProcessingInput, ProcessingOutput

sklearn_processor = SKLearnProcessor(framework_version='0.20.0',
                                      role=role,
                                      instance_type='ml.m5.xlarge',
                                      instance_count=1)

sklearn_processor.run(code='preprocessing.py',
                       inputs=[ProcessingInput(source='s3://path/to/my/input-data.csv',
                                               destination='/opt/ml/processing/input')],
                       outputs=[ProcessingOutput(source='/opt/ml/processing/output/train'),
                                 ProcessingOutput(source='/opt/ml/processing/output/validation'),
                                 ProcessingOutput(source='/opt/ml/processing/output/test')])
```

To process data in parallel using Scikit-Learn on Amazon SageMaker Processing, you can shard input objects by S3 key by setting s3_data_distribution_type='ShardedByS3Key' inside a ProcessingInput so that each instance receives about the same number of input objects.

Data Processing with Framework Processors

A FrameworkProcessor can run Processing jobs with a specified machine learning framework, providing you with an Amazon SageMaker–managed container for whichever machine learning
framework you choose. FrameworkProcessor provides premade containers for the following machine
learning frameworks: Hugging Face, MXNet, PyTorch, TensorFlow, and XGBoost.

The FrameworkProcessor class also provides you with customization over the container configuration.
The FrameworkProcessor class supports specifying a source directory source_dir for your
processing scripts and dependencies. With this capability, you can give the processor access to multiple
scripts in a directory instead of only specifying one script. FrameworkProcessor also supports
including a requirements.txt file in the source_dir for customizing the Python libraries to install in
the container.

For more information on the FrameworkProcessor class and its methods and parameters, see
FrameworkProcessor in the Amazon SageMaker Python SDK.

To see examples of using a FrameworkProcessor for each of the supported machine learning
frameworks, see the following topics.

Topics
- Hugging Face Framework Processor (p. 1025)
- MXNet Framework Processor (p. 1026)
- PyTorch Framework Processor (p. 1027)
- TensorFlow Framework Processor (p. 1028)
- XGBoost Framework Processor (p. 1029)

Hugging Face Framework Processor

Hugging Face is an open-source provider of natural language processing (NLP) models. The
HuggingFaceProcessor in the Amazon SageMaker Python SDK provides you with the ability to
run processing jobs with Hugging Face scripts. When you use the HuggingFaceProcessor, you can
leverage an Amazon-built Docker container with a managed Hugging Face environment so that you don't
need to bring your own container.

The following code example shows how you can use the HuggingFaceProcessor to run your
Processing job using a Docker image provided and maintained by SageMaker. Note that when you
run the job, you can specify a directory containing your scripts and dependencies in the source_dir
argument, and you can have a requirements.txt file located inside your source_dir directory that
specifies the dependencies for your processing script(s). SageMaker Processing installs the dependencies
in requirements.txt in the container for you.

```python
from sagemaker.huggingface import HuggingFaceProcessor
from sagemaker.processing import ProcessingInput, ProcessingOutput
from sagemaker import get_execution_role

#Initialize the HuggingFaceProcessor
hfp = HuggingFaceProcessor(
    role=get_execution_role(),
    instance_count=1,
    instance_type='ml.g4dn.xlarge',
    transformers_version='4.4.2',
    pytorch_version='1.6.0',
    base_job_name='frameworkprocessor-hf'
)

#Run the processing job
hfp.run(
    code='processing-script.py',
    source_dir='scripts',
    inputs=[
        ProcessingInput(
```
MXNet Framework Processor

Apache MXNet is an open-source deep learning framework commonly used for training and deploying neural networks. The MXNetProcessor in the Amazon SageMaker Python SDK provides you with the ability to run processing jobs with MXNet scripts. When you use the MXNetProcessor, you can leverage an Amazon-built Docker container with a managed MXNet environment so that you don't need to bring your own container.

The following code example shows how you can use the MXNetProcessor to run your Processing job using a Docker image provided and maintained by SageMaker. Note that when you run the job, you can specify a directory containing your scripts and dependencies in the source_dir argument, and you can have a requirements.txt file located inside your source_dir directory that specifies the dependencies for your processing script(s). SageMaker Processing installs the dependencies in requirements.txt in the container for you.

```python
from sagemaker.mxnet import MXNetProcessor
from sagemaker.processing import ProcessingInput, ProcessingOutput
from sagemaker import get_execution_role

#Initialize the MXNetProcessor
mxp = MXNetProcessor(
    framework_version='1.8.0',
    py_version='py37',
    role=get_execution_role(),
    instance_count=1,
    instance_type='ml.c5.xlarge',
    base_job_name='frameworkprocessor-mxnet'
)

#Run the processing job
mxp.run(
    code='processing-script.py',
    source_dir='scripts',
    inputs=[
        ProcessingInput(
            input_name='data',
            source=f's3://(BUCKET)/{S3_INPUT_PATH}',
            destination='/opt/ml/processing/input/data/
        ),
    ],
    outputs=[
        ProcessingOutput(output_name='train', source='/opt/ml/processing/output/train/',
            destination=f's3://(BUCKET)/{S3_OUTPUT_PATH}'),
        ProcessingOutput(output_name='test', source='/opt/ml/processing/output/test/',
            destination=f's3://(BUCKET)/{S3_OUTPUT_PATH}'),
        ProcessingOutput(output_name='val', source='/opt/ml/processing/output/val/',
            destination=f's3://(BUCKET)/{S3_OUTPUT_PATH}')
    ]
)
```

If you have a requirements.txt file, it should be a list of libraries you want to install in the container. The path for source_dir can be a relative, absolute, or Amazon S3 URI path. However, if you use an Amazon S3 URI, then it must point to a tar.gz file. You can have multiple scripts in the directory you specify for source_dir. To learn more about the HuggingFaceProcessor class, see Hugging Face Estimator in the Amazon SageMaker Python SDK.
If you have a requirements.txt file, it should be a list of libraries you want to install in the container. The path for source_dir can be a relative, absolute, or Amazon S3 URI path. However, if you use an Amazon S3 URI, then it must point to a tar.gz file. You can have multiple scripts in the directory you specify for source_dir. To learn more about the MXNetProcessor class, see MXNet Estimator in the Amazon SageMaker Python SDK.

**PyTorch Framework Processor**

PyTorch is an open-source machine learning framework. The PyTorchProcessor in the Amazon SageMaker Python SDK provides you with the ability to run processing jobs with PyTorch scripts. When you use the PyTorchProcessor, you can leverage an Amazon-built Docker container with a managed PyTorch environment so that you don't need to bring your own container.

The following code example shows how you can use the PyTorchProcessor to run your Processing job using a Docker image provided and maintained by SageMaker. Note that when you run the job, you can specify a directory containing your scripts and dependencies in the source_dir argument, and you can have a requirements.txt file located inside your source_dir directory that specifies the dependencies for your processing script(s). SageMaker Processing installs the dependencies in requirements.txt in the container for you.

```python
from sagemaker.pytorch.processing import PyTorchProcessor
from sagemaker.processing import ProcessingInput, ProcessingOutput
from sagemaker import get_execution_role

#Initialize the PyTorchProcessor
pytorch_processor = PyTorchProcessor(
    framework_version='1.8',
    role=get_execution_role(),
    instance_type='ml.m5.xlarge',
    instance_count=1,
    base_job_name='frameworkprocessor-PT'
)

#Run the processing job
pytorch_processor.run(
    code='processing-script.py',
    source_dir='scripts',
    inputs=[
        ProcessingInput(
            input_name='data',
            source=f's3://{BUCKET}/{S3_INPUT_PATH}',
            destination='/opt/ml/processing/input'
        )
    ],
    outputs=[
        ProcessingOutput(output_name='processed_data', source='/opt/ml/processing/output/',
                        destination=f's3://{BUCKET}/{S3_OUTPUT_PATH}'),
        ProcessingOutput(output_name='train', source='/opt/ml/processing/output/train',
                         destination=f's3://{BUCKET}/{S3_OUTPUT_PATH}'),
        ProcessingOutput(output_name='validation', source='/opt/ml/processing/output/val',
                         destination=f's3://{BUCKET}/{S3_OUTPUT_PATH}'),
        ProcessingOutput(output_name='test', source='/opt/ml/processing/output/test',
                         destination=f's3://{BUCKET}/{S3_OUTPUT_PATH}'),
    ]
)
```
If you have a requirements.txt file, it should be a list of libraries you want to install in the container. The path for source_dir can be a relative, absolute, or Amazon S3 URI path. However, if you use an Amazon S3 URI, then it must point to a tar.gz file. You can have multiple scripts in the directory you specify for source_dir. To learn more about the PyTorchProcessor class, see PyTorch Estimator in the Amazon SageMaker Python SDK.

TensorFlow Framework Processor

TensorFlow is an open-source machine learning and artificial intelligence library. The TensorFlowProcessor in the Amazon SageMaker Python SDK provides you with the ability to run processing jobs with TensorFlow scripts. When you use the TensorFlowProcessor, you can leverage an Amazon-built Docker container with a managed TensorFlow environment so that you don’t need to bring your own container.

The following code example shows how you can use the TensorFlowProcessor to run your Processing job using a Docker image provided and maintained by SageMaker. Note that when you run the job, you can specify a directory containing your scripts and dependencies in the source_dir argument, and you can have a requirements.txt file located inside your source_dir directory that specifies the dependencies for your processing script(s). SageMaker Processing installs the dependencies in requirements.txt in the container for you.

```
from sagemaker.tensorflow import TensorFlowProcessor
from sagemaker.processing import ProcessingInput, ProcessingOutput
from sagemaker import get_execution_role

#Initialize the TensorFlowProcessor
tp = TensorFlowProcessor(
    framework_version='2.3',
    role=get_execution_role(),
    instance_type='ml.m5.xlarge',
    instance_count=1,
    base_job_name='frameworkprocessor-TF',
    py_version='py37'
)

#Run the processing job
tp.run(
    code='processing-script.py',
    source_dir='scripts',
    inputs=[
        ProcessingInput(
            input_name='data',
            source=f's3://(BUCKET)/(S3_INPUT_PATH)',
            destination='/opt/ml/processing/input/data'
        ),
        ProcessingInput(
            input_name='model',
            source=f's3://(BUCKET)/(S3_PATH_TO_MODEL)',
            destination='/opt/ml/processing/input/model'
        )
    ],
    outputs=[
        ProcessingOutput(
            output_name='predictions',
            source='/opt/ml/processing/output',
            destination=f's3://(BUCKET)/(S3_OUTPUT_PATH)'
        )
    ]
)
```
If you have a requirements.txt file, it should be a list of libraries you want to install in the container. The path for source_dir can be a relative, absolute, or Amazon S3 URI path. However, if you use an Amazon S3 URI, then it must point to a tar.gz file. You can have multiple scripts in the directory you specify for source_dir. To learn more about the TensorFlowProcessor class, see TensorFlow Estimator in the Amazon SageMaker Python SDK.

XGBoost Framework Processor

XGBoost is an open-source machine learning framework. The XGBoostProcessor in the Amazon SageMaker Python SDK provides you with the ability to run processing jobs with XGBoost scripts. When you use the XGBoostProcessor, you can leverage an Amazon-built Docker container with a managed XGBoost environment so that you don't need to bring your own container.

The following code example shows how you can use the XGBoostProcessor to run your Processing job using a Docker image provided and maintained by SageMaker. Note that when you run the job, you can specify a directory containing your scripts and dependencies in the source_dir argument, and you can have a requirements.txt file located inside your source_dir directory that specifies the dependencies for your processing script(s). SageMaker Processing installs the dependencies in requirements.txt in the container for you.

```python
from sagemaker.xgboost import XGBoostProcessor
from sagemaker.processing import ProcessingInput, ProcessingOutput
from sagemaker import get_execution_role

#Initialize the XGBoostProcessor
xgb = XGBoostProcessor(
    framework_version='1.2-2',
    role=get_execution_role(),
    instance_type='ml.m5.xlarge',
    instance_count=1,
    base_job_name='frameworkprocessor-XGB',
)

#Run the processing job
xgb.run(
    code='processing-script.py',
    source_dir='scripts',
    inputs=[
        ProcessingInput(
            input_name='data',
            source=f's3://{BUCKET}/{S3_INPUT_PATH}',
            destination='/opt/ml/processing/input/data'
        )
    ],
    outputs=[
        ProcessingOutput(
            output_name='processed_data',
            source='/opt/ml/processing/output/',
            destination=f's3://{BUCKET}/{S3_OUTPUT_PATH}'
        )
    ]
)
```

If you have a requirements.txt file, it should be a list of libraries you want to install in the container. The path for source_dir can be a relative, absolute, or Amazon S3 URI path. However, if you use an Amazon S3 URI, then it must point to a tar.gz file. You can have multiple scripts in the directory you
specify for source_dir. To learn more about the XGBoostProcessor class, see XGBoost Estimator in the Amazon SageMaker Python SDK.

Use Your Own Processing Code

You can install libraries to run your scripts in your own processing container or, in a more advanced scenario, you can build your own processing container that satisfies the contract to run in Amazon SageMaker. For more information about containers in SageMaker, see Using Docker containers with SageMaker (p. 3149). For a formal specification that defines the contract for an Amazon SageMaker Processing container, see Build Your Own Processing Container (Advanced Scenario) (p. 1031).

Topics
- Run Scripts with Your Own Processing Container (p. 1030)
- Build Your Own Processing Container (Advanced Scenario) (p. 1031)

Run Scripts with Your Own Processing Container

You can use scikit-learn scripts to preprocess data and evaluate your models. To see how to run scikit-learn scripts to perform these tasks, see the scikit-learn Processing sample notebook. This notebook uses the ScriptProcessor class from the Amazon SageMaker Python SDK for Processing.

The following example shows a general workflow for using a ScriptProcessor class with your own processing container. The workflow shows how to create your own image, build your container, and use a ScriptProcessor class to run a Python preprocessing script with the container. The processing job processes your input data and saves the processed data in Amazon Simple Storage Service (Amazon S3).

Before using the following examples, you need to have your own input data and a Python script prepared to process your data. For an end-to-end, guided example of this process, refer back to the scikit-learn Processing sample notebook.

1. Create a Docker directory and add the Dockerfile used to create the processing container. Install pandas and scikit-learn into it. (You could also install your own dependencies with a similar RUN command.)

```
mkdir docker
%%writefile docker/Dockerfile
FROM python:3.7-slim-buster
RUN pip3 install pandas==0.25.3 scikit-learn==0.21.3
ENV PYTHONUNBUFFERED=True
ENTRYPOINT ["python3"]
```

2. Build the container using the docker command, create an Amazon Elastic Container Registry (Amazon ECR) repository, and push the image to Amazon ECR.

```
import boto3
account_id = boto3.client('sts').get_caller_identity().get('Account')
region = boto3.Session().region_name
ecr_repository = 'sagemaker-processing-container'
tag = ':latest'
processing_repository_uri = '{}.dkr.ecr.{}.amazonaws.com/{}'.format(account_id, region, ecr_repository + tag)
```
# Create ECR repository and push docker image
`docker build -t $ecr_repository docker`
`aws ecr get-login-password --region {region} | docker login --username AWS --password-stdin {account_id}.dkr.ecr.{region}.amazonaws.com`
`aws ecr create-repository --repository-name $ecr_repository`
`docker tag {ecr_repository + tag} $processing_repository_uri`
`docker push $processing_repository_uri`

3. Set up the `ScriptProcessor` from the SageMaker Python SDK to run the script. Replace `image_uri` with the URI for the image you created, and replace `role_arn` with the ARN for an AWS Identity and Access Management role that has access to your target Amazon S3 bucket.

```python
from sagemaker.processing import ScriptProcessor, ProcessingInput, ProcessingOutput

script_processor = ScriptProcessor(command=['python3'],
                                   image_uri='image_uri',
                                   role='role_arn',
                                   instance_count=1,
                                   instance_type='ml.m5.xlarge')
```

4. Run the script. Replace `preprocessing.py` with the name of your own Python processing script, and replace `s3://path/to/my/input-data.csv` with the Amazon S3 path to your input data.

```python
script_processor.run(code='preprocessing.py',
                     inputs=[ProcessingInput(
                         source='s3://path/to/my/input-data.csv',
                         destination='/opt/ml/processing/input')],
                     outputs=[ProcessingOutput(source='/opt/ml/processing/output/train'),
                              ProcessingOutput(source='/opt/ml/processing/output/validation'),
                              ProcessingOutput(source='/opt/ml/processing/output/test')])
```

You can use the same procedure with any other library or system dependencies. You can also use existing Docker images. This includes images that you run on other platforms such as Kubernetes.

## Build Your Own Processing Container (Advanced Scenario)

You can provide Amazon SageMaker Processing with a Docker image that has your own code and dependencies to run your data processing, feature engineering, and model evaluation workloads.

The following example of a Dockerfile builds a container with the Python libraries scikit-learn and pandas, which you can run as a processing job.

```Dockerfile
FROM python:3.7-slim-buster
# Install scikit-learn and pandas
RUN pip3 install pandas==0.25.3 scikit-learn==0.21.3
# Add a Python script and configure Docker to run it
ADD processing_script.py /
ENTRYPOINT ["python3", "/processing_script.py"]
```

Build and push this Docker image to an Amazon Elastic Container Registry (Amazon ECR) repository and ensure that your SageMaker IAM role can pull the image from Amazon ECR. Then you can run this image on Amazon SageMaker Processing.
How Amazon SageMaker Processing Runs Your Processing Container Image

Amazon SageMaker Processing runs your processing container image in a similar way as the following command, where AppSpecification.ImageUri is the Amazon ECR image URI that you specify in a CreateProcessingJob operation.

```
docker run [AppSpecification.ImageUri]
```

This command runs the ENTRYPOINT command configured in your Docker image.

You can also override the entrypoint command in the image or give command-line arguments to your entrypoint command using the AppSpecification.ContainerEntrypoint and AppSpecification.ContainerArguments parameters in your CreateProcessingJob request. Specifying these parameters configures Amazon SageMaker Processing to run the container similar to the way that the following command does.

```
```

For example, if you specify the ContainerEntrypoint to be `[python3, -v, /processing_script.py]` in your CreateProcessingJob request, and ContainerArguments to be `[data-format, csv]`, Amazon SageMaker Processing runs your container with the following command.

```
python3 -v /processing_script.py data-format csv
```

When building your processing container, consider the following details:

- Amazon SageMaker Processing decides whether the job completes or fails depending on the exit code of the command run. A processing job completes if all of the processing containers exit successfully with an exit code of 0, and fails if any of the containers exit with a non-zero exit code.
- Amazon SageMaker Processing lets you override the processing container's entrypoint and set command-line arguments just like you can with the Docker API. Docker images can also configure the entrypoint and command-line arguments using the ENTRYPOINT and CMD instructions. The way CreateProcessingJob's ContainerEntrypoint and ContainerArgument parameters configure a Docker image's entrypoint and arguments mirrors how Docker overrides the entrypoint and arguments through the Docker API:
  - If neither ContainerEntrypoint nor ContainerArguments are provided, Processing uses the default ENTRYPOINT or CMD in the image.
  - If ContainerEntrypoint is provided, but not ContainerArguments, Processing runs the image with the given entrypoint, and ignores the ENTRYPOINT and CMD in the image.
  - If ContainerArguments is provided, but not ContainerEntrypoint, Processing runs the image with the default ENTRYPOINT in the image and with the provided arguments.
  - If both ContainerEntrypoint and ContainerArguments are provided, Processing runs the image with the given entrypoint and arguments, and ignores the ENTRYPOINT and CMD in the image.
  - You must use the exec form of the ENTRYPOINT instruction in your Dockerfile (ENTRYPOINT ["executable", "param1", "param2"]) instead of the shell form (ENTRYPOINT command param1 param2). This lets your processing container receive SIGINT and SIGKILL signals, which Processing uses to stop processing jobs with the StopProcessingJob API.
  - `/opt/ml` and all its subdirectories are reserved by SageMaker. When building your Processing Docker image, don't place any data required by your processing container in these directories.
• If you plan to use GPU devices, make sure that your containers are nvidia-docker compatible. Include only the CUDA toolkit in containers. Don't bundle NVIDIA drivers with the image. For more information about nvidia-docker, see NVIDIA/nvidia-docker.

How Amazon SageMaker Processing Configures Input and Output For Your Processing Container

When you create a processing job using the CreateProcessingJob operation, you can specify multiple ProcessingInput and ProcessingOutput values.

You use the ProcessingInput parameter to specify an Amazon Simple Storage Service (Amazon S3) URI to download data from, and a path in your processing container to download the data to. The ProcessingOutput parameter configures a path in your processing container from which to upload data, and where in Amazon S3 to upload that data to. For both ProcessingInput and ProcessingOutput, the path in the processing container must begin with /opt/ml/processing/.

For example, you might create a processing job with one ProcessingInput parameter that downloads data from s3://your-data-bucket/path/to/input/csv/data into /opt/ml/processing/csv in your processing container, and a ProcessingOutput parameter that uploads data from /opt/ml/processing/processed_csv to s3://your-data-bucket/path/to/output/csv/data. Your processing job would read the input data, and write output data to /opt/ml/processing/processed_csv. Then it uploads the data written to this path to the specified Amazon S3 output location.

Important
Symbolic links (symlinks) cannot be used to upload output data to Amazon S3. Symlinks are not followed when uploading output data.

How Amazon SageMaker Processing Provides Logs and Metrics for Your Processing Container

When your processing container writes to stdout or stderr, Amazon SageMaker Processing saves the output from each processing container and puts it in Amazon CloudWatch logs. For information about logging, see Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675).

Amazon SageMaker Processing also provides CloudWatch metrics for each instance running your processing container. For information about metrics, see Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663).

How Amazon SageMaker Processing Configures Your Processing Container

Amazon SageMaker Processing provides configuration information to your processing container through environment variables and two JSON files—/opt/ml/config/processingjobconfig.json and /opt/ml/config/resourceconfig.json—at predefined locations in the container.

When a processing job starts, it uses the environment variables that you specified with the Environment map in the CreateProcessingJob request. The /opt/ml/config/processingjobconfig.json file contains information about the hostnames of your processing containers, and is also specified in the CreateProcessingJob request.

The following example shows the format of the /opt/ml/config/processingjobconfig.json file.

```
{
"ProcessingJobArn": "<processing_job_arn>",
"ProcessingJobName": "<processing_job_name>"
}
```
The `/opt/ml/config/resourceconfig.json` file contains information about the hostnames of your processing containers. Use the following hostnames when creating or running distributed processing code.

```json
{
    "current_host": "algo-1",
    "hosts": ["algo-1","algo-2","algo-3"]
}
```

Don't use the information about hostnames contained in `/etc/hostname` or `/etc/hosts` because it might be inaccurate.

Hostname information might not be immediately available to the processing container. We recommend adding a retry policy on hostname resolution operations as nodes become available in the cluster.
Save and Access Metadata Information About Your Processing Job

To save metadata from the processing container after exiting it, containers can write UTF-8 encoded text to the /opt/ml/output/message file. After the processing job enters any terminal status ("Completed", "Stopped", or "Failed"), the "ExitMessage" field in DescribeProcessingJob contains the first 1 KB of this file. Access that initial part of file with a call to DescribeProcessingJob, which returns it through the ExitMessage parameter. For failed processing jobs, you can use this field to communicate information about why the processing container failed.

**Important**
Don't write sensitive data to the /opt/ml/output/message file.

If the data in this file isn't UTF-8 encoded, the job fails and returns a ClientError. If multiple containers exit with an ExitMessage, the content of the ExitMessage from each processing container is concatenated, then truncated to 1 KB.

Run Your Processing Container Using the SageMaker Python SDK

You can use the SageMaker Python SDK to run your own processing image by using the Processor class. The following example shows how to run your own processing container with one input from Amazon Simple Storage Service (Amazon S3) and one output to Amazon S3.

```python
from sagemaker.processing import Processor, ProcessingInput, ProcessingOutput

processor = Processor(image_uri='<your_ecc_image_uri>',
                       role=role,
                       instance_count=1,
                       instance_type="ml.m5.xlarge")

processor.run(inputs=[
    ProcessingInput(
        source='<s3_uri or local path>',
        destination='/opt/ml/processing/input_data')],
    outputs=[
        ProcessingOutput(
            source='/opt/ml/processing/processed_data',
            destination='<s3_uri>')])
```

Instead of building your processing code into your processing image, you can provide a ScriptProcessor with your image and the command that you want to run, along with the code that you want to run inside that container. For an example, see Run Scripts with Your Own Processing Container (p. 1030).

You can also use the scikit-learn image that Amazon SageMaker Processing provides through SKLearnProcessor to run scikit-learn scripts. For an example, see Data Processing with scikit-learn (p. 1024).
Create, Store, and Share Features with Amazon SageMaker Feature Store

The machine learning (ML) development process often begins with extracting data signals also known as features from data to train ML models. Amazon SageMaker Feature Store makes it easy for data scientists, machine learning engineers, and general practitioners to create, share, and manage features for machine learning (ML) development. Feature Store accelerates this process by reducing repetitive data processing and curation work required to convert raw data into features for training an ML algorithm.

Further, the processing logic for your data is authored only once, and features generated are used for both training and inference, reducing the training-serving skew. Feature Store is a centralized store for features and associated metadata so features can be easily discovered and reused. You can create an online or an offline store. The online store is used for low latency real-time inference use cases, and the offline store is used for training and batch inference.

The following diagram shows how you can use Amazon SageMaker Feature Store as part of your machine learning pipeline. First, you read in your raw data and process it. You can ingest data via streaming to the online and offline store, or in batches directly to the offline store. You first create a FeatureGroup and configure it to an online or offline store, or both. Then, you can ingest data into your FeatureGroup and store it in your store. A FeatureGroup is a group of features that is defined via a schema in Feature Store to describe a record.

Online store is primarily designed for supporting real-time predictions that need low millisecond latency reads and high throughput writes. Offline store is primarily intended for batch predictions and model training. Offline store is an append only store and can be used to store and access historical feature data. The offline store can help you store and serve features for exploration and model training. The online store retains only the latest feature data. Feature group definitions are immutable after they are created.

How Feature Store Works

In Feature Store, features are stored in a collection called a feature group. You can visualize a feature group as a table in which each column is a feature, with a unique identifier for each row. In principle, a
feature group is composed of features and values specific to each feature. A Record is a collection of values for features that correspond to a unique RecordIdentifier. Altogether, a FeatureGroup is a group of features defined in your FeatureStore to describe a Record.

You can use Feature Store in the following modes:

- **Online** – In online mode, features are read with low latency (milliseconds) reads and used for high throughput predictions. This mode requires a feature group to be stored in an online store.
- **Offline** – In offline mode, large streams of data are fed to an offline store, which can be used for training and batch inference. This mode requires a feature group to be stored in an offline store. The offline store uses your S3 bucket for storage and can also fetch data using Athena queries.
- **Online and Offline** – This includes both online and offline modes.

You can ingest data into feature groups in Feature Store in two ways: streaming or in batches. When you ingest data through streaming, a collection of records are pushed to Feature Store by calling a synchronous PutRecord API call. This API enables you to maintain the latest feature values in Feature Store and to push new feature values as soon an update is detected.

Alternatively, Feature Store can process and ingest data in batches. You can author features using Amazon SageMaker Data Wrangler, create feature groups in Feature Store and ingest features in batches using a SageMaker Processing job with a notebook exported from Data Wrangler. This mode allows for batch ingestion into the offline store. It also supports ingestion into the online store if the feature group is configured for both online and offline use.

### Create Feature Groups

To ingest features into Feature Store, you must first define the feature group and the feature definitions (feature name and data type) for all features that belong to the feature group. After they are created, feature groups are immutable. Feature group names are unique within an AWS Region and AWS account. When creating a feature group, you can also create the metadata for the feature group, such as a short description, storage configuration, features for identifying each record, and the event time, as well as tags to store information such as the author, data source, version, and more.

**Important**

FeatureGroup names or associated metadata such as description or tags should not contain any personal identifiable information (PII) or confidential information.

### Find, Discover, and Share Features

After you create a feature group in Feature Store, other authorized users of the feature store can share and discover it. Users can browse through a list of all feature groups in Feature Store or discover existing feature groups by searching by feature group name, description, record identifier name, creation date, and tags.

### Real-Time Inference for Features Stored in the Online Store

With Feature Store, you can enrich your features stored in the online store in real time with data from a streaming source (clean stream data from another application) and serve the features with low millisecond latency for real-time inference.
You can also perform joins across different FeatureGroups for real-time inference by querying two different FeatureGroups in the client application.

Offline Store for Model Training and Batch Inference

Feature Store provides offline storage for feature values in your S3 bucket. Your data is stored in your S3 bucket using a prefixing scheme based on event time. The offline store is an append-only store, enabling Feature Store to maintain a historical record of all feature values. Data is stored in the offline store in Parquet format for optimized storage and query access.

You can query, explore, and visualize features using Data Wrangler from Amazon SageMaker Studio. Feature Store supports combining data to produce, train, validate, and test data sets, and allows you to extract data at different points in time.

Feature Data Ingestion

Feature generation pipelines can be created to process large batches (1 million rows of data or more) or small batches, and to write feature data to the offline or online store. Streaming sources such as Amazon Managed Streaming for Apache Kafka or Amazon Kinesis can also be used as data sources from which features are extracted and directly fed to the online store for training, inference, or feature creation.

You can push records to Feature Store by calling the synchronous PutRecord API call. Since this is a synchronous API call, it allows small batches of updates to be pushed in a single API call. This enables you to maintain high freshness of the feature values and publish values as soon as an update is detected. These are also called streaming features.

When feature data is ingested and updated, Feature Store stores historical data for all features in the offline store. For batch ingest, you can pull feature values from your S3 bucket or use Athena to query. You can also use Data Wrangler to process and engineer new features that can then be exported to a chosen S3 bucket to be accessed by Feature Store. For batch ingestion, you can configure a processing job to batch ingest your data into Feature Store, or you can pull feature values from your S3 bucket using Athena.

To remove a Record from your online store, use the DeleteRecord API call. This will also add the deleted record to the offline store.

Get started with Amazon SageMaker Feature Store

To get started using Amazon SageMaker Feature Store, review the basic concepts, learn how to ingest data for your feature store, and then walk through a Feature Store example. The following sections explain how to create feature groups, ingest data into the groups, and how to manage security for your feature store.

Topics
- Feature Store Concepts (p. 1039)
- Create Feature Groups (p. 1039)
- Adding required policies to your IAM role (p. 1051)
Feature Store Concepts

The following list of terms are key to understanding the capabilities of Amazon SageMaker Feature Store:

• **Feature store** – Serves as the single source of truth to store, retrieve, remove, track, share, discover, and control access to features.

• **Feature** – A measurable property or characteristic that encapsulates an observed phenomenon. In the Amazon SageMaker Feature Store API, a feature is an attribute of a record. You can define a name and type for every feature stored in Feature Store. Name uniquely identifies a feature within a feature group. Type identifies the datatype for the values of the feature. Supported datatypes are: String, Integral and Fractional.

• **Feature group** – A FeatureGroup is the main Feature Store resource that contains the metadata for all the data stored in Amazon SageMaker Feature Store. A feature group is a logical grouping of features, defined in the feature store, to describe records. A feature group’s definition is composed of a list of feature definitions, a record identifier name, and configurations for its online and offline store.

• **Feature definition** – A FeatureDefinition consists of a name and one of the following data types: an Integral, String or Fractional. A FeatureGroup contains a list of feature definitions.

• **Record identifier name** – Each feature group is defined with a record identifier name. The record identifier name must refer to one of the names of a feature defined in the feature group’s feature definitions.

• **Record** – A Record is a collection of values for features for a single record identifier value. A combination of record identifier name and a timestamp uniquely identify a record within a feature group.

• **Event time** – A point in time when a new event occurs that corresponds to the creation or update of a record in a feature group. All records in the feature group must have a corresponding EventTime. It can be used to track changes to a record over time. The online store contains the record corresponding to the last EventTime for a record identifier name, whereas the offline store contains all historic records. Event time values can either be of a fractional or string type. Fractional values must be UNIX timestamps. Strings must follow the ISO 8601 standard. The following formats are supported yyyy-MM-dd’T’HH:mm:ssZ and yyyy-MM-dd’T’HH:mm:ss.SSSZ where yyyy, MM, dd represent the year, month, and day respectively and HH, mm, ss, and if applicable, SSS represent the hour, month, second and milliseconds respectively. T and Z are constants.

• **Online Store** – The low latency, high availability cache for a feature group that enables real-time lookup of records. The online store allows quick access to the latest value for a Record via the GetRecord API. A feature group contains an OnlineStoreConfig controlling where the data is stored.

• **Offline store** – The OfflineStore, stores historical data in your S3 bucket. It is used when low (sub-second) latency reads are not needed. For example, when you want to store and serve features for exploration, model training, and batch inference. A feature group contains an OfflineStoreConfig controlling where the data is stored.

• **Ingestion** – The act of populating feature groups in the feature store.

Create Feature Groups

A FeatureGroup is the main Feature Store resource that contains the metadata for all the data stored in Amazon SageMaker Feature Store. A feature group is a logical grouping of features, defined in the feature store, to describe records. A feature group’s definition is composed of a list of feature definitions, a record identifier name, and configurations for its online and offline store. The example code in this
topic uses the SageMaker Python SDK. The underlying APIs are available for developers using other languages.

Prior to using a feature store you typically load your dataset, run transformations, and set up your features for ingestion. This process has a lot of variation and is highly dependent on your data. The example code in the following topics refer to the Introduction to Feature Store, Fraud Detection with Amazon SageMaker FeatureStore example notebooks respectively. We recommend that you run this notebook in Amazon SageMaker Studio because the code in this guide is conceptual and not fully functional if copied.

Feature Store supports the following data types: String, Fractional (IEEE 64-bit floating point value), and Integral (Int64 - 64 bit signed integral value). The default type is set to String. This means that, if a column in your dataset is not a float or long type, it defaults to String in your feature store.

You may use a schema to describe your data's columns and data types. You pass this schema into FeatureDefinitions, a required parameter for a FeatureGroup. You can use the SageMaker Python SDK, which has automatic data type detection when you use the load_feature_definitions function.

The default behavior when a new feature record is added with an already existing record ID is as follows. In the offline store, the new record will be appended. In the online store, if the event time of the new record is less than the existing event time than nothing will happen, however if the event time of the new record is greater than or equal to the existing event time, the record will be over written.

Topics
- Introduction to Feature Store (p. 1040)
- Fraud Detection with Feature Store (p. 1045)

Introduction to Feature Store

The example code in this topic refers to the Introduction to Amazon SageMaker Feature Store example notebook. It is recommended that you run this notebook in Amazon SageMaker Studio because the code in this guide is conceptual and not fully functional if copied.

Step 1: Set Up

To start using Feature Store, create SageMaker, boto3 and a Feature Store sessions. Then set up the S3 bucket you want to use for your features. This is your offline store. The following code uses the SageMaker default bucket and adds a custom prefix to it.

**Note**

The role that you use must have the following managed policies attached to it:

AmazonS3FullAccess and AmazonSageMakerFeatureStoreAccess.

```python
# SageMaker Python SDK version 2.x is required
global sys
import sagemaker
import boto3
import pandas as pd
import numpy as np
import io
from sagemaker import get_execution_role
from sagemaker.session import Session
```
prefix = 'sagemaker-featurestore-introduction'
role = get_execution_role()

sagemaker_session = sagemaker.Session()
region = sagemaker_session.boto_region_name
s3_bucket_name = sagemaker_session.default_bucket()  

**Step 2: Inspect your data**

In this notebook example we ingest synthetic data from the Github repository that hosts the full notebook.

```python
import pandas as pd

customer_data = pd.read_csv("data/feature_store_introduction_customer.csv")
orders_data = pd.read_csv("data/feature_store_introduction_orders.csv")

print(customer_data.head())
print(orders_data.head())
```

The following diagram illustrates the steps the data goes through before it is ingested into Feature Store. In this notebook, we illustrate the use-case where you have data from multiple sources and want to store them independently in a feature store. Our example considers data from a data warehouse (customer data), and data from a real-time streaming service (order data).
Create Feature Groups
Step 3: Create feature groups

We first start by creating feature group names for customer_data and orders_data. Following this, we create two Feature Groups, one for customer_data and another for orders_data.

```python
import time
from time import strftime, gmtime

customers_feature_group_name = 'customers-feature-group-' + strftime('%d-%H-%M-%S', gmtime())
orders_feature_group_name = 'orders-feature-group-' + strftime('%d-%H-%M-%S', gmtime())

customers_feature_group = FeatureGroup(name=customers_feature_group_name, sagemaker_session=sagemaker_session)
orders_feature_group = FeatureGroup(name=orders_feature_group_name, sagemaker_session=sagemaker_session)
```

Instantiate a FeatureGroup object for customers_data and orders_data.

```python
from sagemaker.feature_store.feature_group import FeatureGroup

customers_feature_group = FeatureGroup(
   name=customers_feature_group_name, sagemaker_session=sagemaker_session)
orders_feature_group = FeatureGroup(
   name=orders_feature_group_name, sagemaker_session=sagemaker_session)
```

```python
import time
current_time_sec = int(round(time.time()))
record_identifier_feature_name = "customer_id"
```

Append EventTime feature to your data frame. This parameter is required, and time stamps each data point.

```python
customer_data["EventTime"] = pd.Series([current_time_sec]*len(customer_data), dtype="float64")
orders_data["EventTime"] = pd.Series([current_time_sec]*len(orders_data), dtype="float64")
```

Load feature definitions to your feature group.

```python
customers_feature_group.load_feature_definitions(data_frame=customer_data)
orders_feature_group.load_feature_definitions(data_frame=orders_data)
```

Below we call create to create two feature groups, customers_feature_group and orders_feature_group respectively.

```python
customers_feature_group.create(
   s3_uri=f"s3://{s3_bucket_name}/{prefix}",
   record_identifier_name=record_identifier_feature_name,
   event_time_feature_name="EventTime",
   role_arn=role,
   enable_online_store=True
)

orders_feature_group.create(
   s3_uri=f"s3://{s3_bucket_name}/{prefix}",
   record_identifier_name=record_identifier_feature_name,
   event_time_feature_name="EventTime",
   role_arn=role,
   enable_online_store=True
)
```
To confirm that your FeatureGroup has been created we use DescribeFeatureGroup and ListFeatureGroups APIs to display the created feature group.

```python
customers_feature_group.describe()
orders_feature_group.describe()
sagemaker_session.boto_session.client('sagemaker', region_name=region).list_feature_groups() # We use the boto client to list FeatureGroups
```

**Step 4: Ingest data into a feature group**

After the FeatureGroups have been created, we can put data into the FeatureGroups. If you are using the SageMaker Python SDK, use the `ingest` API call. If you are using boto3 then use the `PutRecord` API. It will take less than 1 minute to ingest data both of these FeatureGroups. This example uses the SageMaker Python SDK, and so it uses the `ingest` API call.

```python
def check_feature_group_status(feature_group):
    status = feature_group.describe().get("FeatureGroupStatus")
    while status == "Creating":
        print("Waiting for Feature Group to be Created")
        time.sleep(5)
        status = feature_group.describe().get("FeatureGroupStatus")
        print(f"FeatureGroup {feature_group.name} successfully created.")
check_feature_group_status(customers_feature_group)
check_feature_group_status(orders_feature_group)

customers_feature_group.ingest(  
data_frame=customer_data, max_workers=3, wait=True
)

orders_feature_group.ingest(  
data_frame=orders_data, max_workers=3, wait=True
)
```

Using an arbitrary customer record id, 573291 we use get_record to check that the data has been ingested into the feature group.

```python
customer_id = 573291
sample_record = sagemaker_session.boto_session.client('sagemaker-featurestore-runtime', region_name=region).get_record(FeatureGroupName=customers_feature_group_name, RecordIdentifierValueAsString=str(customer_id))
print(sample_record)
```

Below demonstrates how to use the `batch_get_record` to get a batch of records.

```python
all_records = sagemaker_session.boto_session.client(  
    "sagemaker-featurestore-runtime", region_name=region
).batch_get_record(
    Identifiers=[
        
        "FeatureGroupName": customers_feature_group_name,
        "RecordIdentifiersValueAsString": ["573291", "109382", "828400", "124013"],
    ]
)
Step 5: Clean up

Here we remove the Feature Groups we created.

```python
customers_feature_group.delete()
orders_feature_group.delete()
```

Step 6: Next steps

In this example notebook, you learned how to quickly get started with Feature Store, create feature groups, and ingest data into them.

For an advanced example on how to use Feature Store for a Fraud Detection use-case, see Fraud Detection with Feature Store.

Step 7: Programmers note

In this notebook we used a variety of different API calls. Most of them are accessible through the Python SDK, however some only exist within boto3. You can invoke the Python SDK API calls directly on your Feature Store objects, whereas to invoke API calls that exist within boto3, you must first access a boto client through your boto and sagemaker sessions: e.g., `sagemaker_session.boto_session.client()`.

Below we list API calls used in this notebook that exist within the Python SDK and ones that exist in boto3 for your reference.

**Python SDK API Calls**

- `describe()`
- `ingest()`
- `delete()`
- `create()`
- `load_feature_definitions()`

**Boto3 API Calls**

- `list_feature_groups()`
- `get_record()`

Fraud Detection with Feature Store

Step 1: Set Up Feature Store

To start using Feature Store, create a SageMaker session, boto3 session, and a Feature Store session. Also, set up the S3 bucket you want to use for your features. This is your offline store. The following code uses the SageMaker default bucket and adds a custom prefix to it.
Note
The role that you use must have the following managed policies attached to it:
AmazonSageMakerFullAccess and AmazonSageMakerFeatureStoreAccess.

```python
import boto3
import sagemaker
from sagemaker.session import Session

sagemaker_session = sagemaker.Session()
region = sagemaker_session.boto_region_name
boto_session = boto3.Session(region_name=region)
role = sagemaker.get_execution_role()
default_bucket = sagemaker_session.default_bucket()
offline_feature_store_bucket = 's3://{}/{}'.format(default_bucket, prefix)

sagemaker_client = boto_session.client(service_name='sagemaker', region_name=region)
featurestore_runtime = boto_session.client(service_name='sagemaker-featurestore-runtime', region_name=region)

feature_store_session = Session(
boto_session=boto_session,
sagemaker_client=sagemaker_client,
sagemaker_featurestore_runtime_client=featurestore_runtime
)
```

**Step 2: Load Datasets and Partition Data into Feature Groups**

Load your data into data frames for each of your features. You use these data frames after you set up the feature group. In the fraud detection example, you can see these steps in the following code.

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import io

fraud_detection_bucket_name = 'sagemaker-featurestore-fraud-detection'
identity_file_key = 'sampled_identity.csv'
transaction_file_key = 'sampled_transactions.csv'

identity_data_object = s3_client.get_object(Bucket=fraud_detection_bucket_name,
Key=identity_file_key)
transaction_data_object = s3_client.get_object(Bucket=fraud_detection_bucket_name,
Key=transaction_file_key)

identity_data = pd.read_csv(io.BytesIO(identity_data_object['Body'].read()))
transaction_data = pd.read_csv(io.BytesIO(transaction_data_object['Body'].read()))

identity_data = identity_data.round(5)
transaction_data = transaction_data.round(5)

identity_data = identity_data.fillna(0)
transaction_data = transaction_data.fillna(0)

# Feature transformations for this dataset are applied before ingestion into FeatureStore.
# One hot encode card4, card6
encoded_card_bank = pd.get_dummies(transaction_data['card4'], prefix = 'card_bank')
encoded_card_type = pd.get_dummies(transaction_data['card6'], prefix = 'card_type')

transformed_transaction_data = pd.concat([transaction_data, encoded_card_type, encoded_card_bank], axis=1)
```
transformed_transaction_data =
transformed_transaction_data.rename(columns={"card_bank_american express": "card_bank_american_express"})

Step 3: Set Up Feature Groups

When you set up your feature groups, you need to customize the feature names with a unique name and set up each feature group with the FeatureGroup class.

```python
from sagemaker.feature_store.feature_group import FeatureGroup
feature_group_name = "some string for a name"
feature_group = FeatureGroup(name=feature_group_name,
sagemaker_session=feature_store_session)
```

For example, in the fraud detection example, the two feature groups are `identity` and `transaction`.
In the following code you can see how the names are customized with a timestamp, and then each group is set up by passing in the name and the session.

```python
import time
from time import gmtime, strftime, sleep
from sagemaker.feature_store.feature_group import FeatureGroup

identity_feature_group_name = 'identity-feature-group-' + strftime('%d-%H-%M-%S', gmtime())
transaction_feature_group_name = 'transaction-feature-group-' + strftime('%d-%H-%M-%S', gmtime())

identity_feature_group = FeatureGroup(name=identity_feature_group_name,
sagemaker_session=feature_store_session)
transaction_feature_group = FeatureGroup(name=transaction_feature_group_name,
sagemaker_session=feature_store_session)
```

Step 4: Set Up Record Identifier and Event Time Features

In this step, you specify a record identifier name and an event time feature name. This name maps to the column of the corresponding features in your data. For example, in the fraud detection example, the column of interest is `TransactionID`. `EventTime` can be appended to your data when no timestamp is available. In the following code, you can see how these variables are set, and then `EventTime` is appended to both feature's data.

```python
record_identifier_name = "TransactionID"
event_time_feature_name = "EventTime"
current_time_sec = int(round(time.time()))
identity_data[event_time_feature_name] = pd.Series([current_time_sec]*len(identity_data),
dtype="float64")
transformed_transaction_data[event_time_feature_name] =
pd.Series([current_time_sec]*len(transaction_data), dtype="float64")
```

Step 5: Load Feature Definitions

You can now load the feature definitions by passing a data frame containing the feature data. In the following code for the fraud detection example, the identity feature and transaction feature are each loaded by using `load_feature_definitions`, and this function automatically detects the data type of each column of data. For developers using a schema rather than automatic detection, see the Export Feature Groups from Data Wrangler example for code that shows how to load the schema, map it, and add it as a FeatureDefinition that you can use to create the FeatureGroup. This example also covers a boto3 implementation, which you can use instead of the SageMaker Python SDK.

```python
identity_feature_group.load_feature_definitions(data_frame=identity_data); # output is suppressed
```
Step 6: Create a Feature Group

In this step, you use the `create` function to create the feature group. The following code shows all of the available parameters. The online store is not created by default, so you must set this as `True` if you want to enable it. The `s3_uri` is the S3 bucket location of your offline store.

```python
# create a FeatureGroup
feature_group.create(  
    description = "Some info about the feature group",  
    feature_group_name = feature_group_name,  
    record_identifier_name = record_identifier_name,  
    event_time_feature_name = event_time_feature_name,  
    feature_definitions = feature_definitions,  
    role_arn = role,  
    s3_uri = offline_feature_store_bucket,  
    enable_online_store = True,  
    online_store_kms_key_id = None,  
    offline_store_kms_key_id = None,  
    disable_glue_table_creation = False,  
    data_catalog_config = None,  
    tags = ["tag1","tag2"])
```

The following code from the fraud detection example shows a minimal `create` call for each of the two features groups being created.

```python
identity_feature_group.create(  
    s3_uri=offline_feature_store_bucket,  
    record_identifier_name=record_identifier_name,  
    event_time_feature_name=event_time_feature_name,  
    role_arn=role,  
    enable_online_store=True  
)

transaction_feature_group.create(  
    s3_uri=offline_feature_store_bucket,  
    record_identifier_name=record_identifier_name,  
    event_time_feature_name=event_time_feature_name,  
    role_arn=role,  
    enable_online_store=True  
)
```

When you create a feature group, it takes time to load the data, and you need to wait until the feature group is created before you can use it. You can check status using the following method.

```python
status = feature_group.describe().get("FeatureGroupStatus")
```

While the feature group is being created, you receive `Creating` as a response. When this step has finished successfully, the response is `Created`. Other possible statuses are `CreateFailed`, `Deleting`, or `DeleteFailed`.

Step 7: Work with Feature Groups

Now that you've set up your feature group, you can perform any of the following tasks:
• Describe a Feature Group (p. 1049)
• List Feature Groups (p. 1049)
• Put Records in a Feature Group (p. 1049)
• Get Records from a Feature Group (p. 1049)
• Generate Hive DDL Commands (p. 1050)
• Build a Training Dataset (p. 1050)
• Write and Execute an Athena Query (p. 1050)
• Delete a Feature Group (p. 1050)

Describe a Feature Group

You can retrieve information about your feature group with the `describe` function.

```python
feature_group.describe()
```

List Feature Groups

You can list all of your feature groups with the `list_feature_groups` function.

```python
sagemaker_client.list_feature_groups()
```

Put Records in a Feature Group

You can use the `ingest` function to load your feature data. You pass in a data frame of feature data, set the number of workers, and choose to wait for it to return or not. The following example demonstrates using the `ingest` function.

```python
feature_group.ingest(
    data_frame=feature_data, max_workers=3, wait=True
)
```

For each feature group you have, run the `ingest` function on the feature data you want to load.

Get Records from a Feature Group

You can use the `get_record` function to retrieve the data for a specific feature by its record identifier. The following example uses an example identifier to retrieve the record.

```python
record_identifier_value = str(2990130)
featurestore_runtime.get_record(FeatureGroupName=transaction_feature_group_name,
    RecordIdentifierValueAsString=record_identifier_value)
```

An example response from the fraud detection example:

```python
...
'Record': [{'FeatureName': 'TransactionID', 'ValueAsString': '2990130'},
    {'FeatureName': 'isFraud', 'ValueAsString': '0'},
    {'FeatureName': 'TransactionDT', 'ValueAsString': '152647'},
    {'FeatureName': 'TransactionAmt', 'ValueAsString': '75.0'},
    {'FeatureName': 'ProductCD', 'ValueAsString': 'H'},
    {'FeatureName': 'card1', 'ValueAsString': '4577'},
    ...
...
Generate Hive DDL Commands

The SageMaker Python SDK's FeatureStore class also provides the functionality to generate Hive DDL commands. The schema of the table is generated based on the feature definitions. Columns are named after feature name and data-type are inferred based on feature type.

```python
print(feature_group.as_hive_ddl())
```

Example output:

```
CREATE EXTERNAL TABLE IF NOT EXISTS sagemaker_featurestore.identity-feature-group-27-19-33-00 (
    TransactionID INT
    id_01 FLOAT
    id_02 FLOAT
    id_03 FLOAT
    id_04 FLOAT
    ...
```

Build a Training Dataset

Feature Store automatically builds an AWS Glue data catalog when you create feature groups and you can turn this off if you want. The following describes how to create a single training dataset with feature values from both identity and transaction feature groups created earlier in this topic. Also, the following describes how to run an Amazon Athena query to join data stored in the offline store from both identity and transaction feature groups.

To start, create an Athena query using `athena_query()` for both identity and transaction feature groups. The `table_name` is the AWS Glue table that is autogenerated by Feature Store.

```python
identity_query = identity_feature_group.athena_query()
transaction_query = transaction_feature_group.athena_query()

identity_table = identity_query.table_name
transaction_table = transaction_query.table_name
```

Write and Execute an Athena Query

You write your query using SQL on these feature groups, and then execute the query with the `.run()` command and specify your S3 bucket location for the data set to be saved there.

```python
# Athena query
query_string = 'SELECT * FROM "' + transaction_table + '" LEFT JOIN "' + identity_table + '" ON ' + transaction_table + '.transactionid = ' + identity_table + '.transactionid'

# run Athena query. The output is loaded to a Pandas dataframe.
dataset = pd.DataFrame()
identity_query.run(query_string=query_string,
                  output_location='s3://'+default_s3_bucket_name+'/query_results/)
identity_query.wait()
dataset = identity_query.as_dataframe()
```

From here you can train a model using this data set and then perform inference.

Delete a Feature Group

You can delete a feature group with the `delete` function.
Adding required policies to your IAM role

To get started with Amazon SageMaker Feature Store you must add the required policy to your role, AmazonSageMakerFeatureStoreAccess. Below is a walkthrough on how to add it to your role through the console.

Step 1: Access AWS Management Console

Sign in to the AWS Management Console and open the IAM console.

Step 2: Choose Roles

In the navigation pane on the left, choose Roles. The navigation pane is illustrated below with Roles outlined in red.
Identity and Access Management (IAM)

Dashboard

- Access management
  - Groups
  - Users
    - Roles
  - Policies
    - Identity providers
    - Account settings

- Access reports
  - Access analyzer
    - Archive rules
    - Analyzers
    - Settings
  - Credential report
  - Organization activity
  - Service control policies (SCPs)
Step 3: Find your role

In the search bar, enter the role you are using for Amazon SageMaker Feature Store. Below illustrates with a red arrow where you enter your role.

Roles

What are IAM roles?

IAM roles are a secure way to grant permissions to entities that you trust. Examples of entities include:

- IAM user in another account
- Application code running on an EC2 instance that needs to perform actions on AWS resources
- An AWS service that needs to act on resources in your account to provide its features
- Users from a corporate directory who use identity federation with SAML

IAM roles issue keys that are valid for short durations, making them a more secure way to grant access.

Additional resources:

- IAM Roles FAQ
- IAM Roles Documentation
- Tutorial: Setting Up Cross Account Access
- Common Scenarios for Roles

Step 4: Attach policy

After you find your role, choose Attach policies. Below illustrates this with a red arrow.
Next you will enter in the search bar the required policy. Below illustrates the search bar you will use to enter the policy.

The policy you will need to add is AmazonSageMakerFeatureStoreAccess. After you enter the policy, select the check box and then choose Attach policy. Below illustrates the this step.
After you have attached both policies to your role, the policy should appear under your IAM role. The following illustrates how it appears under your IAM role.
Use Amazon SageMaker Feature Store with Amazon SageMaker Studio

You can use Studio to create and view details about your feature groups.

**Topics**
- Create a Feature Group in Studio (p. 1056)
- View Feature Group Details in Studio (p. 1061)

**Create a Feature Group in Studio**

The create feature group process in Studio has four steps: enter details, definitions, required features, and tags.

Consider the following options before you start:

- If you plan to only use an online store, you just need the schema for your features. This is your columns and each column’s data type.
- If you plan to use an offline store, you need an S3 bucket URI and a Role ARN.
- If you plan to use encryption, you need a KMS key. You can use the same one for both the online store and your offline store, or have a unique key for each.
- If you plan to use AWS Glue integration, be prepared to provide a data catalog name, database name, and table name.

**To create a feature group in Studio**

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the **Components and registries** icon (🔍).
3. In the file and resource browser, choose Feature Store.
4. The Feature Store tab lists your feature groups.
5. The **Feature Store** tab, choose **Create Feature Group**.

6. Enter the feature group details.

7. (Optional) If you’re using Glue, enter the data catalog details.

8. Enter feature definitions. You have two options for providing a schema for your features: a JSON editor, or a Table editor.
9. The table editor accepts a column name and a data type. In a minimal example, you will need at least two for the next step: one for a record identifier and one for a time event feature. You can have up to 2,500 feature definitions.

10. Set a record identifier and a time feature to use for this feature group.
11. (Optional) Enter tags as key value pairs.

12. Choose **Create feature group**.
13. In the **Actions** column, choose **Open feature store**.

14. When the feature group is finished being created, it appears in your feature groups list. Choose the refresh button to refresh the list.

### View Feature Group Details in Studio

You can view details about your feature groups, and get sample queries to run against your data sources to gather the data for features you have defined.

**To view feature group details in Studio**

1. Double-click or right-click a feature group from your list, and then choose **Open feature group detail**.

2. In the details view, you can review your feature group summary, feature definitions, feature group tags, and sample query.
3. On the **Feature definitions** tab, you can search for features by name.

4. On the **Feature group tags** tab, you can add and remove tags.
5. On the Sample query tab, you can see a variety of sample queries: interactive exploration, time travel, remove tombstone, and remove duplicates.

Data Sources and Ingestion

There are multiple ways to bring your data into Amazon SageMaker Feature Store. Feature Store offers a single API call for data ingestion called PutRecord that enables you to ingest data in batches or from streaming sources. You can use Amazon SageMaker Data Wrangler to engineer features and then ingest your features into your Feature Store. You can also use Amazon EMR for batch data ingestion through a Spark connector.

Topics
- Stream Ingestion (p. 1063)
- Data Wrangler with Feature Store (p. 1064)
- Batch Ingestion Spark Connector Setup (p. 1066)

Stream Ingestion

You can use streaming sources such as Kafka or Kinesis as a data source where features are extracted from there and directly fed to the online feature store for training, inference or feature creation. Records can be pushed into the feature store by calling the synchronous PutRecord API call. Since this is a
synchronous API call it allows small batches of updates to be pushed in a single API call. This enables you to maintain high freshness of the feature values and publish values as soon an update is detected. These are also called *streaming* features.

**Data Wrangler with Feature Store**

Data Wrangler is a feature of Studio that provides an end-to-end solution to import, prepare, transform, featurize, and analyze data. Data Wrangler enables you to engineer your features and ingest them into a feature store.

In Studio, after interacting with Data Wrangler, choose the **Export** tab, choose **Export Step**, and the choose **Feature Store**, as shown in the following screenshot. This exports a Jupyter notebook that has all the source code in it to create a Feature Store feature group that adds your features from Data Wrangler to an offline or online feature store.
After the feature group has been created, you can also select and join data across multiple feature groups to create new engineered features in Data Wrangler and then export your data set to an S3 bucket.
For more information on how to export to Feature Store, see Export to SageMaker Feature Store.

Batch Ingestion Spark Connector Setup

Introduction

Amazon SageMaker Feature Store supports batch data ingestion with Spark, using your existing ETL pipeline, or a pipeline on Amazon EMR. You can also use this functionality from a Amazon SageMaker Notebook Instance.

Methods for installing and implementing batch data ingestion are provided for Python and Scala. Python developers can use the sagemaker-feature-store-pyspark Python library for local development, installation on Amazon EMR, or run it from Jupyter notebooks. Scala developers can use the Feature Store Spark connector available in Maven.

You can use the Spark connector to ingest data in the following ways:

1. Ingest by default – Ingest your dataframe into the online store. When you use the connector to update the online store, The Spark connector uses the PutRecord operation to make the update. Within 15 minutes, Feature Store syncs the data between the online store and the offline store. The online store contains the latest value for the record. For more information about how the online and offline stores work, see Feature Store Concepts (p. 1039).

2. Offline store direct ingestion – Use the Spark connector to ingest your dataframe directly into the offline store. Ingesting the dataframe directly into the offline store doesn't update the online store. For information about using the different ingestion methods, see Example Implementations (p. 1067).

Installation

Scala Users

Requirements

- Spark >= 3.0.0
- Scala >= 2.12.x
- Amazon EMR > 6.x (only if you are using Amazon EMR)

Declare the Dependency in POM.xml

The Feature Store Spark connector is available in the Maven central repository. Declare the following in your project's POM.xml:

```xml
<dependency>
    <groupId>software.amazon.sagemaker.featurestore</groupId>
    <artifactId>sagemaker-feature-store-spark-sdk_2.12</artifactId>
    <version>1.0.0</version>
</dependency>
```

Python Users

Requirements

- PySpark >= 3.0.0
- Python >= 3.8
- Amazon EMR > 6.x (only if you are using Amazon EMR)
A library is available for Python developers, `sagemaker-feature-store-pyspark`. The following sections describe how to install the library locally, on Amazon EMR, and on Amazon SageMaker.

**Local Installation**

To find more info about the installation, enable verbose mode by appending `--verbose` to the following installation command.

```bash
pip3 install sagemaker-feature-store-pyspark --no-binary :all:
```

**Installation on Amazon EMR**

Create the cluster with the latest version of container (version 6) and enable SSH for troubleshooting.

You can either create a custom step to start the library installation or SSH to your cluster to install the library directly in console.

```bash
sudo -E pip3 install sagemaker-feature-store-pyspark --no-binary :all: --verbose
```

**Installation on a Amazon SageMaker Notebook Instance**

Amazon SageMaker Notebook Instances are using older version of Spark that is not compatible with Feature Store Spark Connector. You must upgrade Spark, then install `sagemaker-feature-store-pyspark`.

Inside your notebook, add and run a cell like the following:

```python
import os
original_spark_version = "2.4.0"
# Install a newer version of Spark which is compatible with spark library
!pip3 install pyspark==3.1.1
!pip3 install sagemaker-feature-store-pyspark --no-binary :all:
```

**Example Implementations**

**Scala**

`FeatureStoreBatchIngestion.scala`

```scala
import software.amazon.sagemaker.featurestore.sparksdk.FeatureStoreManager
import org.apache.spark.sql.types.{StringType, StructField, StructType}
import org.apache.spark.sql.{Row, SparkSession}

object ProgramOffline {
  def main(args: Array[String]): Unit = {
    val spark = SparkSession.builder().getOrCreate()
    // Add your code here
  }
}
```
// Construct test DataFrame
val data = List(
    Row("1", "2021-07-01T12:20:12Z"),
    Row("2", "2021-07-02T12:20:13Z"),
    Row("3", "2021-07-03T12:20:14Z")
)

val schema = StructType(
    List(StructField("RecordIdentifier", StringType), StructField("EventTime", StringType))
)

val df = spark.createDataFrame(spark.sparkContext.parallelize(data), schema)
val featureStoreManager = new FeatureStoreManager()

// Load the feature definitions from input schema. The feature definitions can be used to create a feature group
val featureDefinitions = featureStoreManager.loadFeatureDefinitionsFromSchema(df)


// Ingest by default
featureStoreManager.ingestData(df, featureGroupArn)

// Offline store direct ingestion, flip the flag of direct_offline_store
featureStoreManager.ingestData(df, featureGroupArn, directOfflineStore = true)

---

Python

FeatureStoreBatchIngestion.py

```python
from pyspark.sql import SparkSession
from feature_store_pyspark.FeatureStoreManager import FeatureStoreManager
import feature_store_pyspark
extra_jars = ",".join(feature_store_pyspark.classpath_jars())
spark = SparkSession.builder \
    .config("spark.jars", extra_jars) \
    .getOrCreate()

# Construct test DataFrame
columns = ["RecordIdentifier", "EventTime"]
data = [(["1", "2021-03-02T12:20:12Z"], ["2", "2021-03-02T12:20:13Z"],
        ["3", "2021-03-02T12:20:14Z")]

df = spark.createDataFrame(data).toDF(*columns)
feature_store_manager= FeatureStoreManager()

# Load the feature definitions from input schema. The feature definitions can be used to create a feature group
feature_definitions = feature_store_manager.load_feature_definitions_from_schema(df)

feature_group_arn = "arn:aws:sagemaker:us-west-2:<your-account-id>:feature-group/<your-feature-group-name>"

# Ingest by default
feature_store_manager.ingest_data(input_data_frame=df, feature_group_arn=feature_group_arn)

# Offline store direct ingestion, flip the flag of direct_offline_store
```
Add Features to a Feature Group

You can use the Amazon SageMaker Feature Store API or Amazon SageMaker Studio to add features to your feature group. You can think of a feature group as a data table and a feature as a column in the table. When you add a feature to the feature group, you're effectively adding a column to the table.

The features that you've added don't have any data. You can add new records to the feature group or overwrite them. You can think of a record as a row in the data table.

The following sections provide an overview of using the API and Studio to add features to a feature group. With the API, you can also add or overwrite records after you've updated the feature group.

Studio

To search through your features, do the following.

1. In Amazon SageMaker Studio, navigate to SageMaker resources.
2. On the navigation pane, choose Feature Store.
3. Choose Feature group catalog.
4. Under Feature group name, choose a feature group.
5. From the dropdown list that says Actions, choose Add feature definitions.
6. Specify a name for the Feature name field.
7. For Type, select the feature's data type.
8. Choose **Add new feature definition**.
9. (Optional) Choose **Add new feature definition** to add feature definitions.
10. Specify information for the additional features.
11. Choose **Save changes**.
12. Choose **Confirm**.

**API**

Use the **UpdateFeatureGroup** operation to add features to a feature group.

You can use the **DescribeFeatureGroup** operation to see if you've added the features successfully.

To add or overwrite records, use the **PutRecord** operation.

To see the updates that you've made to a record, use the **GetRecord** operation. To see the updates that you've made to multiple records, use the **BatchGetRecord** operation. It can take up to five minutes for the updates that you've made to appear.

You can use the example code in the following section to walk through adding features and records using the AWS SDK for Python (Boto3).

**Example Code**

The example code walks you through the following process:

1. Adding features to the feature group
2. Verifying that you've added them successfully
3. Adding a record to the feature group
4. Verifying that you've added it successfully

**Step 1: Add Features To a Feature Group**

The following code uses the **UpdateFeatureGroup** operation to add new features to the feature group. It assumes that you've set up Feature Store and created a feature group. For more information about getting started, see **Introduction to Feature Store** (p. 1040).

```python
import boto3

sagemaker_client = boto3.client("sagemaker")

sagemaker_client.update_feature_group(
    FeatureGroupName=feature_group_name,
    FeatureAdditions=[
        {"FeatureName": "new-feature-1", "FeatureType": "Integral"},
        {"FeatureName": "new-feature-2", "FeatureType": "Fractional"},
        {"FeatureName": "new-feature-3", "FeatureType": "String"}
    ]
)
```

The following code uses the **DescribeFeatureGroup** operation to check the status of the update. If the **LastUpdateStatus** field is **Successful**, you've added the features successfully.
Step 2: Add a New Record To The Feature Group

The following code uses the `PutRecord` operation to add records to the feature group that you've created.

```python
record_identifier_value = 'new_record'
sagemaker_featurestore_runtime_client = boto3.client("sagemaker-featurestore-runtime")
sagemaker_runtime_client.put_record(
    FeatureGroupName=feature_group_name,
    Record=[
        {
            'FeatureName': "record-identifier-feature-name",
            'ValueAsString': record_identifier_value
        },
        {
            'FeatureName': "event-time-feature",
            'ValueAsString': "timestamp-that-feature-store-returns"
        },
        {
            'FeatureName': "new-feature-1",
            'ValueAsString': "value-as-string"
        },
        {
            'FeatureName': "new-feature-2",
            'ValueAsString': "value-as-string"
        },
        {
            'FeatureName': "new-feature-3",
            'ValueAsString': "value-as-string"
        }
    ]
)
```

Use the `GetRecord` operation to see which records in your feature group don't have data for the features that you've added. You can use the `PutRecord` operation to overwrite the records that don't have data for the features that you've added.

Find Features in Your Feature Groups

With Amazon SageMaker Feature Store, you can search for the features that you've created in your feature groups. You can search through all of your features without needing to first select a feature group. You can use the search functionality to quickly find the features that are relevant to your use case.

To search for features in your feature groups, the feature groups must be within the same AWS account and Region.

**Important**
Use the latest version of Amazon SageMaker Studio to make sure that you're using the most recent version of the search functionality. For information on updating Studio, see Shut down and Update SageMaker Studio (p. 179).
If you’re on a team, you might have teammates that are looking for features to use in their models, they can search through all the features in all of the feature groups.

You can add searchable parameters and descriptions to make your features more discoverable. For more information, see Adding Searchable Metadata to Your Features (p. 1074).

The following are the types of metadata that you can use in your search.

You can search for features using either Amazon SageMaker Studio or the Search operation in the SageMaker API. The following table lists all of the searchable metadata and whether you can search for it in Studio.

<table>
<thead>
<tr>
<th>Searchable metadata</th>
<th>API field name</th>
<th>Searchable in Studio?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feature name</td>
<td>FeatureName</td>
<td>Yes</td>
</tr>
<tr>
<td>Feature group name</td>
<td>FeatureGroupName</td>
<td>No</td>
</tr>
<tr>
<td>Description</td>
<td>Description</td>
<td>Yes</td>
</tr>
<tr>
<td>Parameters</td>
<td>Parameters_key</td>
<td>Yes</td>
</tr>
<tr>
<td>All Parameters</td>
<td>AllParameters</td>
<td>Yes</td>
</tr>
<tr>
<td>Feature type</td>
<td>FeatureType</td>
<td>No</td>
</tr>
<tr>
<td>Creation time</td>
<td>CreationTime</td>
<td>Yes</td>
</tr>
<tr>
<td>Last modified time</td>
<td>LastModifiedTime</td>
<td>No</td>
</tr>
</tbody>
</table>

The following sections show you how to search for your features.

**Studio**

Use the following procedure to search through all the features that you’ve created.

To search through your features, do the following.

1. In Amazon SageMaker Studio, navigate to SageMaker resources.
2. On the navigation pane, choose Feature Store.
3. Choose Feature Catalog.
4. Specify a text query with at least three characters to search for your features.
5. (Optional) Use advanced filters after you’ve specified a query. You can use filters to specify parameters or date ranges in your search results. If you’re searching for a parameter, specify both its key and value. To find your features more easily, you can do the following:

   • Specify time ranges.
   • Deselect columns that you don’t want to query.

**SDK for Python (Boto3)**

The example uses the Search operation in the AWS SDK for Python (Boto3) to run the search query. For information about the other languages to submit a query, see See Also in the Amazon SageMaker API Reference.

The following code shows different example search queries using the API.
# Return all features in your feature groups
```python
sagemaker_client.search(
    Resource="FeatureMetadata",
)
```

# Search for all features that belong to a feature group that contain the "ver" substring
```python
sagemaker_client.search(
    Resource="FeatureMetadata",
    SearchExpression={
        'Filters': [
            {'Name': 'FeatureGroupName', 'Operator': 'Contains', 'Value': 'ver'},
        ],
    },
)
```

# Search for all features that belong to a feature group that have the EXACT name "airport"
```python
sagemaker_client.search(
    Resource="FeatureMetadata",
    SearchExpression={
        'Filters': [
            {'Name': 'FeatureGroupName', 'Operator': 'Equals', 'Value': 'airport'},
        ],
    },
)
```

# Search for all features that belong to a feature group that contains the name "ver" AND have a name that contains "wha" AND have a parameter (key or value) that contains "hea"
```python
sagemaker_client.search(
    Resource="FeatureMetadata",
    SearchExpression={
        'Filters': [
            {'Name': 'FeatureGroupName', 'Operator': 'Contains', 'Value': 'ver'},
            {'Name': 'FeatureName', 'Operator': 'Contains', 'Value': 'wha'},
            {'Name': 'AllParameters', 'Operator': 'Contains', 'Value': 'hea'},
        ],
    },
)
```

# Search for all features that belong to a feature group with substring "ver" in its name OR features that have a name that contain "wha" OR features that have a parameter (key or value) that contains "hea"
```python
sagemaker_client.search(
    Resource="FeatureMetadata",
    SearchExpression={
        'Filters': [
            {'Name': 'FeatureGroupName', 'Operator': 'Contains', 'Value': 'ver'},
            {'Name': 'FeatureName', 'Operator': 'Contains', 'Value': 'wha'},
            {'Name': 'AllParameters', 'Operator': 'Contains', 'Value': 'hea'},
        ],
    },
)
```
Adding Searchable Metadata to Your Features

In Amazon SageMaker Feature Store, you can search through all of your features. To make your features more discoverable, you can add metadata to them. You can add the following types of metadata:

```python
sagemaker_client.search(
    Resource="FeatureMetadata",
    SearchExpression={
        "Filters": [
            {
                "Name": "FeatureGroupName",
                "Operator": "Contains",
                "Value": "ver"
            },
            {
                "Name": "FeatureName",
                "Operator": "Contains",
                "Value": "wha"
            },
            {
                "Name": "AllParameters",
                "Operator": "Contains",
                "Value": "hea"
            }
        ],
        "Operator": "Or" # note that this is explicitly set to "Or"- the default is "And"
    }
)
```

# Search for all features that belong to a feature group with substring "ver" in its name
OR features that have a name that contain "wha"
OR parameters with the value 'Sage' for the 'org' key

```python
sagemaker_client.search(
    Resource="FeatureMetadata",
    SearchExpression={
        "Filters": [
            {
                "Name": "FeatureGroupName",
                "Operator": "Contains",
                "Value": "ver"
            },
            {
                "Name": "FeatureName",
                "Operator": "Contains",
                "Value": "wha"
            },
            {
                "Name": "Parameters.org",
                "Operator": "Contains",
                "Value": "Sage"
            }
        ],
        "Operator": "Or" # note that this is explicitly set to "Or"- the default is "And"
    }
)
```
• Description – A searchable description of the feature.
• Parameters – Searchable key-value pairs.

The description can have up to 255 characters.

For parameters, you must specify a key-value pair in your search. You can add up to 25 parameters.

To update the metadata of a feature, you can use either Amazon SageMaker Studio or the UpdateFeatureMetadata operation.

Use the following procedure to update the metadata using Amazon SageMaker Studio.

To update the feature metadata with Studio, do the following.

1. In Amazon SageMaker Studio, navigate to SageMaker resources.
2. On the navigation pane, choose Feature Store.
3. Choose Feature catalog.
4. In the Feature name column, choose a feature name.
5. Choose Edit metadata.
6. In the Description field, add or update the description.
7. In the Parameters field under Parameters, specify a key-value pair for the parameter.
8. (Optional) Choose Add new parameter to add another parameter.
9. Choose Save changes.
10. Choose Confirm.

The following describes how you can use the UpdateFeatureMetadata operation for different scenarios.

Add a list of parameters to a feature

To add a list of parameters to a feature, specify values for the following fields:

• FeatureGroupName
• Feature
• Parameters

The following example code uses the AWS SDK for Python (Boto3) to add two parameters.

```python
sagemaker_client.update_feature_metadata(
    FeatureGroupName="/feature_group_name",
    FeatureName="/feature-name",
    ParameterAdditions=[
        {"Key": "example-key-0", "Value": "example-value-0"},
        {"Key": "example-key-1", "Value": "example-value-1"},
    ]
)
```

Add a description to a feature

To add a description to a feature, specify values for the following fields:

• FeatureGroupName
Adding Searchable Metadata to Your Features

- Feature
- Description

```python
sagemaker_client.update_feature_metadata(
    FeatureGroupName="feature-group-name",
    FeatureName="feature-name",
    Description="description"
)
```

Remove parameters for a feature

To remove all parameters for a feature, do the following.

Specify values for the following fields:

- FeatureGroupName
- Feature

Specify the keys for the parameters that you're removing under ParameterRemovals.

```python
sagemaker_client.update_feature_metadata(
    FeatureGroupName="feature_group_name",
    FeatureName="feature-name",
    ParameterRemovals=[
        {"Key": "example-key-0"},
        {"Key": "example-key-1"},
    ]
)
```

Remove the description for a feature

To remove the description for a feature, do the following.

Specify values for the following fields:

- FeatureGroupName
- Feature

Specify an empty string for Description.

```python
sagemaker_client.update_feature_metadata(
    FeatureGroupName="feature-group-name",
    FeatureName="feature-name",
    Description=""
)
```

After you've updated the metadata for a feature, you can use the `DescribeFeatureMetadata` operation to see the updates that you've made.

The following code goes through an example workflow using the AWS SDK for Python (Boto3).
Example Code

The example code does the following:

1. Sets up your SageMaker environment.
2. Creates a feature group.
3. Adds features to the group.
4. Adds metadata to the features.

Step 1: Setup

To start using Feature Store, create SageMaker, boto3 and Feature Store sessions. Then set up the S3 bucket you want to use for your features. This is your offline store. The following code uses the SageMaker default bucket and adds a custom prefix to it.

Note
The role that you use must have the following managed policies attached to it:
AmazonS3FullAccess and AmazonSageMakerFeatureStoreAccess.

```python
# SageMaker Python SDK version 2.x is required
!pip install 'sagemaker>=2.0.0'
import sagemaker
import sys
import boto3
import pandas as pd
import numpy as np
import io
from sagemaker.session import Session
from sagemaker import get_execution_role
from botocore.exceptions import ClientError

prefix = 'sagemaker-featurestore-introduction'
role = get_execution_role()
sagemaker_session = sagemaker.Session()
region = sagemaker_session.boto_region_name
s3_bucket_name = sagemaker_session.default_bucket()
```

Step 2: Create a Feature Group and Add Features

```python
feature_group_name = "test-for-feature-metadata"
feature_definitions = [
    {
        "FeatureName": "feature-1", "FeatureType": "String"},
    {
        "FeatureName": "feature-2", "FeatureType": "String"},
    {
        "FeatureName": "feature-3", "FeatureType": "String"},
    {
        "FeatureName": "feature-4", "FeatureType": "String"},
    {
        "FeatureName": "feature-5", "FeatureType": "String"
    }
]
try:
    sagemaker_client.create_feature_group(
        FeatureGroupName=feature_group_name,
        RecordIdentifierFeatureName="feature-1",
        EventTimeFeatureName="feature-2",
```
FeatureDefinitions=feature_definitions,
OnlineStoreConfig={"EnableOnlineStore": True}
)
except ClientError as e:
    if e.response["Error"]["Code"] == "ResourceInUse":
        pass
    else:
        raise e

### Step 3: Add Metadata

Before you add metadata, use the `DescribeFeatureGroup` operation to make sure that the status of the feature group is `Created`.

```python
sagemaker_client.describe_feature_group(
    FeatureGroupName=feature_group_name
)
```

Add a description to the feature.

```python
sagemaker_client.update_feature_metadata(
    FeatureGroupName=feature_group_name,
    FeatureName="feature-1",
    Description="new description"
)
```

You can use the `DescribeFeatureMetadata` operation to see if you have successfully updated the description for the feature group.

```python
sagemaker_client.describe_feature_metadata(
    FeatureGroupName=feature_group_name,
    FeatureName="feature-1"
)
```

You can also use it to add parameters to the feature group.

```python
sagemaker_client.update_feature_metadata(
    FeatureGroupName=feature_group_name,
    FeatureName="feature-1",
    ParameterAdditions=[
        {"Key": "team", "Value": "featurestore"},
        {"Key": "org", "Value": "sagemaker"},
    ]
)
```

You can use the `DescribeFeatureMetadata` operation again to see if you have successfully added the parameters.

```python
sagemaker_client.describe_feature_metadata(
    FeatureGroupName=feature_group_name,
    FeatureName="feature-1"
)
```
Query Feature Store with Athena and AWS Glue

After a Feature Store feature group has been created in an offline feature store, you can choose to run queries using Amazon Athena on a AWS Glue catalog. This requires data to be registered in a data catalog with other catalog details which is auto-registered for you in Feature Store. In other words, Feature Store automatically builds an AWS Glue data catalog when feature groups are created and you can turn them off. This is particularly useful when you want to build a dataset by executing SQL queries and then train a model for inference.

After your FeatureStore has been created and populated with your data in the offline store, you have the capability to write SQL queries to join data stored in the offline store from different FeatureGroups. To do this, you can use Amazon Athena to write and execute SQL queries. You can set up a AWS Glue crawler to run on a schedule to ensure your catalog is always up to date as well.

If you want to do this please define a role which can be used by the AWS Glue crawler to access the offline store's S3 buckets. For more information, see Create an IAM role.

For more information on how to use AWS Glue and Athena to build a training dataset for model training and inference, see Build Training Dataset: Create Feature Groups.

Sample Athena Queries

Below we provide some sample queries that act as a template for you to quickly write queries using Athena.

Interactive Exploration

This query selects the first 1000 records.

```
SELECT *
FROM <FeatureGroup.DataCatalogConfig.DatabaseName>.<FeatureGroup.DataCatalogConfig.TableName>
LIMIT 1000
```

Latest snapshot without duplicates

This query selects the latest non-duplicate records.

```
SELECT *
FROM (SELECT *,
    row_number() OVER (PARTITION BY <RecordIdentifierFeatureName>
    ORDER BY <EventTimeFeatureName> desc, Api_Invocation_Time DESC, write_time DESC) AS row_num
FROM <FeatureGroup.DataCatalogConfig.DatabaseName>.<FeatureGroup.DataCatalogConfig.TableName>)
WHERE row_num = 1;
```

Latest snapshot without duplicates and deleted records in the offline store

This query filters out any deleted records and selects non-duplicate records from the offline store.

```
SELECT *
FROM (SELECT *,
    row_number()...
Cross-Account Offline Store Access

Amazon SageMaker Feature Store allows users to create a feature group in one account (Account A) and configure it with an offline store using an Amazon S3 bucket in another account (Account B). This can be set up using the steps in the following section.

Topics
- **Step 1:** Set Up the Offline Store Access Role in Account A (p. 1080)
- **Step 2:** Set up an Offline Store S3 Bucket in Account B (p. 1081)
- **Step 3:** Set up an Offline Store KMS Encryption Key in Account A (p. 1082)
- **Step 4:** Create a Feature Group in Account A (p. 1083)

### Step 1: Set Up the Offline Store Access Role in Account A

First, set up a role for Amazon SageMaker Feature Store to write the data into the offline store. The simplest way to accomplish this is to create a new role using the AmazonSageMakerFeatureStoreAccess policy or to use an existing role that already has the AmazonSageMakerFeatureStoreAccess policy attached. This document refers to this policy as Account-A-Offline-Feature-Store-Role-ARN.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [  
```
Step 2: Set up an Offline Store S3 Bucket in Account B

Create an S3 bucket in Account B. If you are using the default AmazonSageMakerFeatureStoreAccess policy, the bucket name must include SageMaker, Sagemaker, or sagemaker. Edit the bucket policy as shown in the following example to allow Account A to read and write objects.

This document refers to the following example bucket policy as Account-B-Offline-Feature-Store-Bucket.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "S3CrossAccountBucketAccess",
            "Effect": "Allow",
            "Action": [
                "s3:PutObject",
                "s3:GetBucketAcl",
                "s3:PutObjectAcl"
            ],
            "Resource": [
                "arn:aws:s3:::*SageMaker*",
                "arn:aws:s3:::*Sagemaker*",
                "arn:aws:s3:::*sagemaker*"
            ]
        }
    ]
}
```

The preceding code snippet shows the AmazonSageMakerFeatureStoreAccess policy. The Resource section of the policy is scoped down by default to S3 buckets with names that contain SageMaker, Sagemaker, or sagemaker. This means the offline store S3 bucket being used must follow this naming convention. If this is not your case, or if you want to further scope down the resource, you can copy and paste the policy to your S3 bucket policy in the console, customize the Resource section to be arn:aws:s3:::your-offline-store-bucket-name, and then attach to the role.

Additionally, this role must have KMS permissions attached. At a minimum, it requires the kms:GenerateDataKey permission to be able to write to the offline store using your customer managed key. See Step 3 to learn about why a customer managed key is needed for the cross-account scenario and how to set it up. The following example shows an inline policy:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "VisualEditor0",
            "Effect": "Allow",
            "Action": [
                "kms:GenerateDataKey"
            ],
        }
    ]
}
```

The Resource section of this policy is scoped to any key in Account A. To further scope this down, after setting up the offline store KMS key in Step 3, return to this policy and replace it with the key ARN.

Step 2: Set up an Offline Store S3 Bucket in Account B

Create an S3 bucket in Account B. If you are using the default AmazonSageMakerFeatureStoreAccess policy, the bucket name must include SageMaker, Sagemaker, or sagemaker. Edit the bucket policy as shown in the following example to allow Account A to read and write objects.

This document refers to the following example bucket policy as Account-B-Offline-Feature-Store-Bucket.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "S3CrossAccountBucketAccess",
            "Effect": "Allow",
```
Step 3: Set up an Offline Store KMS Encryption Key in Account A

Amazon SageMaker Feature Store ensures that server-side encryption is always enabled for S3 objects in the offline store. For cross-account use cases, you must provide a customer managed key so that you are in control of who can write to the offline store (in this case, Account-A-Offline-Feature-Store-Role-ARN from Account A) and who can read from the offline store (in this case, identities from Account B).

This document refers to the following example key policy as Account-A-Offline-Feature-Store-KMS-Key-ARN.

```json
{
  "Version": "2012-10-17",
  "Id": "key-consolepolicy-3",
  "Statement": [
    {
      "Sid": "Enable IAM User Permissions",
      "Effect": "Allow",
      "Principal": {
        "AWS": "arn:aws:iam::Account-A-Account-Id:root"
      },
      "Action": "kms:*",
      "Resource": "*"
    },
    {
      "Sid": "Allow access for Key Administrators",
      "Effect": "Allow",
      "Principal": {
        "AWS": [
          "arn:aws:iam::Account-A-Account-Id:role/Administrator",
          "arn:aws:iam::Account-A-Account-Id:root"
        ]
      },
      "Resource": "*"
    }
  ]
}
```

In the preceding policy, the principal is Account-A-Offline-Feature-Store-Role-ARN, which is the role created in Account A in Step 1 and provided to Amazon SageMaker Feature Store to write to the offline store. You can provide multiple ARN roles under Principal.
Step 4: Create a Feature Group in Account A

Next, create the feature group in Account A, with an offline store S3 bucket in Account B. To do this, provide the following parameters for RoleArn, OfflineStoreConfig.S3StorageConfig.KmsKeyId and OfflineStoreConfig.S3StorageConfig.S3Uri respectively:

- Provide **Account-A-Offline-Feature-Store-Role-ARN** as the RoleArn.
- Provide **Account-A-Offline-Feature-Store-KMS-Key-ARN** for OfflineStoreConfig.S3StorageConfig.KmsKeyId.
- Provide **Account-B-Offline-Feature-Store-Bucket** for OfflineStoreConfig.S3StorageConfig.S3Uri.
Security and Access Control

Amazon SageMaker Feature Store enables you to create two types of stores: an online store or offline store. The online store is used for low latency real-time inference use cases whereas the offline store is used for training and batch inference use cases. When you create a feature group for online or offline use you can provide a AWS Key Management Service customer managed key to encrypt all your data at rest. In case you do not provide a AWS KMS key then we ensure that your data is encrypted on the server side using an AWS owned AWS KMS key or AWS managed AWS KMS key. While creating a feature group, you can select storage type and optionally provide a AWS KMS key for encrypting data, then you can call various APIs for data management such as PutRecord, GetRecord, DeleteRecord.

Feature Store allows you to grant or deny access to individuals at the feature group-level and enables cross-account access to Feature Store. For example, you can set up developer accounts to access the offline store for model training and exploration that do not have write access to production accounts. You can set up production accounts to access both online and offline stores. Feature Store uses unique customer AWS KMS keys for offline and online store data at-rest encryption. Access control is enabled through both API and AWS KMS key access. You can also create feature group-level access control.

For more information about customer managed key, see customer managed keys. For more information about AWS KMS, see AWS KMS.

Using AWS KMS Permissions for Amazon SageMaker Feature Store

Encryption at rest protects Feature Store under an AWS KMS customer managed key. By default, it uses an AWS owned customer managed key for OnlineStore and AWS managed customer managed key for OfflineStore. Feature Store supports an option to encrypt your online or offline store under customer managed key. You can select the customer managed key for Feature Store when you create your online or offline store, and they can be different for each store.

Feature Store supports only symmetric customer managed keys. You cannot use an asymmetric customer managed key to encrypt your data in your online or offline store. For help determining whether a customer managed key is symmetric or asymmetric, see Identifying symmetric and asymmetric customer managed keys.

When you use a customer managed key, you can take advantage of the following features:

- You create and manage the customer managed key, including setting the key policies, IAM policies and grants to control access to the customer managed key. You can enable and disable the customer managed key, enable and disable automatic key rotation, and delete the customer managed key when it is no longer in use.
- You can use a customer managed key with imported key material or a customer managed key in a custom key store that you own and manage.
- You can audit the encryption and decryption of your online or offline store by examining the API calls to AWS KMS in AWS CloudTrail logs.

You do not pay a monthly fee for AWS owned customer managed keys. Customer managed keys will incur a charge for each API call and AWS Key Management Service quotas apply to each customer managed key.
Authorizing Use of a Customer Managed Key for Your Online Store

If you use a customer managed key to protect your online store, the policies on that customer managed key must give Feature Store permission to use it on your behalf. You have full control over the policies and grants on a customer managed key.

Feature Store does not need additional authorization to use the default AWS owned KMS key to protect your online or offline stores in your AWS account.

Customer managed key policy

When you select a customer managed key to protect your Online Store, Feature Store must have permission to use the customer managed key on behalf of the principal who makes the selection. That principal, a user or role, must have the permissions on the customer managed key that Feature Store requires. You can provide these permissions in a key policy, an IAM policy, or a grant. At a minimum, Feature Store requires the following permissions on a customer managed key:

- "kms:Encrypt", "kms:Decrypt", "kms:DescribeKey", "kms:CreateGrant", "kms:RetireGrant",
  "kms:ReEncryptFrom", "kms:ReEncryptTo", "kms:GenerateDataKey", "kms:ListAliases", "kms:ListGrants",
  "kms:RevokeGrant"

For example, the following example key policy provides only the required permissions. The policy has the following effects:

- Allows Feature Store to use the customer managed key in cryptographic operations and create grants, but only when it is acting on behalf of principals in the account who have permission to use your Feature Store. If the principals specified in the policy statement don't have permission to use your Feature Store, the call fails, even when it comes from the Feature Store service.
- The kms:ViaService condition key allows the permissions only when the request comes from FeatureStore on behalf of the principals listed in the policy statement. These principals can't call these operations directly. The value for kms:ViaService should be sagemaker.*.amazonaws.com.
  
  **Note**
  The kms:ViaService condition key can only be used for the online store customer managed AWS KMS key, and cannot be used for the offline store. If you add this special condition to your customer managed key, and use the same AWS KMS key for both the online and offline store, then it will fail the CreateFeatureGroup API operation.
- Gives the customer managed key administrators read-only access to the customer managed key and permission to revoke grants, including the grants that Feature Store uses to protect your data.

Before using an example key policy, replace the example principals with actual principals from your AWS account.

```json
{"Id": "key-policy-feature-store",
 "Version":"2012-10-17",
 "Statement": [
  {"Sid": "Allow access through Amazon SageMaker Feature Store for all principals in the account that are authorized to use Amazon SageMaker Feature Store", 
  "Effect": "Allow",
  "Principal": {"AWS": "arn:aws:iam::111122223333:user/featurestore-user"},
  "Action": [
    "kms:Encrypt",
    "kms:Decrypt",
    "kms:DescribeKey",
  ]
]
```
Using Grants to Authorize Feature Store

In addition to key policies, Feature Store uses grants to set permissions on the customer managed key. To view the grants on a customer managed key in your account, use the `ListGrants` operation. Feature Store does not need grants, or any additional permissions, to use the AWS owned customer managed key to protect your online store.

Feature Store uses the grant permissions when it performs background system maintenance and continuous data protection tasks.

Each grant is specific to an online store. If the account includes multiple stores encrypted under the same customer managed key, there will be unique grants per FeatureGroup using the same customer managed key.

The key policy can also allow the account to revoke the grant on the customer managed key. However, if you revoke the grant on an active encrypted online store, Feature Store won't be able to protect and maintain the store.

Monitoring Feature Store interaction with AWS KMS

If you use a customer managed key to protect your online or offline store, you can use AWS CloudTrail logs to track the requests that Feature Store sends to AWS KMS on your behalf.
Accessing Data in Your Online Store

The caller (either IAM user or IAM role) to ALL DataPlane operations (Put, Get, DeleteRecord) must have below permissions on the customer managed key:

"kms:Decrypt"

Authorizing Use of a Customer Managed Key for your Offline Store

The roleArn that is passed as a parameter to createFeatureGroup must have below permissions to the OfflineStore KmsKeyId:

"kms:GenerateDataKey"

Note
The key policy for the online store also works for the offline store, only when the kms:ViaService condition is not specified.

Important
You can specify a AWS KMS encryption key to encrypt the Amazon S3 location used for your offline feature store when you create a feature group. If AWS KMS encryption key is not specified, by default we encrypt all data at rest using AWS KMS key. By defining your bucket-level key for SSE, you can reduce AWS KMS requests costs by up to 99 percent.

Quotas, Naming Rules and Data Types

Limits and Quotas

Note
Soft limits can be increased based on your needs.

- Maximum number of feature groups per AWS account: Soft limit of 100.
- Maximum number of feature definitions per feature group: 2500.
- Maximum Transactions per second (TPS) per API per AWS account: Soft limit of 10000 TPS per API excluding the BatchGetRecord API call, which has a soft limit of 500 TPS.
- Maximum size of a record: 350KB.
- Maximum size of a record identifier: 2KB.
- Maximum size of a feature value: 350KB.
- Maximum number of concurrent feature group creation workflows: 4.
- BatchGetRecord API: Can contain as many as 100 records and can query up to 10 feature groups.

Naming Rules

- Reserved Words: The following are reserved words and cannot be used as feature names in feature definitions: is_deleted, write_time, and api_invocation_time.
Data Types

- **String Feature Type**: Strings are Unicode with UTF-8 binary encoding. The minimum length of a string can be zero, the maximum length is constrained by the maximum size of a record.

- **Fractional Feature Type**: Fractional feature values must conform to a double precision floating point number as defined by the IEEE 754 standard.

- **Integral Feature Type**: Feature Store supports integral values in the range of a 64-bit signed integer. Minimum value of \(-2^{63}\) and a maximum value: \(2^{63} - 1\).

- **Event Time Features**: All feature groups have an event time feature. The feature can have a feature type of either String or Fractional. A string event time is accepted in ISO-8601 format, in UTC time, conforming to the pattern(s): [yyyy-MM-dd'T'HH:mm:ssZ, yyyy-MM-ddTH:mm:ss.SSSZ]. A fractional event time value is accepted as seconds from unix epoch, with millisecond precision. Event times must be in the range of \([0000-01-01T00:00:00.000Z, 9999-12-31T23:59:59.999Z]\).

Amazon SageMaker Feature Store Offline Store

Amazon SageMaker Feature Store offline store data is stored in an Amazon S3 bucket within your account. When you call `PutRecord`, your data is buffered, batched, and written into Amazon S3 within 15 minutes. Feature Store only supports the Parquet file format. Specifically, when your data is written to your offline store, the data can only be retrieved from your Amazon S3 bucket in Parquet format. Each file can contain multiple Records.

Files are organized with the following naming convention:

```
```

Records in the offline store are partitioned by event time into hourly partitions as shown in the preceding example. The partitioning scheme is not configurable. The following code shows an example of a Parquet file:

```
s3://my-bucket/my-prefix/123456789012/sagemaker/us-east-1/offline-store/customer-purchase-history-patterns-1593511200/data/year=2020/month=06/day=31/hour=00/20200631T064401Z_108934320012Az11.parquet
```

Feature Store also exposes the `OfflineStoreConfig.S3StorageConfig.ResolvedOutputS3Uri` field, which can be found from in the `DescribeFeatureGroup` API call. This is the S3 path under which the files for the specific feature group are written.

Example value of `ResolvedOutputS3Uri`:

```
```

The following additional fields are added by Feature Store to each Record when they persist in the offline store:

- **api_invocation_time** – The timestamp when the service receives the `PutRecord` or `DeleteRecord` call. If using managed ingestion (e.g. Data Wrangler), this is the timestamp when data was written into the offline store.
Amazon SageMaker Developer Guide
Amazon SageMaker Feature Store Notebook Examples

- **write_time** – The timestamp when data was written into the offline store. Can be used for constructing time-travel related queries.
- **is_deleted** – False by default. If `DeleteRecord` is called, a new `Record` is inserted into `RecordIdentifierValue` and set to `True` in the offline store.

Amazon SageMaker Feature Store Notebook Examples

To get started using Amazon SageMaker Feature Store, you can choose from a variety of example Jupyter notebooks in the table below. If this is your first time using Feature Store, try out the Introduction to Feature Store notebook. To run any these notebooks, you must attach this policy to your IAM execution role: `AmazonSageMakerFeatureStoreAccess`.

See [IAM Roles](#) to access your role and attach this policy. For a walkthrough see [Adding policies to your IAM role](#). The following screenshot illustrates how the policy appears under your IAM role after it has been attached.

### Feature Store sample notebooks

The following table outlines a variety of sample notebooks that address different use cases of Amazon SageMaker Feature Store.

<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Description</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Introduction to Feature Store</td>
<td>An introduction to key Feature Store capabilities such as how to create, configure a feature group, and how to ingest data into an online or offline feature store.</td>
<td></td>
</tr>
<tr>
<td>Fraud Detection with Feature Store</td>
<td>An advanced example on how to train a fraud detection model by ingesting data into a Feature Store, querying it to form a training dataset, and how to train a simple model for inference.</td>
<td></td>
</tr>
<tr>
<td>Encrypt Data in your Online or Offline Feature Store using KMS key</td>
<td>An advanced example on how to encrypt and decrypt data in an Online or Offline Feature Store using KMS key and how to verify that your data is encrypted. Note that this notebook tackles encryption at rest.</td>
<td></td>
</tr>
<tr>
<td>Notebook Title</td>
<td>Description</td>
<td></td>
</tr>
<tr>
<td>-----------------------------------------------------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td><strong>Client-side Encryption with Feature Store using AWS Encryption SDK</strong></td>
<td>An advanced example how to do client-side encryption with Feature Store using the <em>AWS Encryption SDK library</em> which encrypts your data prior to ingesting it into your Online or Offline Feature Store.</td>
<td></td>
</tr>
<tr>
<td><strong>How to securely store an image dataset in Feature Store with KMS key?</strong></td>
<td>An advanced example that demonstrates how to securely store a dataset of images into your Feature Store using KMS key for server-side encryption.</td>
<td></td>
</tr>
<tr>
<td><strong>Create a machine learning workflow from a Ground Truth classification labelling job to Feature Store</strong></td>
<td>A machine learning (ML) workflow that demonstrates how to feed the output of an image or text classification labelling job from AWS Ground Truth to Feature Store.</td>
<td></td>
</tr>
</tbody>
</table>
Train Models

For an overview on training models with Amazon SageMaker, see Train a Model with Amazon SageMaker (p. 9).

SageMaker provides features to monitor and manage the training and validation of machine learning models. For guidance on metrics available, incremental training, automatic model tuning, and the use of augmented manifest files to label training data, see the following topics.

- For guidance on choosing a machine learning algorithm and its implementation for your task or problem, see Choose an Algorithm (p. 1092).
- For guidance on debugging and profiling the training of machine learning models, see Debug and Profile Training Jobs Using Amazon SageMaker Debugger (p. 2258).
- For guidance on distributed training of deep learning models, see Amazon SageMaker Distributed Training Libraries (p. 2466).
- For guidance on compiling and training deep learning models, see Amazon SageMaker Training Compiler (p. 2575).
- For guidance on metrics used to monitor and train models, see Monitor and Analyze Training Jobs Using Amazon CloudWatch Metrics (p. 2704).
- For guidance on metrics used to detect model post-processing bias, see Detect Posttraining Data and Model Bias with Amazon SageMaker Clarify (p. 2630).
- For guidance on model explainability, see Amazon SageMaker Clarify Model Explainability (p. 2652).
- For guidance on incremental training in SageMaker, see Incremental Training in Amazon SageMaker (p. 2677).
- For guidance on using managed spot training in SageMaker, see Managed Spot Training in Amazon SageMaker (p. 2695).
- For guidance on using training checkpoints in SageMaker, see Use Checkpoints in Amazon SageMaker (p. 2696).
- For guidance on automatic model tuning, also known as hyperparameter tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).
- For guidance on using an augmented manifest file to label training data, see Provide Dataset Metadata to Training Jobs with an Augmented Manifest File (p. 2700).

Topics

- Choose an Algorithm (p. 1092)
- Manage Machine Learning with Amazon SageMaker Experiments (p. 2231)
- Debug and Profile Training Jobs Using Amazon SageMaker Debugger (p. 2258)
- Perform Automatic Model Tuning with SageMaker (p. 2436)
- Amazon SageMaker Distributed Training Libraries (p. 2466)
- Amazon SageMaker Training Compiler (p. 2575)
- Amazon SageMaker Clarify Bias Detection and Model Explainability (p. 2616)
- Train Using a Heterogeneous Cluster (p. 2662)
- Train Using SageMaker Managed Warm Pools (p. 2671)
- Incremental Training in Amazon SageMaker (p. 2677)
- Amazon SageMaker Training Storage Folders for Training Datasets, Checkpoints, Model Artifacts, and Outputs (p. 2682)
Choose an Algorithm

Machine learning can help you accomplish empirical tasks that require some sort of inductive inference. This task involves induction as it uses data to train algorithms to make generalizable inferences. This means that the algorithms can make statistically reliable predictions or decisions, or complete other tasks when applied to new data that was not used to train them.

To help you select the best algorithm for your task, we classify these tasks on various levels of abstraction. At the highest level of abstraction, machine learning attempts to find patterns or relationships between features or less structured items, such as text in a data set. Pattern recognition techniques can be classified into distinct machine learning paradigms, each of which address specific problem types. There are currently three basic paradigms for machine learning used to address various problem types:

- Supervised learning (p. 1095)
- Unsupervised learning (p. 1095)
- Reinforcement learning (p. 1096)

The types of problems that each learning paradigm can address are identified by considering the inferences (or predictions, decisions, or other tasks) you want to make from the type of data that you have or could collect. Machine learning paradigms use algorithmic methods to address their various problem types. The algorithms provide recipes for solving these problems.

However, many algorithms, such as neural networks, can be deployed with different learning paradigms and on different types of problems. Multiple algorithms can also address a specific problem type. Some algorithms are more generally applicable and others are quite specific for certain kinds of objectives and data. So the mapping between machine learning algorithms and problem types is many-to-many. Also, there are various implementation options available for algorithms.

The following sections provide guidance concerning implementation options, machine learning paradigms, and algorithms appropriate for different problem types.

Topics
- Choose an algorithm implementation (p. 1092)
- Problem types for the basic machine learning paradigms (p. 1094)
- Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096)
- Use Reinforcement Learning with Amazon SageMaker (p. 2225)

Choose an algorithm implementation

After choosing an algorithm, you must decide which implementation of it you want to use. Amazon SageMaker supports three implementation options that require increasing levels of effort.

- Pre-trained models require the least effort and are models ready to deploy or to fine-tune and deploy using SageMaker JumpStart.
• **Built-in algorithms** require more effort and scale if the data set is large and significant resources are needed to train and deploy the model.

• If there is no built-in solution that works, try to develop one that uses **pre-made images for machine and deep learning frameworks** for supported frameworks such as Scikit-Learn, TensorFlow, PyTorch, MXNet, or Chainer.

• If you need to run custom packages or use any code which isn’t a part of a supported framework or available via PyPi, then you need to build your own custom **Docker image** that is configured to install the necessary packages or software. The custom image must also be pushed to an online repository like the Amazon Elastic Container Registry.

**Topics**
- Use a built-in algorithm (p. 1093)
- Use script mode in a supported framework (p. 1094)
- Use a custom Docker image (p. 1094)

**Algorithm implementation guidance**

<table>
<thead>
<tr>
<th>Implementation</th>
<th>Requires code</th>
<th>Pre-coded algorithms</th>
<th>Support for third party packages</th>
<th>Support for custom code</th>
<th>Level of effort</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built-in</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Low</td>
</tr>
<tr>
<td>Scikit-learn</td>
<td>Yes</td>
<td>Yes</td>
<td>PyPi only</td>
<td>Yes</td>
<td>Medium</td>
</tr>
<tr>
<td>Spark ML</td>
<td>Yes</td>
<td>Yes</td>
<td>PyPi only</td>
<td>Yes</td>
<td>Medium</td>
</tr>
<tr>
<td>XGBoost (open source)</td>
<td>Yes</td>
<td>Yes</td>
<td>PyPi only</td>
<td>Yes</td>
<td>Medium</td>
</tr>
<tr>
<td>TensorFlow</td>
<td>Yes</td>
<td>No</td>
<td>PyPi only</td>
<td>Yes</td>
<td>Medium-high</td>
</tr>
<tr>
<td>PyTorch</td>
<td>Yes</td>
<td>No</td>
<td>PyPi only</td>
<td>Yes</td>
<td>Medium-high</td>
</tr>
<tr>
<td>MXNet</td>
<td>Yes</td>
<td>No</td>
<td>PyPi only</td>
<td>Yes</td>
<td>Medium-high</td>
</tr>
<tr>
<td>Chainer</td>
<td>Yes</td>
<td>No</td>
<td>PyPi only</td>
<td>Yes</td>
<td>Medium-high</td>
</tr>
<tr>
<td>Custom image</td>
<td>Yes</td>
<td>No</td>
<td>Yes, from any source</td>
<td>Yes</td>
<td>High</td>
</tr>
</tbody>
</table>

**Use a built-in algorithm**

When choosing an algorithm for your type of problem and data, the easiest option is to use one of Amazon SageMaker’s built-in algorithms. These built-in algorithms come with two major benefits.

• The built-in algorithms require no coding to start running experiments. The only inputs you need to provide are the data, hyperparameters, and compute resources. This allows you to run experiments more quickly, with less overhead for tracking results and code changes.

• The built-in algorithms come with parallelization across multiple compute instances and GPU support right out of the box for all applicable algorithms (some algorithms may not be included due to inherent limitations). If you have a lot of data with which to train your model, most built-in algorithms can easily scale to meet the demand. Even if you already have a pre-trained model, it may still be easier to use its corollary in SageMaker and input the hyper-parameters you already know than to port it over, using script mode on a supported framework.
For more information on the built-in algorithms provided by SageMaker, see **Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096)**.

For important information about docker registry paths, data formats, recommended EC2 instance types, and CloudWatch logs common to all of the built-in algorithms provided by SageMaker, see **Common Information About Built-in Algorithms (p. 1102)**.

**Use script mode in a supported framework**

If the algorithm you want to use for your model is not supported by a built-in choice and you are comfortable coding your own solution, then you should consider using an Amazon SageMaker supported framework. This is referred to as "script mode" because you write your custom code (script) in a text file with a .py extension. As the table above indicates, SageMaker supports most of the popular machine learning frameworks. These frameworks come preloaded with the corresponding framework and some additional Python packages, such as Pandas and NumPy, so you can write your own code for training an algorithm. These frameworks also allow you to install any Python package hosted on PyPi by including a requirements.txt file with your training code or to include your own code directories. R is also supported natively in SageMaker notebook kernels. Some frameworks, like scikit-learn and Spark ML, have pre-coded algorithms you can use easily, while other frameworks like TensorFlow and PyTorch may require you to implement the algorithm yourself. The only limitation when using a supported framework image is that you cannot import any software packages that are not hosted on PyPi or that are not already included with the framework’s image.

For more information on the frameworks supported by SageMaker, see **Use Machine Learning Frameworks, Python, and R with Amazon SageMaker (p. 13)**.

**Use a custom Docker image**

Amazon SageMaker’s built-in algorithms and supported frameworks should cover most use cases, but there are times when you may need to use an algorithm from a package not included in any of the supported frameworks. You might also have a pre-trained model picked or persisted somewhere which you need to deploy. SageMaker uses Docker images to host the training and serving of all models, so you can supply your own custom Docker image if the package or software you need is not included in a supported framework. This may be your own Python package or an algorithm coded in a language like Stan or Julia. For these images you must also configure the training of the algorithm and serving of the model properly in your Dockerfile. This requires intermediate knowledge of Docker and is not recommended unless you are comfortable writing your own machine learning algorithm. Your Docker image must be uploaded to an online repository, such as the Amazon Elastic Container Registry (ECR) before you can train and serve your model properly.

For more information on custom Docker images in SageMaker, see **Using Docker containers with SageMaker (p. 3149)**.

**Problem types for the basic machine learning paradigms**

The following three sections describe the main problem types addressed by the three basic paradigms for machine learning. For a list of the built-in algorithms that SageMaker provides to address these problem types, see **Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096)**.

**Topics**
- Supervised learning (p. 1095)
- Unsupervised learning (p. 1095)
- Reinforcement learning (p. 1096)
Supervised learning

If your data set consists of features or attributes (inputs) that contain target values (outputs), then you have a supervised learning problem. If your target values are categorical (mathematically discrete), then you have a classification problem. It is a standard practice to distinguish binary from multiclass classification.

- **Binary classification** is a type of supervised learning that assigns an individual to one of two predefined and mutually exclusive classes based on the individual's attributes. It is supervised because the models are trained using examples in which the attributes are provided with correctly labeled objects. A medical diagnosis for whether an individual has a disease or not based on the results of diagnostic tests is an example of binary classification.

- **Multiclass classification** is a type of supervised learning that assigns an individual to one of several classes based on the individual's attributes. It is supervised because the models are trained using examples in which the attributes are provided with correctly labeled objects. An example is the prediction of the topic most relevant to a text document. A document may be classified as being about religion, politics, or finance, or as about one of several other predefined topic classes.

If the target values you are trying to predict are mathematically continuous, then you have a regression problem. Regression estimates the values of a dependent target variable based on one or more other variables or attributes that are correlated with it. An example is the prediction of house prices using features like the number of bathrooms and bedrooms and the square footage of the house and garden. Regression analysis can create a model that takes one or more of these features as an input and predicts the price of a house.

For more information on the built-in supervised learning algorithms provided by SageMaker, see Supervised Learning (p. 1100).

Unsupervised learning

If your data set consists of features or attributes (inputs) that do not contain labels or target values (outputs), then you have an unsupervised learning problem. In this type of problem, the output must be predicted based on the pattern discovered in the input data. The goal in unsupervised learning problems is to discover patterns such as groupings within the data. There are a large variety of tasks or problem types to which unsupervised learning can be applied. Principal component and cluster analyses are two of the main methods commonly deployed for preprocessing data. Here is a short list of problem types that can be addressed by unsupervised learning:

- **Dimension reduction** is typically part of a data exploration step used to determine the most relevant features to use for model construction. The idea is to transform data from a high-dimensional, sparsely populated space into a low-dimensional space that retains most significant properties of the original data. This provides relief for the curse of dimensionality that can arise with sparsely populated, high-dimensional data on which statistical analysis becomes problematic. It can also be used to help understand data, reducing high-dimensional data to a lower dimensionality that can be visualized.

- **Cluster analysis** is a class of techniques that are used to classify objects or cases into groups called clusters. It attempts to find discrete groupings within data, where members of a group are as similar as possible to one another and as different as possible from members of other groups. You define the features or attributes that you want the algorithm to use to determine similarity, select a distance function to measure similarity, and specify the number of clusters to use in the analysis.

- **Anomaly detection** is the identification of rare items, events, or observations in a data set which raise suspicions because they differ significantly from the rest of the data. The identification of anomalous items can be used, for example, to detect bank fraud or medical errors. Anomalies are also referred to as outliers, novelties, noise, deviations, and exceptions.

- **Density estimation** is the construction of estimates of unobservable underlying probability density functions based on observed data. A natural use of density estimates is for data exploration. Density
estimates can discover features such as skewness and multimodality in the data. The most basic form of density estimation is a rescaled histogram.

SageMaker provides several built-in machine learning algorithms that you can use for these unsupervised learning tasks. For more information on the built-in unsupervised algorithms provided by SageMaker, see Unsupervised Learning (p. 1101).

Reinforcement learning

Reinforcement learning is a type of learning that is based on interaction with the environment. This type of learning is used by an agent that must learn behavior through trial-and-error interactions with a dynamic environment in which the goal is to maximize the long-term rewards that the agent receives as a result of its actions. Rewards are maximized by trading off exploring actions that have uncertain rewards with exploiting actions that have known rewards.

For more information on SageMaker’s frameworks, toolkits, and environments for reinforcement learning, see Use Reinforcement Learning with Amazon SageMaker (p. 2225).

Use Amazon SageMaker Built-in Algorithms or Pre-trained Models

Amazon SageMaker provides a suite of built-in algorithms, pre-trained models, and pre-built solution templates to help data scientists and machine learning practitioners get started on training and deploying machine learning models quickly. For someone who is new to SageMaker, choosing the right algorithm for your particular use case can be a challenging task. The following table provides a quick cheat sheet that shows how you can start with an example problem or use case and find an appropriate built-in algorithm offered by SageMaker that is valid for that problem type. Additional guidance organized by learning paradigms (supervised and unsupervised) and important data domains (text and images) is provided in the sections following the table.

Table: Mapping use cases to built-in algorithms

<table>
<thead>
<tr>
<th>Example problems and use cases</th>
<th>Learning paradigm or domain</th>
<th>Problem types</th>
<th>Data input format</th>
<th>Built-in algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Here a few examples out of the 15 problem types that can be addressed by the pre-trained models and pre-built solution templates provided by SageMaker JumpStart:</td>
<td>Pre-trained models and pre-built solution templates</td>
<td>Image Classification</td>
<td>Image, Text, Tabular</td>
<td>Popular models, including Mobilenet, YOLO, Faster R-CNN, BERT, lightGBM, and CatBoost</td>
</tr>
<tr>
<td>Question answering: chatbot that outputs an answer for a given question.</td>
<td>Tabular Classification</td>
<td>Tabular Regression</td>
<td>For a list of pre-trained models available, see JumpStart Models.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Text Classification</td>
<td>Object Detection</td>
<td>For a list of pre-built solution templates available, see JumpStart Solutions.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Text Embedding</td>
<td>Sentence Pair Classification</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Question Answering</td>
<td>Image Embedding</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Example problems and use cases</td>
<td>Learning paradigm or domain</td>
<td>Problem types</td>
<td>Data input format</td>
<td>Built-in algorithms</td>
</tr>
<tr>
<td>--------------------------------</td>
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<td>---------------------</td>
</tr>
<tr>
<td>Text analysis: analyze texts from models specific to an industry domain such as finance.</td>
<td></td>
<td>Named Entity Recognition</td>
<td>Tabular</td>
<td>AutoGluon-Tabular (p. 1971), CatBoost (p. 1978), Factorization Machines Algorithm (p. 1986), K-Nearest Neighbors (k-NN) Algorithm (p. 1996), LightGBM (p. 2005), Linear Learner Algorithm (p. 2014), TabTransformer (p. 2031), XGBoost Algorithm (p. 2038)</td>
</tr>
<tr>
<td>Predict if an item belongs to a category: an email spam filter</td>
<td><strong>Supervised Learning</strong> (p. 1100)</td>
<td>Binary/multi-class classification</td>
<td>Tabular</td>
<td>AutoGluon-Tabular (p. 1971), CatBoost (p. 1978), Factorization Machines Algorithm (p. 1986), K-Nearest Neighbors (k-NN) Algorithm (p. 1996), LightGBM (p. 2005), Linear Learner Algorithm (p. 2014), TabTransformer (p. 2031), XGBoost Algorithm (p. 2038)</td>
</tr>
<tr>
<td>Example problems and use cases</td>
<td>Learning paradigm or domain</td>
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</tr>
<tr>
<td>Based on historical data for a behavior, predict future behavior: predict sales on a new product based on previous sales data.</td>
<td>Time-series forecasting</td>
<td>Tabular</td>
<td>DeepAR Forecasting Algorithm (p. 2126)</td>
<td></td>
</tr>
<tr>
<td>Improve the data embeddings of the high-dimensional objects: identify duplicate support tickets or find the correct routing based on similarity of text in the tickets</td>
<td>Embeddings: convert high-dimensional objects into low-dimensional space.</td>
<td>Tabular</td>
<td>Object2Vec Algorithm (p. 2087)</td>
<td></td>
</tr>
<tr>
<td>Drop those columns from a dataset that have a weak relation with the label/target variable: the color of a car when predicting its mileage.</td>
<td>Feature engineering: dimensionality reduction</td>
<td>Tabular</td>
<td>Principal Component Analysis (PCA) Algorithm (p. 2159)</td>
<td></td>
</tr>
<tr>
<td>Detect abnormal behavior in application: spot when an IoT sensor is sending abnormal readings</td>
<td>Anomaly detection</td>
<td>Tabular</td>
<td>Random Cut Forest (RCF) Algorithm (p. 2163)</td>
<td></td>
</tr>
<tr>
<td>Protect your application from suspicious users: detect if an IP address accessing a service might be from a bad actor</td>
<td>IP anomaly detection</td>
<td>Tabular</td>
<td>IP Insights (p. 2142)</td>
<td></td>
</tr>
<tr>
<td>Group similar objects/data together: find high-, medium-, and low-spending customers from their transaction histories</td>
<td>Clustering or grouping</td>
<td>Tabular</td>
<td>K-Means Algorithm (p. 2151)</td>
<td></td>
</tr>
<tr>
<td>Example problems and use cases</td>
<td>Learning paradigm or domain</td>
<td>Problem types</td>
<td>Data input format</td>
<td>Built-in algorithms</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>----------------------------</td>
<td>---------------</td>
<td>-------------------</td>
<td>---------------------</td>
</tr>
<tr>
<td>Organize a set of documents into topics (not known in advance): tag a document as belonging to a medical category based on the terms used in the document.</td>
<td></td>
<td>Topic modeling</td>
<td>Text</td>
<td>Latent Dirichlet Allocation (LDA) Algorithm (p. 2076), Neural Topic Model (NTM) Algorithm (p. 2081)</td>
</tr>
<tr>
<td>Assign predefined categories to documents in a corpus: categorize books in a library into academic disciplines</td>
<td>Textual Analysis (p. 1101)</td>
<td>Text classification</td>
<td>Text</td>
<td>BlazingText algorithm (p. 2066), Text Classification - TensorFlow (p. 2116)</td>
</tr>
<tr>
<td>Convert text from one language to other: Spanish to English</td>
<td>Machine translation algorithm</td>
<td>Machine translation algorithm</td>
<td>Text</td>
<td>Sequence-to-Sequence Algorithm (p. 2103)</td>
</tr>
<tr>
<td>Summarize a long text corpus: an abstract for a research paper</td>
<td>Text summarization</td>
<td>Text summarization</td>
<td>Text</td>
<td>Sequence-to-Sequence Algorithm (p. 2103)</td>
</tr>
<tr>
<td>Convert audio files to text: transcribe call center conversations for further analysis</td>
<td>Speech-to-text</td>
<td>Speech-to-text</td>
<td>Text</td>
<td>Sequence-to-Sequence Algorithm (p. 2103)</td>
</tr>
<tr>
<td>Label/tag an image based on the content of the image: alerts about adult content in an image</td>
<td>Image Processing (p. 1102)</td>
<td>Image and multi-label classification</td>
<td>Image</td>
<td>Image Classification - MXNet (p. 2172)</td>
</tr>
<tr>
<td>Classify something in an image using transfer learning.</td>
<td>Image classification</td>
<td>Image classification</td>
<td>Image</td>
<td>Image Classification - TensorFlow (p. 2183)</td>
</tr>
<tr>
<td>Detect people and objects in an image: police review a large photo gallery for a missing person</td>
<td>Object detection and classification</td>
<td>Object detection and classification</td>
<td>Image</td>
<td>Object Detection - MXNet (p. 2196), Object Detection - TensorFlow (p. 2207)</td>
</tr>
</tbody>
</table>
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Example problems and use cases</th>
<th>Learning paradigm or domain</th>
<th>Problem types</th>
<th>Data input format</th>
<th>Built-in algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tag every pixel of an image individually with a category: self-driving cars prepare to identify objects in their way</td>
<td>Computer vision</td>
<td>Image</td>
<td>Semantic Segmentation Algorithm (p. 2215)</td>
<td></td>
</tr>
</tbody>
</table>

For important information about Docker registry paths, data formats, recommenced Amazon EC2 instance types, and CloudWatch logs common to all of the built-in algorithms provided by SageMaker, see Common Information About Built-in Algorithms (p. 1102).

The following sections provide additional guidance for the Amazon SageMaker built-in algorithms grouped by the supervised and unsupervised learning paradigms to which they belong. For descriptions of these learning paradigms and their associated problem types, see Choose an Algorithm (p. 1092). Sections are also provided for the SageMaker built-in algorithms available to address two important machine learning domains: textual analysis and image processing.

- Pre-trained Models and Solution Templates (p. 1100)
- Supervised Learning (p. 1100)
- Unsupervised Learning (p. 1101)
- Textual Analysis (p. 1101)
- Image Processing (p. 1102)

Pre-trained Models and Solution Templates

SageMaker JumpStart provides a wide range of pre-trained models, pre-built solution templates, and examples for popular problem types that use the SageMaker SDK as well as Studio. For more information about these models, solutions, and the example notebooks provided by SageMaker JumpStart, see SageMaker JumpStart (p. 45).

Supervised Learning

Amazon SageMaker provides several built-in general purpose algorithms that can be used for either classification or regression problems.

- AutoGluon-Tabular (p. 1971)—an open-source AutoML framework that succeeds by ensembling models and stacking them in multiple layers.
- CatBoost (p. 1978)—an implementation of the gradient-boosted trees algorithm that introduces ordered boosting and an innovative algorithm for processing categorical features.
- Factorization Machines Algorithm (p. 1986)—an extension of a linear model that is designed to economically capture interactions between features within high-dimensional sparse datasets.
- K-Nearest Neighbors (k-NN) Algorithm (p. 1996)—a non-parametric method that uses the k nearest labeled points to assign a label to a new data point for classification or a predicted target value from the average of the k nearest points for regression.
- LightGBM (p. 2005)—an implementation of the gradient-boosted trees algorithm that adds two novel techniques for improved efficiency and scalability: Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB).
• **Linear Learner Algorithm** (p. 2014)—learns a linear function for regression or a linear threshold function for classification.

• **TabTransformer** (p. 2031)—a novel deep tabular data modeling architecture built on self-attention-based Transformers.

• **XGBoost Algorithm** (p. 2038)—an implementation of the gradient-boosted trees algorithm that combines an ensemble of estimates from a set of simpler and weaker models.

Amazon SageMaker also provides several built-in supervised learning algorithms that are used for more specialized tasks during feature engineering and forecasting from time series data.

• **Object2Vec Algorithm** (p. 2087)—a new highly customizable multi-purpose algorithm used for feature engineering. It can learn low-dimensional dense embeddings of high-dimensional objects to produce features that improve training efficiencies for downstream models. While this is a supervised algorithm, as it requires labeled data for training, there are many scenarios in which the relationship labels can be obtained purely from natural clusterings in data, without any explicit human annotation.

• **DeepAR Forecasting Algorithm** (p. 2126)—a supervised learning algorithm for forecasting scalar (one-dimensional) time series using recurrent neural networks (RNN).

### Unsupervised Learning

Amazon SageMaker provides several built-in algorithms that can be used for a variety of unsupervised learning tasks such as clustering, dimension reduction, pattern recognition, and anomaly detection.

• **Principal Component Analysis (PCA) Algorithm** (p. 2159)—reduces the dimensionality (number of features) within a dataset by projecting data points onto the first few principal components. The objective is to retain as much information or variation as possible. For mathematicians, principal components are eigenvectors of the data's covariance matrix.

• **K-Means Algorithm** (p. 2151)—finds discrete groupings within data, where members of a group are as similar as possible to one another and as different as possible from members of other groups.

• **IP Insights** (p. 2142)—learns the usage patterns for IPv4 addresses. It is designed to capture associations between IPv4 addresses and various entities, such as user IDs or account numbers.

• **Random Cut Forest (RCF) Algorithm** (p. 2163)—detects anomalous data points within a data set that diverge from otherwise well-structured or patterned data.

### Textual Analysis

SageMaker provides algorithms that are tailored to the analysis of textual documents used in natural language processing, document classification or summarization, topic modeling or classification, and language transcription or translation.

• **BlazingText algorithm** (p. 2066)—a highly optimized implementation of the Word2vec and text classification algorithms that scale to large datasets easily. It is useful for many downstream natural language processing (NLP) tasks.

• **Sequence-to-Sequence Algorithm** (p. 2103)—a supervised algorithm commonly used for neural machine translation.

• **Latent Dirichlet Allocation (LDA) Algorithm** (p. 2076)—an algorithm suitable for determining topics in a set of documents. It is an *unsupervised algorithm*, which means that it doesn't use example data with answers during training.

• **Neural Topic Model (NTM) Algorithm** (p. 2081)—another unsupervised technique for determining topics in a set of documents, using a neural network approach.

• **Text Classification - TensorFlow** (p. 2116)—a supervised algorithm that supports transfer learning with available pretrained models for text classification.
Image Processing

SageMaker also provides image processing algorithms that are used for image classification, object detection, and computer vision.

- **Image Classification - MXNet (p. 2172)**—uses example data with answers (referred to as a *supervised algorithm*). Use this algorithm to classify images.
- **Image Classification - TensorFlow (p. 2183)**—uses pretrained TensorFlow Hub models to fine-tune for specific tasks (referred to as a *supervised algorithm*). Use this algorithm to classify images.
- **Semantic Segmentation Algorithm (p. 2215)**—provides a fine-grained, pixel-level approach to developing computer vision applications.
- **Object Detection - MXNet (p. 2196)**—detects and classifies objects in images using a single deep neural network. It is a supervised learning algorithm that takes images as input and identifies all instances of objects within the image scene.
- **Object Detection - TensorFlow (p. 2207)**—detects bounding boxes and object labels in an image. It is a supervised learning algorithm that supports transfer learning with available pretrained TensorFlow models.

Topics

- Common Information About Built-in Algorithms (p. 1102)
- Built-in SageMaker Algorithms for Text Data (p. 2065)
- Built-in SageMaker Algorithms for Time-Series Data (p. 2126)
- Unsupervised Built-in SageMaker Algorithms (p. 2141)
- Built-in SageMaker Algorithms for Computer Vision (p. 2171)

Common Information About Built-in Algorithms

The following table lists parameters for each of the algorithms provided by Amazon SageMaker.

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>AutoGluon-Tabular</td>
<td>training and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU or GPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>BlazingText</td>
<td>train</td>
<td>File or Pipe</td>
<td>Text file (one sentence per line with space-separated tokens)</td>
<td>CPU or GPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>CatBoost</td>
<td>training and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>DeepAR Forecasting</td>
<td>train and (optionally) test</td>
<td>File</td>
<td>JSON Lines or Parquet</td>
<td>CPU or GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Algorithm name</td>
<td>Channel name</td>
<td>Training input mode</td>
<td>File type</td>
<td>Instance class</td>
<td>Parallelizable</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------------------------</td>
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<td>---------------------------</td>
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<td>----------------</td>
</tr>
<tr>
<td>Factorization Machines</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf</td>
<td>CPU (GPU for dense data)</td>
<td>Yes</td>
</tr>
<tr>
<td>Image Classification - MXNet</td>
<td>train and validation, (optionally) train_lst, validation_lst, and model</td>
<td>File or Pipe</td>
<td>recordIO or image files (.jpg or .png)</td>
<td>GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Image Classification - TensorFlow</td>
<td>training and validation</td>
<td>File</td>
<td>image files (.jpg, jpeg, or .png)</td>
<td>CPU or GPU</td>
<td>Yes (only across multiple GPUs on a single instance)</td>
</tr>
<tr>
<td>IP Insights</td>
<td>train and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU or GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>K-Means</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU or GPU (single GPU device on one or more instances)</td>
<td>No</td>
</tr>
<tr>
<td>K-Nearest-Neighbors (k-NN)</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU or GPU (single GPU device on one or more instances)</td>
<td>Yes</td>
</tr>
<tr>
<td>LDA</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>LightGBM</td>
<td>training and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>Linear Learner</td>
<td>train and (optionally) validation, test, or both</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU or GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Neural Topic Model</td>
<td>train and (optionally) validation, test, or both</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU or GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Algorithm name</td>
<td>Channel name</td>
<td>Training input mode</td>
<td>File type</td>
<td>Instance class</td>
<td>Parallelizable</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>---------------------------------------------------</td>
<td>---------------------</td>
<td>-----------------------</td>
<td>------------------------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Object2Vec</td>
<td>train and (optionally) validation, test, or both</td>
<td>File</td>
<td>JSON Lines</td>
<td>CPU or GPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>Object Detection - MXNet</td>
<td>train and validation, (optionally) train_annotation, validation_annotation, and model</td>
<td>File or Pipe</td>
<td>recordIO or image files (.jpg or .png)</td>
<td>GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Object Detection - TensorFlow</td>
<td>training and validation</td>
<td>File</td>
<td>image files (.jpg, .jpeg, or .png)</td>
<td>GPU</td>
<td>Yes (only across multiple GPUs on a single instance)</td>
</tr>
<tr>
<td>PCA</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU or GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Random Cut Forest</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Semantic Segmentation</td>
<td>train and validation, train_annotation, validation_annotation, and (optionally) label_map and model</td>
<td>File or Pipe</td>
<td>Image files</td>
<td>GPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>Seq2Seq Modeling</td>
<td>train, validation, and vocab</td>
<td>File</td>
<td>recordIO-protobuf</td>
<td>GPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>TabTransformer</td>
<td>training and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU or GPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>Text Classification - TensorFlow</td>
<td>training and validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU or GPU</td>
<td>Yes (only across multiple GPUs on a single instance)</td>
</tr>
</tbody>
</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>XGBoost (0.90-1, 0.90-2, 1.0-1, 1.2-1, 1.2-2)</td>
<td>train and (optionally) validation</td>
<td>File or Pipe</td>
<td>CSV, LibSVM, or Parquet</td>
<td>CPU (or GPU for 1.2-1)</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Algorithms that are parallelizable can be deployed on multiple compute instances for distributed training.

The following topics provide information about Docker registry paths, data formats, recommended Amazon EC2 instance types, and CloudWatch logs common to all of the built-in algorithms provided by Amazon SageMaker.

**Topics**
- Docker Registry Paths and Example Code (p. 1105)
- Common Data Formats for Built-in Algorithms (p. 1959)
- Instance Types for Built-in Algorithms (p. 1968)
- Logs for Built-in Algorithms (p. 1969)

### Docker Registry Paths and Example Code

The following topics list the Docker registry path and other parameters for each of the Amazon SageMaker provided algorithms and Deep Learning Containers (DLC).

Use the path as follows:

- To create a training job (create_training_job), specify the Docker registry path (TrainingImage) and the training input mode (TrainingInputMode) for the training image. You create a training job to train a model using a specific dataset.
- To create a model (create_model), specify the Docker registry path (Image) for the inference image (PrimaryContainer Image). SageMaker launches machine learning compute instances that are based on the endpoint configuration and deploys the model, which includes the artifacts (the result of model training).

**Note**
For the registry path, use the :1 version tag to ensure that you are using a stable version of the algorithm/DLC. You can reliably host a model trained using an image with the :1 tag on an inference image that has the :1 tag. Using the :latest tag in the registry path provides you with the most up-to-date version of the algorithm/DLC, but might cause problems with backward compatibility. Avoid using the :latest tag for production purposes.

**Important**
When you retrieve the SageMaker XGBoost image URI, do not use :latest or :1 for the image URI tag. You must specify one of the Supported versions (p. 2039) to choose the SageMaker-managed XGBoost container with the native XGBoost package version that you want to use. To find the package version migrated into the SageMaker XGBoost containers, see Docker Registry Paths and Example Code, choose your AWS Region, and navigate to the XGBoost (algorithm) section.

To find the registry path, choose the AWS Region, then choose the algorithm or DLC.

**Topics**
Docker Registry Paths and Example Code for US East (Ohio) (us-east-2) (p. 1106)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics
- AutoGluon (algorithm) (p. 1107)
- BlazingText (algorithm) (p. 1108)
- Chainer (DLC) (p. 1109)
- Clarify (algorithm) (p. 1109)
- Data Wrangler (algorithm) (p. 1110)
- Debugger (algorithm) (p. 1110)
- DeepAR Forecasting (algorithm) (p. 1110)
- Factorization Machines (algorithm) (p. 1110)
- Hugging Face (algorithm) (p. 1111)
- IP Insights (algorithm) (p. 1114)
- Image classification (algorithm) (p. 1114)
- Inferentia MXNet (DLC) (p. 1114)
- Inferentia PyTorch (DLC) (p. 1115)
- K-Means (algorithm) (p. 1115)
- KNN (algorithm) (p. 1116)
Use Built-in Algorithms

- LDA (algorithm) (p. 1116)
- Linear Learner (algorithm) (p. 1116)
- MXNet (DLC) (p. 1117)
- MXNet Coach (DLC) (p. 1119)
- Model Monitor (algorithm) (p. 1120)
- NTM (algorithm) (p. 1120)
- Neo Image Classification (algorithm) (p. 1120)
- Neo MXNet (DLC) (p. 1121)
- Neo PyTorch (DLC) (p. 1121)
- Neo Tensorflow (DLC) (p. 1122)
- Neo XGBoost (algorithm) (p. 1122)
- Object Detection (algorithm) (p. 1123)
- Object2Vec (algorithm) (p. 1123)
- PCA (algorithm) (p. 1123)
- PyTorch (DLC) (p. 1123)
- Random Cut Forest (algorithm) (p. 1127)
- Ray PyTorch (DLC) (p. 1127)
- Scikit-learn (algorithm) (p. 1128)
- Semantic Segmentation (algorithm) (p. 1128)
- Seq2Seq (algorithm) (p. 1128)
- Spark (algorithm) (p. 1129)
- SparkML Serving (algorithm) (p. 1129)
- Tensorflow (DLC) (p. 1130)
- Tensorflow Coach (DLC) (p. 1138)
- Tensorflow Inferentia (DLC) (p. 1139)
- Tensorflow Ray (DLC) (p. 1139)
- VW (algorithm) (p. 1140)
- XGBoost (algorithm) (p. 1141)

**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='us-east-2',image_scope='inference',version='0.4')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>763104351884.dkr.ecr.us-east-2.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td>0.5.2</td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-east-2.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td>0.5.2</td>
<td>inference</td>
</tr>
<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
</tr>
<tr>
<td>-----------------------------------------------------------------------------</td>
<td>--------------</td>
<td>-------------------------</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.4.3 east-2.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td></td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.4.3 east-2.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.4.2 east-2.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td></td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.4.2 east-2.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.4.0 east-2.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td></td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.4.0 east-2.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.3.2 east-2.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td></td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.3.2 east-2.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.3.1 east-2.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td></td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-0.3.1 east-2.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

**BlazingText (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='blazingtext',region='us-east-2')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>825641698319.dkr.ecr.us-east-2.amazonaws.com/blazingtext:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Chainer (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='us-east-2',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>520713654638.dkr.ecr.us-east-2.amazonaws.com/sagemaker-chainer:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
<tr>
<td>520713654638.dkr.ecr.us-east-2.amazonaws.com/sagemaker-chainer:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
<tr>
<td>520713654638.dkr.ecr.us-east-2.amazonaws.com/sagemaker-chainer:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

**Clarify (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='us-east-2',version='1.0',image_scope='processing')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>211330385671.dkr.ecr.us-east-2.amazonaws.com/sagemaker-clarify-processing:&lt;tag&gt;</td>
<td></td>
<td>processing</td>
</tr>
</tbody>
</table>
**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>415677184552.dkr.ecr.us-east-2.amazonaws.com/sagemaker-data-wrangler-container:&lt;tag&gt;</td>
<td></td>
<td>processing</td>
</tr>
</tbody>
</table>

**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>915447279597.dkr.ecr.us-east-2.amazonaws.com/sagemaker-debugger-rules:&lt;tag&gt;</td>
<td></td>
<td>debugger</td>
</tr>
</tbody>
</table>

**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>566113047672.dkr.ecr.us-east-2.amazonaws.com/forecasting-deepar:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='us-east-2')
```
## Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<td>inference, training</td>
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</table>

### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='us-east-2', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```

<table>
<thead>
<tr>
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<tbody>
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<tr>
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763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-tensorflow-inference:tag | 4.10.2 | inference
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-tensorflow-inference:tag | 4.10.2 | inference
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-pytorch-training:tag | 4.6.1 | training
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-pytorch-training:tag | 4.6.1 | training
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-pytorch-training:tag | 4.6.1 | training
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-pytorch-training:tag | 4.6.1 | training
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-pytorch-inference:tag | 4.6.1 | inference
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-pytorch-inference:tag | 4.6.1 | inference
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-pytorch-training:tag | 4.5.0 | training
### Registry path | Version | Job types (image scope)
--- | --- | ---
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763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-pytorch-training:tag | 4.4.2 | training
763104351884.dkr.ecr.us-east-2.amazonaws.com/huggingface-tensorflow-training:tag | 4.4.2 | training

**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='us-east-2')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
404615174143.dkr.ecr.us-east-2.amazonaws.com/ipinsights:tag | 1 | inference, training

**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='us-east-2')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
825641698319.dkr.ecr.us-east-2.amazonaws.com/image-classification:tag | 1 | inference, training

**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet',region='us-east-2',version='1.5.1',instance_type='ml.inf1.6xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>007439368137.dkr.ecr.us-east-2.amazonaws.com/sagemaker-neo-mxnet:&lt;tag&gt;</td>
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<td>inference</td>
<td></td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='us-east-2',version='1.9',py_version='py3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
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<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='us-east-2')
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>404615174143.dkr.ecr.us-east-2.amazonaws.com/kmeans:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn',region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**LDA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda',region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
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</tbody>
</table>

**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner',region='us-east-2')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>inference, training</td>
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</tbody>
</table>
MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='us-east-2', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
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<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
</tbody>
</table>

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='us-east-2', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>520713654638.dkr.ecr.us-east-2.amazonaws.com/sagemaker-rl-mxnet:coach0.11.0-&lt;tag&gt;</td>
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<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

**Model Monitor (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>777275614652.dkr.ecr.us-east-2.amazonaws.com/sagemaker-model-monitor-analyzer:&lt;tag&gt;</td>
<td>monitoring</td>
<td></td>
</tr>
</tbody>
</table>

**NTM (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>404615174143.dkr.ecr.us-east-2.amazonaws.com/ntm:&lt;tag&gt;</td>
<td>inference, training</td>
<td></td>
</tr>
</tbody>
</table>

**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='us-east-2')
```
### Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet', region='us-east-2', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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<tbody>
<tr>
<td>007439368137.dkr.ecr.us-east-2.amazonaws.com/image-classification-neo:&lt;tag&gt;</td>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

### Neo PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='us-east-2', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</tbody>
</table>
### Registry path

<table>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

### Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='us-east-2',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tbody>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

### Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>
Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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</tr>
</tbody>
</table>

Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='us-east-2')
```

<table>
<thead>
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<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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<td>inference, training</td>
</tr>
</tbody>
</table>

PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca',region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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<td></td>
<td>inference, training</td>
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</tbody>
</table>

PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch',region='us-east-2',version='1.8.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
</tbody>
</table>
### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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<td>training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch', region='us-east-2', version='0.8.5', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td></td>
<td>training</td>
<td>CPU, GPU</td>
<td>py36</td>
</tr>
</tbody>
</table>
Scikit-learn (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='us-east-2',version='0.23-1',image_scope='inference')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
<th>Job types (image scope)</th>
</tr>
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<td></td>
<td>inference, training</td>
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</tbody>
</table>

Semantic Segmentation (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='us-east-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>825641698319.dkr.ecr.us-east-2.amazonaws.com/semantic-segmentation:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Seq2Seq (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='us-east-2')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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<td>2.2</td>
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</tbody>
</table>

**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='us-east-2', version='3.0', image_scope='processing')
```

**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='us-east-2', version='2.4')
```
**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='us-east-2',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
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### Use Built-in Algorithms

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**Tensorflow Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='us-east-2',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
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</tr>
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</table>
### Registry path

<table>
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<tr>
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<td>CPU, GPU</td>
<td>py3</td>
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</table>

### Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='us-east-2',version='1.15.0',instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
<td></td>
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</tbody>
</table>

### Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow',region='us-east-2',version='0.8.5',instance_type='ml.c5.4xlarge')
```
### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py3</td>
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</table>

### VW (algorithm)

**SageMaker Python SDK example to retrieve registry path.**

```python
from sagemaker import image_uris
tf = image_uris.retrieve(framework='vw', region='us-east-2', version='8.7.0', image_scope='training')
```
### Use Built-in Algorithms

**Registry path**  
**Version**  
**Job types (image scope)**

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
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<td>training</td>
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</table>

**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='us-east-2', version='1.5-1')
```

<table>
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<th>Package version</th>
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Docker Registry Paths and Example Code for US East (N. Virginia) (us-east-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

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- BlazingText (algorithm) (p. 1144)
- Chainer (DLC) (p. 1144)
- Clarify (algorithm) (p. 1145)
- Data Wrangler (algorithm) (p. 1145)
- Debugger (algorithm) (p. 1146)
- DeepAR Forecasting (algorithm) (p. 1146)
- Factorization Machines (algorithm) (p. 1146)
- Hugging Face (algorithm) (p. 1147)
- IP Insights (algorithm) (p. 1150)
- Image classification (algorithm) (p. 1150)
- Inferentia MXNet (DLC) (p. 1151)
- Inferentia PyTorch (DLC) (p. 1151)
- K-Means (algorithm) (p. 1152)
- KNN (algorithm) (p. 1152)
- LDA (algorithm) (p. 1152)
- Linear Learner (algorithm) (p. 1153)
- MXNet (DLC) (p. 1153)
- MXNet Coach (DLC) (p. 1156)
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- Neo Image Classification (algorithm) (p. 1157)
- Neo MXNet (DLC) (p. 1157)
- Neo PyTorch (DLC) (p. 1158)
- Neo Tensorflow (DLC) (p. 1159)
- Neo XGBoost (algorithm) (p. 1159)
- Object Detection (algorithm) (p. 1159)
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- Spark (algorithm) (p. 1166)
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- Tensorflow (DLC) (p. 1167)
- Tensorflow Coach (DLC) (p. 1175)
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AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='us-east-1',image_scope='inference',version='0.4')

# Output path
'763104351884.dkr.ecr.us-east-1.amazonaws.com/autogluon-inference:0.4-cpu-py38'
```

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<th>Job types (image scope)</th>
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</table>
### Using Built-in Algorithms

<table>
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<th>Job types (image scope)</th>
</tr>
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<td>0.3.1</td>
<td>inference</td>
</tr>
</tbody>
</table>

**BlazingText (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext',region='us-east-1')
# Output path
'811284229777.dkr.ecr.us-east-1.amazonaws.com/blazingtext:1'
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
<td>811284229777.dkr.ecr.us-east-1.amazonaws.com/blazingtext:</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Chainer (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='us-east-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
# Output path
```
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Processor types</th>
<th>Python versions</th>
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<td>py2, py3</td>
</tr>
<tr>
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<td>inference, training</td>
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<td></td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='us-east-1',version='1.0',image_scope='processing')

# Output path
'205585389593.dkr.ecr.us-east-1.amazonaws.com/sagemaker-clarify-processing:1.0'
```

Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='us-east-1')

# Output path
'663277389841.dkr.ecr.us-east-1.amazonaws.com/sagemaker-data-wrangler-container:1.x'
```
Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='us-east-1')
# Output path '503895931360.dkr.ecr.us-east-1.amazonaws.com/sagemaker-debugger-rules:latest'
```

DeepAR Forecasting (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='us-east-1')
# Output path '522234722520.dkr.ecr.us-east-1.amazonaws.com/forecasting-deepar:1'
```

Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='us-east-1')
# Output path '382416733822.dkr.ecr.us-east-1.amazonaws.com/factorization-machines:1'
```
## Use Built-in Algorithms

### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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</tbody>
</table>

### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='us-east-1', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
# Output path
'763104351884.dkr.ecr.us-east-1.amazonaws.com/huggingface-tensorflow-training:2.4.1-transformers4.4.2-gpu-py37'
```
<table>
<thead>
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<th>Registry path</th>
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</tbody>
</table>
### IP Insights (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='us-east-1')
# Output path
'382416733822.dkr.ecr.us-east-1.amazonaws.com/ipinsights:1'
```

<table>
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<th>Version</th>
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</table>

### Image classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='us-east-1')
# Output path
'811284229777.dkr.ecr.us-east-1.amazonaws.com/image-classification:1'
```

<table>
<thead>
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<th>Registry path</th>
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### Registry path

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### Inferentia MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='us-east-1', version='1.5.1', instance_type='ml.inf1.6xlarge')

# Output path
'78557368785.dkr.ecr.us-east-1.amazonaws.com/sagemaker-neo-mxnet:1.5.1-inf-py3'
```

### Inferentia PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='us-east-1', version='1.9', py_version='py3')

# Output path
'78557368785.dkr.ecr.us-east-1.amazonaws.com/sagemaker-neo-pytorch:1.9-inf-py3'
```
### K-Means (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='us-east-1')

# Output path
'382416733822.dkr.ecr.us-east-1.amazonaws.com/kmeans:1'
```

<table>
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### KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='us-east-1')

# Output path
'382416733822.dkr.ecr.us-east-1.amazonaws.com/knn:1'
```

<table>
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### LDA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='us-east-1')

# Output path
'766337827248.dkr.ecr.us-east-1.amazonaws.com/lda:1'
```

<table>
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### Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='us-east-1')
# Output path
'382416733822.dkr.ecr.us-east-1.amazonaws.com/linear-learner:1'
```

### MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='us-east-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
# Output path
'763104351884.dkr.ecr.us-east-1.amazonaws.com/mxnet-inference:1.4.1-cpu-py3'
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Use Built-in Algorithms

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<td>py2, py3</td>
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MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
device = 'cpu'
image_uris.retrieve(framework='coach-mxnet', region='us-east-1', version='0.11', image_scope='training', instance_type='ml.c5.4xlarge')
```

Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='us-east-1')
```
### NTM (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='us-east-1')
```

# Output path
'382416733822.dkr.ecr.us-east-1.amazonaws.com/ntm:1'

### Neo Image Classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='us-east-1')
```

# Output path
'78557368785.dkr.ecr.us-east-1.amazonaws.com/image-classification-neo:latest'

### Neo MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```

---

# Output path
'156813124566.dkr.ecr.us-east-1.amazonaws.com/sagemaker-model-monitor-analyzer'

<table>
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<th>Version</th>
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---
image.uris.retrieve(framework='neo-mxnet', region='us-east-1', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')

# Output path
'78557368785.dkr.ecr.us-east-1.amazonaws.com/sagemaker-inference-mxnet:1.8-cpu-py3'

<table>
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</table>

*Neo PyTorch (DLC)*

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image.uris
image.uris.retrieve(framework='neo-pytorch', region='us-east-1', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')

# Output path
'78557368785.dkr.ecr.us-east-1.amazonaws.com/sagemaker-inference-pytorch:1.6-cpu-py3'
```

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</table>

**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='us-east-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
# Output path
'78557368785.dkr.ecr.us-east-1.amazonaws.com/sagemaker-inference-tensorflow:1.15.3-cpu-py3'
```

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**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='us-east-1')
# Output path
'78557368785.dkr.ecr.us-east-1.amazonaws.com/xgboost-neo:latest'
```

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</table>

**Object Detection (algorithm)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='us-east-1')

# Output path
'811284229777.dkr.ecr.us-east-1.amazonaws.com/object-detection:1'

<table>
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<th>Version</th>
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Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='us-east-1')

# Output path
'382416733822.dkr.ecr.us-east-1.amazonaws.com/object2vec:1'

<table>
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PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='pca',region='us-east-1')

# Output path
'382416733822.dkr.ecr.us-east-1.amazonaws.com/pca:1'

<table>
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PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.
```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='us-east-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')

# Output path
'763104351884.dkr.ecr.us-east-1.amazonaws.com/pytorch-inference:1.8.0-cpu-py3'
```

<table>
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## Use Built-in Algorithms

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</table>

### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest',region='us-east-1')
# Output path
'382416733822.dkr.ecr.us-east-1.amazonaws.com/randomcutforest:1'
```

<table>
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<tr>
<th>Registry path</th>
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<td>inference, training</td>
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</table>

### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch',region='us-east-1',version='0.8.5',instance_type='ml.c5.4xlarge')
# Output path
'462105765813.dkr.ecr.us-east-1.amazonaws.com/sagemaker-rl-ray-container:ray-0.8.5-torch-cpu-py36'
```
### Use Built-in Algorithms

#### Registry path

<table>
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<tr>
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#### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='us-east-1',version='0.23-1',image_scope='inference')

# Output path
'683313688378.dkr.ecr.us-east-1.amazonaws.com/sagemaker-scikit-learn:0.23-1-cpu-py3'
```

<table>
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#### Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='us-east-1')

# Output path
'811284229777.dkr.ecr.us-east-1.amazonaws.com/semantic-segmentation:1'
```
### Registry path

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<td>inference, training</td>
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</table>

#### Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='us-east-1')
# Output path
'811284229777.dkr.ecr.us-east-1.amazonaws.com/seq2seq:1'
```

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#### Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='us-east-1', version='3.0', image_scope='processing')
# Output path
'173754725891.dkr.ecr.us-east-1.amazonaws.com/sagemaker-spark-processing:3.0-cpu'
```

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</table>
SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='us-east-1', version='2.4')
# Output path
'683313688378.dkr.ecr.us-east-1.amazonaws.com/sagemaker-sparkml-serving:2.4'
```

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Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='us-east-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
# Output path
'520713654638.dkr.ecr.us-east-1.amazonaws.com/sagemaker-tensorflow-serving:1.12.0-cpu'
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<td>CPU, GPU</td>
<td>py2</td>
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</tbody>
</table>

**Tensorflow Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='us-east-1',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```

# Output path
Use Built-in Algorithms

Registry path | Version | Job types (image scope) | Processor types | Python versions
--- | --- | --- | --- | ---
462105765813.dkr.ecr.us-east-1.amazonaws.com/sagemaker-rl-coach-container:coach-1.0.0-tf-<tag> | training | CPU, GPU | py3
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520713654638.dkr.ecr.us-east-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.11.0-<tag> | training | CPU, GPU | py3
520713654638.dkr.ecr.us-east-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.11-<tag> | training | CPU, GPU | py3
520713654638.dkr.ecr.us-east-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.10.1-<tag> | training | CPU, GPU | py3
520713654638.dkr.ecr.us-east-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.10-<tag> | training | CPU, GPU | py3

Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='us-east-1', version='1.15.0', instance_type='ml.inf1.6xlarge')

# Output path
'785573368785.dkr.ecr.us-east-1.amazonaws.com/sagemaker-neo-tensorflow:1.15.0-inf-py3'
```
### Registry path | Version | Job types (image scope) | Processor types | Python versions
--- | --- | --- | --- | ---
785573368785.dkr.ecr.us-east-1.amazonaws.com/sagemaker-neo-tensorflow:tag | inference | inf | py3
785573368785.dkr.ecr.us-east-1.amazonaws.com/sagemaker-neo-tensorflow:tag | inference | inf | py3

### Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='us-east-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

# Output path
`462105765813.dkr.ecr.us-east-1.amazonaws.com/sagemaker-rl-ray-container:ray-0.8.5-tf-cpu-py36`

<table>
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<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
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</table>

**VW (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='vw', region='us-east-1', version='8.7.0', image_scope='training')
```

# Output path
'462105765813.dkr.ecr.us-east-1.amazonaws.com/sagemaker-rl-vw-container:vw-8.7.0-cpu'

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<th>Package version</th>
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<td>8.7.0</td>
<td></td>
<td>training</td>
</tr>
</tbody>
</table>

**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='us-east-1', version='1.5-1')
```

# Output path
'683313688378.dkr.ecr.us-east-1.amazonaws.com/sagemaker-xgboost:1.5-1'

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## Docker Registry Paths and Example Code for US West (N. California) (us-west-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

### Topics

- AutoGluon (algorithm) (p. 1180)
- BlazingText (algorithm) (p. 1182)
- Chainer (DLC) (p. 1182)
- Clarify (algorithm) (p. 1182)
- Data Wrangler (algorithm) (p. 1183)
- Debugger (algorithm) (p. 1183)
- DeepAR Forecasting (algorithm) (p. 1183)
- Factorization Machines (algorithm) (p. 1184)
- Hugging Face (algorithm) (p. 1184)
- IP Insights (algorithm) (p. 1187)
- Image classification (algorithm) (p. 1187)
- Inferentia MXNet (DLC) (p. 1188)
- Inferentia PyTorch (DLC) (p. 1188)
- K-Means (algorithm) (p. 1189)
- KNN (algorithm) (p. 1189)
- LDA (algorithm) (p. 1189)
- Linear Learner (algorithm) (p. 1189)
- MXNet (DLC) (p. 1190)
- MXNet Coach (DLC) (p. 1193)
- Model Monitor (algorithm) (p. 1193)
- NTM (algorithm) (p. 1193)
- Neo Image Classification (algorithm) (p. 1194)
- Neo MXNet (DLC) (p. 1194)
- Neo PyTorch (DLC) (p. 1194)
- Neo Tensorflow (DLC) (p. 1195)
- Neo XGBoost (algorithm) (p. 1195)
- Object Detection (algorithm) (p. 1196)
- Object2Vec (algorithm) (p. 1196)
- PCA (algorithm) (p. 1196)
- PyTorch (DLC) (p. 1197)
- Random Cut Forest (algorithm) (p. 1200)
- Ray PyTorch (DLC) (p. 1200)
- Scikitlearn (algorithm) (p. 1201)
- Semantic Segmentation (algorithm) (p. 1201)
- Seq2Seq (algorithm) (p. 1201)
- Spark (algorithm) (p. 1202)
- SparkML Serving (algorithm) (p. 1202)
- Tensorflow (DLC) (p. 1203)
- Tensorflow Coach (DLC) (p. 1211)
- Tensorflow Inferentia (DLC) (p. 1212)
- Tensorflow Ray (DLC) (p. 1212)
- VW (algorithm) (p. 1213)
- XGBoost (algorithm) (p. 1214)

**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='us-west-1', image_scope='inference', version='0.4')
```

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</table>
BlazingText (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='us-west-1')
```

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Chainer (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='us-west-1', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
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<th>Processor types</th>
<th>Python versions</th>
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</table>

Clarify (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify', region='us-west-1', version='1.0', image_scope='processing')
```

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<th>Version</th>
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Use Built-in Algorithms

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<tbody>
<tr>
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</table>

**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='us-west-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>

**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='debugger',region='us-west-1')
```

<table>
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<th>Registry path</th>
<th>Version</th>
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**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar',region='us-west-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
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<tbody>
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</table>
### Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='us-west-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
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### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='us-west-1', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```

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</table>

**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='us-west-1')
```

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**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='us-west-1')
```
### Use Built-in Algorithms

#### Registry path

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#### Inferentia MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='us-west-1', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

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#### Inferentia PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='us-west-1', version='1.9', py_version='py3')
```

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K-Means (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='us-west-1')
```

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KNN (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='us-west-1')
```

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</tbody>
</table>

LDA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='us-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>inference, training</td>
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</tbody>
</table>

Linear Learner (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='us-west-1')
```
Use Built-in Algorithms

Registry path | Version | Job types (image scope) |
---|---|---|
632365934929.dkr.ecr.us-west-1.amazonaws.com/linear-learner:<tag> | | inference, training |

**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='us-west-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
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<td>CPU, GPU</td>
<td>py38</td>
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<td>CPU, GPU</td>
<td>py2, py3</td>
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<tr>
<td>Registry path</td>
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<td>py2, py3</td>
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</tbody>
</table>
### MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='us-west-1', version='0.11.0', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
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<th>Processor types</th>
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<tr>
<td>&lt;tag&gt;</td>
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<td></td>
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</tbody>
</table>

### Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='us-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<tr>
<td>&lt;tag&gt;</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='us-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>632365934929.dkr.ecr.us-west-1.amazonaws.com/ntm:</td>
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</tbody>
</table>
Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='us-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>710691900526.dkr.ecr.us-west-1.amazonaws.com/image-classification-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='us-west-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
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<td></td>
<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

Neo PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='us-west-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tbody>
<tr>
<td>710691900526.dkr.ecr.us-west-1.amazonaws.com/sagemaker-inference-pytorch:&lt;tag&gt;</td>
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<td>CPU, GPU</td>
<td>py3</td>
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<tr>
<td>710691900526.dkr.ecr.us-west-1.amazonaws.com/sagemaker-inference-pytorch:&lt;tag&gt;</td>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>sagemaker-inference-pytorch:</td>
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<tr>
<td>Neo Tensorflow (DLC)</td>
<td></td>
<td></td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='us-west-1',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
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<td></td>
<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='us-west-1')
```
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>710691900526.dkr.ecr.us-west-1.amazonaws.com/xgboost-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

**Object Detection (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='us-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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</tbody>
</table>

**Object2Vec (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='us-west-1')
```

<table>
<thead>
<tr>
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<tbody>
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</table>

**PCA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='us-west-1')
```

<table>
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</table>
PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch',region='us-west-1',version='1.8.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
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### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='us-west-1')
```

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### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch', region='us-west-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

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</table>
Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='us-west-1', version='0.23-1', image_scope='inference')
```

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Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='us-west-1')
```

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Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='us-west-1')
```
### Use Built-in Algorithms

<table>
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<th>Version</th>
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#### Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='us-west-1', version='3.0', image_scope='processing')
```

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#### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='us-west-1', version='2.4')
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**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='us-west-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='us-west-1',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```

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Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='us-west-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

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Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='us-west-1', version='0.8.5', instance_type='ml.c5.4xlarge')
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**VW (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='vw', region='us-west-1', version='8.7.0', image_scope='training')
```
Use Built-in Algorithms

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**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost',region='us-west-1',version='1.5-1')
```

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Docker Registry Paths and Example Code for US West (Oregon) (us-west-2)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics

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- BlazingText (algorithm) (p. 1217)
- Chainer (DLC) (p. 1217)
- Clarify (algorithm) (p. 1218)
- Data Wrangler (algorithm) (p. 1218)
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- DeepAR Forecasting (algorithm) (p. 1219)
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- IP Insights (algorithm) (p. 1223)
- Image classification (algorithm) (p. 1223)
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AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='us-west-2',image_scope='inference',version='0.4')
```

<table>
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<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
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</tbody>
</table>

**BlazingText (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='us-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Chainer (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='us-west-2', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>py2, py3</td>
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<td>CPU, GPU</td>
<td>py2, py3</td>
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</table>

#### Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify', region='us-west-2', version='1.0', image_scope='processing')
```

### Registry path

<table>
<thead>
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<th>Job types (image scope)</th>
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</table>

#### Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='us-west-2')
```

### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
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</table>

#### Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris

DeepAR Forecasting (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris

Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris

Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tr>
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<td>4.4.2</td>
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</tr>
</tbody>
</table>
IP Insights (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='us-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td>inference, training</td>
</tr>
</tbody>
</table>

Image classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification', region='us-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
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<td>inference, training</td>
</tr>
</tbody>
</table>

Inferentia MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='us-west-2', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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Inferentia PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.
```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='us-west-2', version='1.9', py_version='py3')
```

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<th>Version</th>
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<th>Processor types</th>
<th>Python versions</th>
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<td></td>
<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='us-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td>inference, training</td>
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</tbody>
</table>

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='us-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>174872318107.dkr.ecr.us-west-2.amazonaws.com/knn:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
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</tbody>
</table>
LDA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='us-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
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<td></td>
<td>inference, training</td>
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</table>

Linear Learner (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='us-west-2')
```

<table>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='us-west-2', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py38</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.us-west-2.amazonaws.com/mxnet-training:&lt;tag&gt;</td>
<td></td>
<td>training</td>
<td>CPU, GPU</td>
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<tr>
<td>Registry path</td>
<td>Version</td>
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Use Built-in Algorithms

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<td>py2, py3</td>
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</table>

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='us-west-2', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

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<td>CPU, GPU</td>
<td>py3</td>
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</tbody>
</table>

**Model Monitor (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='us-west-2')
```
Use Built-in Algorithms

<table>
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**NTM (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='us-west-2')
```

<table>
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**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='us-west-2')
```

<table>
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</table>

**Neo MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet', region='us-west-2', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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</table>
Neo PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='us-west-2', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
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<th>Python versions</th>
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<th>Python versions</th>
</tr>
</thead>
</table>

Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='us-west-2', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```
### Use Built-in Algorithms

<table>
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<td>CPU, GPU</td>
<td>py3</td>
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</table>

#### Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='us-west-2')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
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#### Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='us-west-2')
```

<table>
<thead>
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#### Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='us-west-2')
```
### PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='us-west-2')
```

### PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='us-west-2', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
<table>
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<th>Python versions</th>
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### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='randomcutforest',region='us-west-2')

<table>
<thead>
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<th>Job types (image scope)</th>
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<tbody>
<tr>
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**Ray PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch',region='us-west-2',version='0.8.5',instance_type='ml.c5.4xlarge')
```

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**Scikit-learn (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='us-west-2',version='0.23-1',image_scope='inference')
```

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### Use Built-in Algorithms

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#### Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='us-west-2')
```

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#### Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='us-west-2')
```

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#### Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark',region='us-west-2',version='3.0',image_scope='processing')
```

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## Use Built-in Algorithms

### Registry path

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### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='us-west-2', version='2.4')
```

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### Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='us-west-2', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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1244
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</table>
Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='us-west-2',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```
Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='us-west-2',version='1.15.0',instance_type='ml.inf1.6xlarge')
```

<table>
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<th>Python versions</th>
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Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow',region='us-west-2',version='0.8.5',instance_type='ml.c5.4xlarge')
```

<table>
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### Use Built-in Algorithms

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**VW (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
debug_text = image_uris.retrieve(framework='vw', region='us-west-2', version='8.7.0', image_scope='training')
```

### XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
debug_text = image_uris.retrieve(framework='xgboost', region='us-west-2', version='1.5-1')
```

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**Docker Registry Paths and Example Code for Africa (Cape Town) (af-south-1)**

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**

- AutoGluon (algorithm) (p. 1251)
- BlazingText (algorithm) (p. 1253)
- Chainer (DLC) (p. 1253)
- Clarify (algorithm) (p. 1253)
- Data Wrangler (algorithm) (p. 1254)
- Debugger (algorithm) (p. 1254)
- DeepAR Forecasting (algorithm) (p. 1254)
- Factorization Machines (algorithm) (p. 1255)
- Hugging Face (algorithm) (p. 1255)
- IP Insights (algorithm) (p. 1258)
- Image classification (algorithm) (p. 1258)
• Inferentia MXNet (DLC) (p. 1259)
• Inferentia PyTorch (DLC) (p. 1259)
• K-Means (algorithm) (p. 1260)
• KNN (algorithm) (p. 1260)
• Linear Learner (algorithm) (p. 1260)
• MXNet (DLC) (p. 1260)
• MXNet Coach (DLC) (p. 1263)
• Model Monitor (algorithm) (p. 1264)
• NTM (algorithm) (p. 1264)
• Neo Image Classification (algorithm) (p. 1264)
• Neo MXNet (DLC) (p. 1265)
• Neo PyTorch (DLC) (p. 1265)
• Neo Tensorflow (DLC) (p. 1266)
• Neo XGBoost (algorithm) (p. 1266)
• Object Detection (algorithm) (p. 1266)
• Object2Vec (algorithm) (p. 1267)
• PCA (algorithm) (p. 1267)
• PyTorch (DLC) (p. 1267)
• Random Cut Forest (algorithm) (p. 1271)
• Scikit-learn (algorithm) (p. 1271)
• Semantic Segmentation (algorithm) (p. 1271)
• Seq2Seq (algorithm) (p. 1272)
• Spark (algorithm) (p. 1272)
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• Tensorflow (DLC) (p. 1273)
• Tensorflow Coach (DLC) (p. 1281)
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• Tensorflow Ray (DLC) (p. 1282)
• XGBoost (algorithm) (p. 1283)

**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='af-south-1', image_scope='inference', version='0.4')
```

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### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='af-south-1')
```

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### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='af-south-1', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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<td>py2, py3</td>
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### Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify', region='af-south-1', version='1.0', image_scope='processing')
```

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### Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='af-south-1')
```

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### Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>314341159256.dkr.ecr.af-latest-south-1.amazonaws.com/sagemaker-debugger-rules:&lt;tag&gt;</td>
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<td>debugger</td>
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</table>

### DeepAR Forecasting (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td>1</td>
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</table>
Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='af-south-1')
```

<table>
<thead>
<tr>
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<th>Version</th>
<th>Job types (image scope)</th>
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</table>

Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='af-south-1', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
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</table>
### Use Built-in Algorithms

#### Registry path

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<table>
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<td>4.5.0</td>
</tr>
<tr>
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<td>4.4.2</td>
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<table>
<thead>
<tr>
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</thead>
<tbody>
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</tr>
<tr>
<td>training</td>
</tr>
<tr>
<td>training</td>
</tr>
<tr>
<td>inference, training</td>
</tr>
</tbody>
</table>

#### IP Insights (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='af-south-1')
```

#### Image classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification', region='af-south-1')
```
Inferentia MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet',region='af-south-1',version='1.5.1',instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>inference, training</td>
</tr>
</tbody>
</table>

Inferentia PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='af-south-1',version='1.9',py_version='py3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>774647643957.dkr.ecr.af-south-1.amazonaws.com/sagemaker-neo-mxnet:&lt;tag&gt;</td>
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<td>py3</td>
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<tr>
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<td>774647643957.dkr.ecr.af-south-1.amazonaws.com/sagemaker-neo-mxnet:&lt;tag&gt;</td>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>
**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>455444449433.dkr.ecr.af-south-1.amazonaws.com/kmeans:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>455444449433.dkr.ecr.af-south-1.amazonaws.com/knn:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>455444449433.dkr.ecr.af-south-1.amazonaws.com/linear-learner:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='af-south-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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### Registry path | Version | Job types (image scope) | Processor types | Python versions
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**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='af-south-1', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

### Registry path | Version | Job types (image scope) | Processor types | Python versions
--- | --- | --- | --- | ---
313743910680.dkr.ecr.af-south-1.amazonaws.com/sagemaker-rl-mxnet:coach0.11.0-<tag> | training | CPU, GPU | py3
313743910680.dkr.ecr.af-south-1.amazonaws.com/sagemaker-rl-mxnet:coach0.11.0-<tag> | training | CPU, GPU | py3
Use Built-in Algorithms

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<th>Python versions</th>
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```python
def from_sagemaker_sdk_example_to_retrieve_registry_path():
    import image_uris
    image_uris.retrieve(framework='model-monitor', region='af-south-1')
```

```python
def from_sagemaker_sdk_example_to_retrieve_registry_path():
    import image_uris
    image_uris.retrieve(framework='ntm', region='af-south-1')
```

```python
def from_sagemaker_sdk_example_to_retrieve_registry_path():
    import image_uris
    image_uris.retrieve(framework='image-classification-neo', region='af-south-1')
```

```python
def from_sagemaker_sdk_example_to_retrieve_registry_path():
    import image_uris
    image_uris.retrieve(framework='image-classification-neo', region='af-south-1')
```
Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='af-south-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<td>CPU, GPU</td>
<td>py3</td>
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</table>

Neo PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='af-south-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
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</table>

**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='af-south-1',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>py3</td>
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</table>

**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
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</thead>
<tbody>
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</table>

**Object Detection (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='af-south-1')
```
Use Built-in Algorithms

Registry path  | Version  | Job types (image scope) |
----------------|----------|-------------------------|
455444449433.dkr.ecr.af-south-1.amazonaws.com/object-detection:<tag> | 1 | inference, training |

**Object2Vec (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='af-south-1')
```

**PCA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca',region='af-south-1')
```

**PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch',region='af-south-1',version='1.8.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

Registry path  | Version  | Job types (image scope)  | Processor types | Python versions |
----------------|----------|--------------------------|-----------------|----------------|
626614931356.dkr.ecr.-0.amazonaws.com/pytorch-pytorch-inf: | 1 | inference | CPU, GPU | py38 |
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<td></td>
<td>training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
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</tbody>
</table>
Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td></td>
<td>inference, training</td>
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</tbody>
</table>

Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='af-south-1', version='0.23-1', image_scope='inference')
```

<table>
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</table>

Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
<td>455444449433.dkr.ecr.af-south-1.amazonaws.com/</td>
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<td>inference, training</td>
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</table>
### Semantic Segmentation

**Example**

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='af-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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### Seq2Seq (algorithm)

**Example**

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='af-south-1')
```

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### Spark (algorithm)

**Example**

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark',region='af-south-1',version='3.0',image_scope='processing')
```

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### SparkML Serving (algorithm)

**Example**

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving',region='af-south-1',version='2.4')
```

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Use Built-in Algorithms

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**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='af-south-1',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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<td>py2</td>
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</table>
## Use Built-in Algorithms

### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow', region='af-south-1', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
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<th>Processor types</th>
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### Use Built-in Algorithms

#### Registry path | Version | Job types (image scope) | Processor types | Python versions
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| 313743910680.dkr.ecr.af-south-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.11-<tag> | training | CPU, GPU | py3 |
| 313743910680.dkr.ecr.af-south-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.10.1-<tag> | training | CPU, GPU | py3 |
| 774647643957.dkr.ecr.af-south-1.amazonaws.com/sagemaker-neo-tensorflow:<tag> | inference | inf | py3 |
| 774647643957.dkr.ecr.af-south-1.amazonaws.com/sagemaker-neo-tensorflow:<tag> | inference | inf | py3 |

### Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
tensorflow = sagemaker.Image_uris.retrieve(framework='inferentia-tensorflow', region='af-south-1', instance_type='ml.inf2.6xlarge')
```

### Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
tensorflow = sagemaker.Image_uris.retrieve(framework='ray-tensorflow', region='af-south-1', instance_type='ml.inf2.6xlarge')
```
image_uris.retrieve(framework='ray-tensorflow',region='af-south-1',version='0.8.5',instance_type='ml.c5.4xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost',region='af-south-1',version='1.5-1')
```

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510948584623.dkr.ecr.af-south-1.amazonaws.com/sagemaker-xgboost:tag | 1.0 | 1.0 | inference, training
455444449433.dkr.ecr.af-south-1.amazonaws.com/xgboost:tag | 0.72 | 0.72 | inference, training
510948584623.dkr.ecr.af-south-1.amazonaws.com/sagemaker-xgboost:tag | 0.90 | 0.90 | inference, training
510948584623.dkr.ecr.af-south-1.amazonaws.com/sagemaker-xgboost:tag | 0.90 | 0.90 | inference, training

**Docker Registry Paths and Example Code for Asia Pacific (Hong Kong) (ap-east-1)**

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**

- AutoGluon (algorithm) (p. 1285)
- BlazingText (algorithm) (p. 1286)
- Chainer (DLC) (p. 1287)
- Clarify (algorithm) (p. 1287)
- Data Wrangler (algorithm) (p. 1287)
- Debugger (algorithm) (p. 1288)
- DeepAR Forecasting (algorithm) (p. 1288)
- Factorization Machines (algorithm) (p. 1288)
- Hugging Face (algorithm) (p. 1289)
- IP Insights (algorithm) (p. 1292)
- Image classification (algorithm) (p. 1292)
- Inferentia MXNet (DLC) (p. 1292)
- Inferentia PyTorch (DLC) (p. 1293)
- K-Means (algorithm) (p. 1293)
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• Neo Image Classification (algorithm) (p. 1298)
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• Neo XGBoost (algorithm) (p. 1300)
• Object Detection (algorithm) (p. 1300)
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• Tensorflow Ray (DLC) (p. 1316)
• XGBoost (algorithm) (p. 1317)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='ap-east-1', image_scope='inference', version='0.4')
```

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### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext',region='ap-east-1')
```
Use Built-in Algorithms

<table>
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### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='ap-east-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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<td>py2, py3</td>
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### Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='ap-east-1',version='1.0',image_scope='processing')
```

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### Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='ap-east-1')

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**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='ap-east-1')

<table>
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<th>Version</th>
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<td>debugger</td>
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**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='ap-east-1')

<table>
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<th>Version</th>
<th>Job types (image scope)</th>
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**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='ap-east-1')
### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='ap-east-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
```

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### Use Built-in Algorithms

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#### IP Insights (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='ap-east-1')
```

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#### Image classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification', region='ap-east-1')
```

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#### Inferentia MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='ap-east-1', version='1.5.1', instance_type='ml.inf1.6xlarge')

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</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='ap-east-1', version='1.9', py_version='py3')

<table>
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</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='ap-east-1')
### KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn',region='ap-east-1')
```

### Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner',region='ap-east-1')
```

### MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet',region='ap-east-1',version='1.4.1',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

---

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**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='ap-east-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Processor types</th>
<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py3</td>
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</table>
### Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='ap-east-1')
```

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### NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='ap-east-1')
```

<table>
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### Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='ap-east-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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### Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='neo-mxnet',region='ap-east-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')

<table>
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<th>Registry path</th>
<th>Version</th>
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<td>py3</td>
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</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='ap-east-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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<td>CPU, GPU</td>
<td>py3</td>
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</tbody>
</table>

```python
```
Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='ap-east-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</table>

Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='ap-east-1')
```

<table>
<thead>
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<th>Registry path</th>
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</table>

Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='ap-east-1')
```

<table>
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<td>inference, training</td>
</tr>
</tbody>
</table>
## Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='ap-east-1')
```

<table>
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</table>

## PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='ap-east-1')
```

<table>
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</table>

## PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='ap-east-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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<td>py2, py3</td>
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</tr>
</tbody>
</table>

**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='ap-east-1')
```
### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='ap-east-1', version='0.23-1', image_scope='inference')
```

### Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='ap-east-1')
```

### Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
```
image_uris.retrieve(framework='seq2seq', region='ap-east-1')
```

<table>
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<tbody>
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</table>

**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='ap-east-1', version='3.0', image_scope='processing')
```

<table>
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</table>

**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='ap-east-1', version='2.4')
```

<table>
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<td>inference</td>
</tr>
</tbody>
</table>
## Use Built-in Algorithms

### TensorFlow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='ap-east-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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057415533634.dkr.ecr.ap-east-1.amazonaws.com/sagemaker-tensorflow:<tag> | 1.5.0 | inference | CPU, GPU | py2
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057415533634.dkr.ecr.ap-east-1.amazonaws.com/sagemaker-tensorflow:<tag> | 1.4.1 | inference | CPU, GPU | py2
057415533634.dkr.ecr.ap-east-1.amazonaws.com/sagemaker-tensorflow:<tag> | 1.4.1 | training | CPU, GPU | py2

**Tensorflow Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
def retrieve(framework='coach-tensorflow', region='ap-east-1', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```

### Registry path | Version | Job types (image scope) | Processor types | Python versions
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057415533634.dkr.ecr.ap-east-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.11.1-<tag> | 0.11.1 | training | CPU, GPU | py3
057415533634.dkr.ecr.ap-east-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.11.0-<tag> | 0.11.0 | training | CPU, GPU | py3
### Tensorflow Inference (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='ap-east-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

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### Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='ap-east-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

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### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</table>

**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
dl = image_uris.retrieve(framework='xgboost', region='ap-east-1', version='1.5-1')
```

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Docker Registry Paths and Example Code for Asia Pacific (Mumbai) (ap-south-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics
- AutoGluon (algorithm) (p. 1319)
- BlazingText (algorithm) (p. 1320)
- Chainer (DLC) (p. 1321)
- Clarify (algorithm) (p. 1321)
- Data Wrangler (algorithm) (p. 1321)
- Debugger (algorithm) (p. 1322)
- DeepAR Forecasting (algorithm) (p. 1322)
- Factorization Machines (algorithm) (p. 1322)
- Hugging Face (algorithm) (p. 1323)
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- Image classification (algorithm) (p. 1326)
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- K-Means (algorithm) (p. 1327)
- KNN (algorithm) (p. 1328)
- LDA (algorithm) (p. 1328)
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• Neo XGBoost (algorithm) (p. 1334)
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• Semantic Segmentation (algorithm) (p. 1340)
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• Spark (algorithm) (p. 1341)
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• VW (algorithm) (p. 1352)
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**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='ap-south-1',image_scope='inference',version='0.4')
```

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### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='ap-south-1')
```

<table>
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</table>

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Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='ap-south-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py2, py3</td>
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</table>

Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='ap-south-1',version='1.0',image_scope='processing')
```

<table>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='ap-south-1')
```

<table>
<thead>
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<th>Version</th>
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### Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger',region='ap-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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### DeepAR Forecasting (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar',region='ap-south-1')
```

<table>
<thead>
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### Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines',region='ap-south-1')
```

<table>
<thead>
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</table>
Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='ap-south-1', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```

<table>
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<th>Registry path</th>
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**Use Built-in Algorithms**

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**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='ap-south-1')
```

<table>
<thead>
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<th>Job types (image scope)</th>
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</table>

**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='ap-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='ap-south-1', version='1.5.1', instance_type='ml.inf1.6xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
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</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='ap-south-1', version='1.9', py_version='py3')

<table>
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<th>Python versions</th>
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<td></td>
<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='ap-south-1')
### Registry path | Version | Job types (image scope)
---|---|---
991648021394.dkr.ecr.ap-south-1.amazonaws.com/kmeans:<tag> | | inference, training

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='ap-south-1')
```

### Registry path | Version | Job types (image scope)
---|---|---
991648021394.dkr.ecr.ap-south-1.amazonaws.com/knn:<tag> | | inference, training

**LDA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='ap-south-1')
```

### Registry path | Version | Job types (image scope)
---|---|---
991648021394.dkr.ecr.ap-south-1.amazonaws.com/lda:<tag> | | inference, training

**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='ap-south-1')
```

### Registry path | Version | Job types (image scope)
---|---|---
991648021394.dkr.ecr.ap-south-1.amazonaws.com/linear-learner:<tag> | | inference, training
**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='ap-south-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
</tbody>
</table>

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='ap-south-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```
## Use Built-in Algorithms

### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

### Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='ap-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td>monitoring</td>
</tr>
</tbody>
</table>

### NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='ap-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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</thead>
<tbody>
<tr>
<td>991648021394.dkr.ecr.ap-south-1.amazonaws.com/ntm:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

### Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='ap-south-1')
```
**Neo MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='ap-south-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
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<th>Processor types</th>
<th>Python versions</th>
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<td></td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='ap-south-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
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<th>Processor types</th>
<th>Python versions</th>
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<tr>
<td>763008648453.dkr.ecr.ap-south-1.amazonaws.com/sagemaker-inference-pytorch:&lt;tag&gt;</td>
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<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='ap-south-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='ap-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<tbody>
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</table>
Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='ap-south-1')
```

<table>
<thead>
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<td>inference, training</td>
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Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='ap-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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</table>

PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca',region='ap-south-1')
```

<table>
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PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch',region='ap-south-1',version='1.8.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```
<table>
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### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='ap-south-1')
```

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### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch', region='ap-south-1', version='0.8.5', instance_type='ml.c5.xlarge')
```

<table>
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### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.
Use Built-in Algorithms

from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='ap-south-1',version='0.23-1',image_scope='inference')

<table>
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**Semantic Segmentation (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='ap-south-1')

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**Seq2Seq (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='ap-south-1')

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<tr>
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</table>
Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='ap-south-1', version='3.0', image_scope='processing')
```

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SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='ap-south-1', version='2.4')
```

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Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='ap-south-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```
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### Use Built-in Algorithms

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#### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='ap-south-1',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```

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### TensorFlow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='ap-south-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

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### TensorFlow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='ap-south-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

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### VW (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='vw', region='ap-south-1', version='8.7.0', image_scope='training')
```

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### XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='ap-south-1', version='0.8.7.0', image_scope='training')
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1352
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost',region='ap-south-1',version='1.5-1')

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Docker Registry Paths and Example Code for Asia Pacific (Osaka) (ap-northeast-3)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**

- AutoGluon (algorithm) (p. 1354)
- BlazingText (algorithm) (p. 1356)
- Clarify (algorithm) (p. 1356)
- Debugger (algorithm) (p. 1356)
• DeepAR Forecasting (algorithm) (p. 1356)
• Factorization Machines (algorithm) (p. 1357)
• Hugging Face (algorithm) (p. 1357)
• IP Insights (algorithm) (p. 1360)
• Image classification (algorithm) (p. 1360)
• Inferentia MXNet (DLC) (p. 1361)
• Inferentia PyTorch (DLC) (p. 1361)
• K-Means (algorithm) (p. 1362)
• KNN (algorithm) (p. 1362)
• Linear Learner (algorithm) (p. 1362)
• MXNet (DLC) (p. 1362)
• Model Monitor (algorithm) (p. 1364)
• NTM (algorithm) (p. 1364)
• Neo Image Classification (algorithm) (p. 1365)
• Neo MXNet (DLC) (p. 1365)
• Neo PyTorch (DLC) (p. 1365)
• Neo Tensorflow (DLC) (p. 1366)
• Neo XGBoost (algorithm) (p. 1367)
• Object Detection (algorithm) (p. 1367)
• Object2Vec (algorithm) (p. 1367)
• PCA (algorithm) (p. 1367)
• PyTorch (DLC) (p. 1368)
• Random Cut Forest (algorithm) (p. 1371)
• Scikit-learn (algorithm) (p. 1371)
• Semantic Segmentation (algorithm) (p. 1371)
• Seq2Seq (algorithm) (p. 1372)
• Tensorflow (DLC) (p. 1372)
• Tensorflow Inferentia (DLC) (p. 1378)
• XGBoost (algorithm) (p. 1378)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='ap-northeast-3', image_scope='inference', version='0.4')
```

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</table>
BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext',region='ap-northeast-3')
```

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Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='ap-northeast-3',version='1.0',image_scope='processing')
```

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Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger',region='ap-northeast-3')
```

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DeepAR Forecasting (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar',region='ap-northeast-3')
```
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**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

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from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines',region='ap-northeast-3')
```

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**Hugging Face (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='ap-northeast-3',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
```

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**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='ap-northeast-3')
```

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**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='image-classification', region='ap-northeast-3')

<table>
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<th>Python versions</th>
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**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='ap-northeast-3', version='1.5.1', instance_type='ml.inf1.6xlarge')

<table>
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**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='ap-northeast-3', version='1.9', py_version='py3')

<table>
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Use Built-in Algorithms

<table>
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**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='ap-northeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
</table>
| 867004704886.dkr.ecr.ap-1
northeast-3.amazonaws.com/
kmeans: |         | inference, training    |

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='ap-northeast-3')
```

<table>
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<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
</table>
| 867004704886.dkr.ecr.ap-1
northeast-3.amazonaws.com/
knn: |         | inference, training    |

**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='ap-northeast-3')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
</table>
| 867004704886.dkr.ecr.ap-1
northeast-3.amazonaws.com/
linear-learner: |         | inference, training    |

**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='ap-northeast-3', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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### Registry path

<table>
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<td>py2, py3</td>
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<td></td>
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<td>CPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

### Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor',region='ap-northeast-3')
```

### NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm',region='ap-northeast-3')
```
### Neo Image Classification (algorithm)

Use the following Registry path for Neo Image Classification:

```
867004704886.dkr.ecr.ap-northeast-3.amazonaws.com/ntm:<tag>
```

This registry supports both inference and training jobs.

### Neo MXNet (DLC)

Use the following Registry path for Neo MXNet:

```
925152966179.dkr.ecr.ap-northeast-3.amazonaws.com/image-classification-neo:<tag>
```

### Neo PyTorch (DLC)

Use the following Registry path for Neo PyTorch:

```
925152966179.dkr.ecr.ap-northeast-3.amazonaws.com/sagemaker-inference-mxnet:<tag>
```

## Registration of Inference and Training Jobs

**Linux**

```
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='ap-northeast-3')
```

**Switch CPU/GPU instance type**

```
instance_type='ml.c5.4xlarge'
```

**Switch version**

```
version='1.6'
```

**Switch PyTorch version**

```
py_version='py3'
```

---

**Regional Registries**

- Inference
- Training
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

### Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='ap-northeast-3', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```
**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='ap-northeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>925152966179.dkr.ecr.ap-northeast-3.amazonaws.com/xgboost-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

**Object Detection (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='ap-northeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>867004704886.dkr.ecr.ap-northeast-3.amazonaws.com/object-detection:&lt;tag&gt;</td>
<td>1</td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Object2Vec (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='ap-northeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
<td>867004704886.dkr.ecr.ap-northeast-3.amazonaws.com/object2vec:&lt;tag&gt;</td>
<td>1</td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**PCA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='ap-northeast-3')
```
Use Built-in Algorithms

**Registry path** | **Version** | **Job types (image scope)**
--- | --- | ---
867004704886.dkr.ecr.ap-northeast-3.amazonaws.com/pca:<tag> | | inference, training

**PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
data = image_uris.retrieve(framework='pytorch',region='ap-northeast-3',version='1.8.0',py_version='py3',image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
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<tr>
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<td>364406365360.dkr.ecr.ap-northeast-3.amazonaws.com/pytorch-inference:&lt;tag&gt;</td>
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<td>CPU, GPU</td>
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<td>Registry path</td>
<td>Version</td>
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<td>Processor types</td>
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<td>py2, py3</td>
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<tr>
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<td></td>
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</tbody>
</table>
Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='ap-northeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>867004704886.dkr.ecr.ap-1northeast-3.amazonaws.com/randomcutforest:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='ap-northeast-3', version='0.23-1', image_scope='inference')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>867004704886.dkr.ecr.ap-1northeast-3.amazonaws.com/sagemaker-scikit-learn:&lt;tag&gt;</td>
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<td>inference, training</td>
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<tr>
<td>867004704886.dkr.ecr.ap-23-1northeast-3.amazonaws.com/sagemaker-scikit-learn:&lt;tag&gt;</td>
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<td>0.20.0</td>
<td></td>
<td>inference, training</td>
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</table>

Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='ap-northeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>867004704886.dkr.ecr.ap-1northeast-3.amazonaws.com/</td>
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<td>inference, training</td>
</tr>
<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
</tr>
<tr>
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<td>-------------------------</td>
</tr>
<tr>
<td>semantic-segmentation:&lt;tag&gt;</td>
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</tr>
<tr>
<td>Seq2Seq (algorithm)</td>
<td>SageMaker Python SDK example to retrieve registry path.</td>
<td></td>
</tr>
<tr>
<td>from sagemaker import image_uris</td>
<td>image_uris.retrieve(framework='seq2seq',region='ap-northeast-3')</td>
<td></td>
</tr>
<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
</tr>
<tr>
<td>867004704886.dkr.ecr.ap-northeast-3.amazonaws.com/seq2seq:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
<tr>
<td>Tensorflow (DLC)</td>
<td>SageMaker Python SDK example to retrieve registry path.</td>
<td></td>
</tr>
<tr>
<td>from sagemaker import image_uris</td>
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Use Built-in Algorithms

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**Tensorflow Inferentia (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='ap-northeast-3', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

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**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='xgboost', region='ap-northeast-3', version='1.5-1')

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**Docker Registry Paths and Example Code for Asia Pacific (Seoul) (ap-northeast-2)**

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**

- AutoGluon (algorithm) (p. 1380)
- BlazingText (algorithm) (p. 1382)
- Chainer (DLC) (p. 1382)
- Clarify (algorithm) (p. 1382)
- Data Wrangler (algorithm) (p. 1383)
• Debugger (algorithm) (p. 1383)
• DeepAR Forecasting (algorithm) (p. 1383)
• Factorization Machines (algorithm) (p. 1384)
• Hugging Face (algorithm) (p. 1384)
• IP Insights (algorithm) (p. 1387)
• Image classification (algorithm) (p. 1387)
• Inferentia MXNet (DLC) (p. 1388)
• Inferentia PyTorch (DLC) (p. 1388)
• K-Means (algorithm) (p. 1389)
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• LDA (algorithm) (p. 1389)
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• Model Monitor (algorithm) (p. 1393)
• NTM (algorithm) (p. 1393)
• Neo Image Classification (algorithm) (p. 1394)
• Neo MXNet (DLC) (p. 1394)
• Neo PyTorch (DLC) (p. 1394)
• Neo Tensorflow (DLC) (p. 1395)
• Neo XGBoost (algorithm) (p. 1396)
• Object Detection (algorithm) (p. 1396)
• Object2Vec (algorithm) (p. 1396)
• PCA (algorithm) (p. 1396)
• PyTorch (DLC) (p. 1397)
• Random Cut Forest (algorithm) (p. 1400)
• Ray PyTorch (DLC) (p. 1400)
• Scikit-learn (algorithm) (p. 1401)
• Semantic Segmentation (algorithm) (p. 1401)
• Seq2Seq (algorithm) (p. 1402)
• Spark (algorithm) (p. 1402)
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• Tensorflow Coach (DLC) (p. 1411)
• Tensorflow Inferentia (DLC) (p. 1412)
• Tensorflow Ray (DLC) (p. 1413)
• VW (algorithm) (p. 1413)
• XGBoost (algorithm) (p. 1414)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='ap-northeast-2',image_scope='inference',version='0.4')
```
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### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='ap-northeast-2')
```

### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='ap-northeast-2', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

### Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='ap-northeast-2',version='1.0',image_scope='processing')

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
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</table>

**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='ap-northeast-2')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='debugger',region='ap-northeast-2')

<table>
<thead>
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<th>Registry path</th>
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<th>Job types (image scope)</th>
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</thead>
<tbody>
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**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar',region='ap-northeast-2')
### Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='ap-northeast-2')
```

### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='ap-northeast-2', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```
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763104351884.dkr.ecr.ap-northeast-2.amazonaws.com/huggingface-pytorch-training:<tag> | 4.4.2 | training
763104351884.dkr.ecr.ap-northeast-2.amazonaws.com/huggingface-tensorflow-training:<tag> | 4.4.2 | training
835164637446.dkr.ecr.ap-northeast-2.amazonaws.com/ipinsights:<tag> | 1 | inference, training

#### IP Insights (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='ap-northeast-2')
```

#### Image classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='image-classification', region='ap-northeast-2')

<table>
<thead>
<tr>
<th>Registry path</th>
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</tbody>
</table>

**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='ap-northeast-2', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='ap-northeast-2', version='1.9', py_version='py3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>
K-Means (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='ap-northeast-2')
```

KNN (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='ap-northeast-2')
```

LDA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='ap-northeast-2')
```

Linear Learner (algorithm)
SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='ap-northeast-2')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='ap-northeast-2', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</tr>
<tr>
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<td>training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
</tbody>
</table>
### MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='ap-northeast-2', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</thead>
<tbody>
<tr>
<td>520713654638.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-mxnet:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

### Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='ap-northeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>709848358524.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-model-monitor-analyzer:&lt;tag&gt;</td>
<td></td>
<td>monitoring</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>
image_uris.retrieve(framework='ntm',region='ap-northeast-2')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>835164637446.dkr.ecr.ap-northeast-2.amazonaws.com/ntm:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='ap-northeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
<td>151534178276.dkr.ecr.ap-latest.northeast-2.amazonaws.com/image-classification-neo:&lt;tag&gt;</td>
<td>1.8</td>
<td>inference</td>
</tr>
</tbody>
</table>

**Neo MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='ap-northeast-2',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='ap-northeast-2',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='ap-northeast-2',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>
Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='ap-northeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>151534178276.dkr.ecr.ap-northeast-2.amazonaws.com/xgboost-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='ap-northeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>306986355934.dkr.ecr.ap-northeast-2.amazonaws.com/object-detection:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='ap-northeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>835164637446.dkr.ecr.ap-northeast-2.amazonaws.com/object2vec:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='ap-northeast-2')
```
## Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

## PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch',region='ap-northeast-2',version='1.8.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>Registry path</td>
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<td>Job types (image scope)</td>
<td>Processor types</td>
<td>Python versions</td>
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<tr>
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</tr>
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<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
<td>Processor types</td>
<td>Python versions</td>
</tr>
<tr>
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<td>------------------</td>
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<td>py2, py3</td>
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<tr>
<td>520713654638.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-pytorch:&lt;tag&gt;</td>
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<tr>
<td>520713654638.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-pytorch:&lt;tag&gt;</td>
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<td>CPU, GPU</td>
<td>py2, py3</td>
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</tr>
<tr>
<td>520713654638.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-pytorch:&lt;tag&gt;</td>
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<tr>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
<tr>
<td>520713654638.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-pytorch:&lt;tag&gt;</td>
<td>training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
<tr>
<td>520713654638.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-pytorch:&lt;tag&gt;</td>
<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
</tbody>
</table>

**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='ap-northeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>835164637446.dkr.ecr.ap-northeast-2.amazonaws.com/randomcutforest:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Ray PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch',region='ap-northeast-2',version='0.8.5',instance_type='ml.c5.4xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>462105765813.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-rl-ray-container:ray-1.6.0-torch</td>
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<td>training</td>
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<td>py36</td>
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<td>462105765813.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-rl-ray-container:ray-0.8.5-torch</td>
<td>training</td>
<td>training</td>
<td>CPU, GPU</td>
<td>py36</td>
</tr>
</tbody>
</table>

### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='ap-northeast-2',version='0.23-1',image_scope='inference')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>inference, training</td>
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<td>0.20.0</td>
<td>0.20.0</td>
<td>inference, training</td>
</tr>
</tbody>
</table>

### Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='ap-northeast-2')
```
### Registry Path, Version, Job Types

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>306986355934.dkr.ecr.ap-northeast-2.amazonaws.com/semantic-segmentation:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
<tr>
<td>306986355934.dkr.ecr.ap-northeast-2.amazonaws.com/seq2seq:&lt;tag&gt;</td>
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<td>860869212795.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-spark-processing:&lt;tag&gt;</td>
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<td>860869212795.dkr.ecr.ap-northeast-2.amazonaws.com/sagemaker-spark-processing:&lt;tag&gt;</td>
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<td>processing</td>
</tr>
</tbody>
</table>

### Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='ap-northeast-2')
```

### Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='ap-northeast-2', version='3.0', image_scope='processing')
```

### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='sparkml-serving',region='ap-northeast-2',version='2.4')

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</table>

**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='ap-northeast-2',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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<td>training</td>
<td>CPU, GPU</td>
<td>py2</td>
</tr>
</tbody>
</table>
### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow', region='ap-northeast-2', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py2</td>
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<td>py3</td>
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<td>Processor types</td>
<td>Python versions</td>
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<td>-----------------</td>
<td>-----------------</td>
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<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Tensorflow Inferentia (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='ap-northeast-2',version='1.15.0',instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</tr>
</tbody>
</table>
Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='ap-northeast-2', version='0.8.5', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py3</td>
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VW (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='vw', region='ap-northeast-2', version='8.7.0', image_scope='training')

<table>
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**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='ap-northeast-2', version='1.5-1')

<table>
<thead>
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<th>Package version</th>
<th>Job types (image scope)</th>
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</thead>
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Docker Registry Paths and Example Code for Asia Pacific (Singapore) (ap-southeast-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics

- AutoGluon (algorithm) (p. 1416)
- BlazingText (algorithm) (p. 1417)
- Chainer (DLC) (p. 1417)
- Clarify (algorithm) (p. 1418)
- Data Wrangler (algorithm) (p. 1418)
- Debugger (algorithm) (p. 1418)
- DeepAR Forecasting (algorithm) (p. 1419)
- Factorization Machines (algorithm) (p. 1419)
- Hugging Face (algorithm) (p. 1419)
- IP Insights (algorithm) (p. 1423)
- Image classification (algorithm) (p. 1423)
- Inferentia MXNet (DLC) (p. 1423)
- Inferentia PyTorch (DLC) (p. 1423)
- K-Means (algorithm) (p. 1424)
- KNN (algorithm) (p. 1424)
- LDA (algorithm) (p. 1425)
- Linear Learner (algorithm) (p. 1425)
- MXNet (DLC) (p. 1425)
- MXNet Coach (DLC) (p. 1428)
- Model Monitor (algorithm) (p. 1428)
- NTM (algorithm) (p. 1429)
- Neo Image Classification (algorithm) (p. 1429)
- Neo MXNet (DLC) (p. 1429)
- Neo PyTorch (DLC) (p. 1430)
- Neo Tensorflow (DLC) (p. 1430)
- Neo XGBoost (algorithm) (p. 1431)
- Object Detection (algorithm) (p. 1431)
- Object2Vec (algorithm) (p. 1431)
- PCA (algorithm) (p. 1432)
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• Ray PyTorch (DLC) (p. 1436)
• Scikit-learn (algorithm) (p. 1436)
• Semantic Segmentation (algorithm) (p. 1437)
• Seq2Seq (algorithm) (p. 1437)
• Spark (algorithm) (p. 1437)
• SparkML Serving (algorithm) (p. 1438)
• Tensorflow (DLC) (p. 1438)
• Tensorflow Coach (DLC) (p. 1447)
• Tensorflow Inferentia (DLC) (p. 1448)
• Tensorflow Ray (DLC) (p. 1448)
• VW (algorithm) (p. 1449)
• XGBoost (algorithm) (p. 1449)

**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='ap-southeast-1',image_scope='inference',version='0.4')
```

<table>
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<th>Version</th>
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</table>
### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext',region='ap-southeast-1')
```

<table>
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</table>

### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='ap-southeast-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Processor types</th>
<th>Python versions</th>
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<td>py2, py3</td>
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<td>py2, py3</td>
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<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

**Clarify (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='ap-southeast-1',version='1.0',image_scope='processing')
```

<table>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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</table>

**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='ap-southeast-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
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**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='debugger',region='ap-southeast-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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</table>

**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar',region='ap-southeast-1')

<table>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<td></td>
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</tbody>
</table>

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines',region='ap-southeast-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
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</table>

**Hugging Face (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='ap-southeast-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>
IP Insights (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='ap-southeast-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Image classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification', region='ap-southeast-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
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<tbody>
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</tr>
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</table>

Inferentia MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='ap-southeast-1', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
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<td>py3</td>
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</table>

Inferentia PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='ap-southeast-1',version='1.9',py_version='py3')

<table>
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<th>Python versions</th>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

K-Means (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='ap-southeast-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<tr>
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</table>

KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='knn',region='ap-southeast-1')

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
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<td>inference, training</td>
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</tbody>
</table>
**LDA (algorithm)**
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='ap-southeast-1')
```

<table>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td></td>
<td>inference, training</td>
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</table>

**Linear Learner (algorithm)**
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='ap-southeast-1')
```

<table>
<thead>
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<th>Registry path</th>
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<tbody>
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<td></td>
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</table>

**MXNet (DLC)**
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='ap-southeast-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Processor types</th>
<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
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</table>
### Registry path | Version | Job types (image scope) | Processor types | Python versions
---|---|---|---|---
520713654638.dkr.ecr.ap-southeast-1.amazonaws.com/sagemaker-mxnet:<tag> | 1.0.0 | training | CPU, GPU | py2, py3
520713654638.dkr.ecr.ap-southeast-1.amazonaws.com/sagemaker-mxnet:<tag> | 0.12.1 | inference | CPU, GPU | py2, py3
520713654638.dkr.ecr.ap-southeast-1.amazonaws.com/sagemaker-mxnet:<tag> | 0.11.0 | training | CPU, GPU | py2, py3
520713654638.dkr.ecr.ap-southeast-1.amazonaws.com/sagemaker-mxnet:<tag> | 0.11-<tag> | training | CPU, GPU | py3

### MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='ap-southeast-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

### Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor',region='ap-southeast-1')
```
### NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm',region='ap-southeast-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

### Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='ap-southeast-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td>inference</td>
</tr>
</tbody>
</table>

### Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='ap-southeast-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>py3</td>
</tr>
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</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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<tbody>
<tr>
<td>sagemaker-inference-mxnet:&lt;tag&gt;</td>
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<td></td>
<td></td>
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</tr>
</tbody>
</table>

#### Neo PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='ap-southeast-1', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
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</tr>
</tbody>
</table>

#### Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='ap-southeast-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='ap-southeast-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>inference</td>
</tr>
</tbody>
</table>

**Object Detection (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='ap-southeast-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>

**Object2Vec (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='ap-southeast-1')
```
Use Built-in Algorithms

Registry path | Version | Job types (image scope) |
---|---|---|
475088953585.dkr.ecr.ap-southeast-1.amazonaws.com/object2vec:<tag> | | inference, training |

**PCA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='ap-southeast-1')
```

Registry path | Version | Job types (image scope) |
---|---|---|
475088953585.dkr.ecr.ap-southeast-1.amazonaws.com/pca:<tag> | | inference, training |

**PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='ap-southeast-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

Registry path | Version | Job types (image scope) | Processor types | Python versions |
---|---|---|---|---|
763104351884.dkr.ecr.ap-southeast-1.amazonaws.com/pytorch-inference:<tag> | | inference | CPU, GPU | py38 |
763104351884.dkr.ecr.ap-southeast-1.amazonaws.com/pytorch-training:<tag> | | training | CPU, GPU | py38 |
763104351884.dkr.ecr.ap-southeast-1.amazonaws.com/pytorch-inference:<tag> | | inference | CPU, GPU | py38 |
763104351884.dkr.ecr.ap-southeast-1.amazonaws.com/pytorch-training:<tag> | | training | CPU, GPU | py38 |
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</table>
## Use Built-in Algorithms

<table>
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<tr>
<th>Registry path</th>
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<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
</tbody>
</table>

**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest',region='ap-southeast-1')
```
Use Built-in Algorithms

Registry path | Version | Job types (image scope) 
---|---|---
475088953585.dkr.ecr.ap-southeast-1.amazonaws.com/randomcutforest:<tag> | | inference, training

**Ray PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch', region='ap-southeast-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td></td>
<td>training</td>
<td>CPU, GPU</td>
<td>py36</td>
</tr>
</tbody>
</table>

**Scikit-learn (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='ap-southeast-1', version='0.23-1', image_scope='inference')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
<th>Job types (image scope)</th>
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</tr>
</tbody>
</table>
## Registry path | Version | Package version | Job types (image scope)
--- | --- | --- | ---
```
| sagemaker-scikit-learn: | | | 
```

### Semantic Segmentation (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='ap-southeast-1')
```

### Seq2Seq (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='ap-southeast-1')
```

### Spark (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark',region='ap-southeast-1',version='3.0',image_scope='processing')
```
Use Built-in Algorithms

### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='ap-southeast-1', version='2.4')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

### Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='ap-southeast-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
<td>Registry path</td>
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### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow', region='ap-southeast-1', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```

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<td>CPU, GPU</td>
<td>py3</td>
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</tbody>
</table>
**Tensorflow Inferentia (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='ap-southeast-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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**Tensorflow Ray (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='ap-southeast-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Processor types</th>
<th>Python versions</th>
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<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### VW (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='vw',region='ap-southeast-1',version='8.7.0',image_scope='training')
```

### XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost',region='ap-southeast-1',version='1.5-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Package version</th>
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</table>
Docker Registry Paths and Example Code for Asia Pacific (Sydney) (ap-southeast-2)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics

- AutoGluon (algorithm) (p. 1451)
- BlazingText (algorithm) (p. 1453)
- Chainer (DLC) (p. 1453)
- Clarify (algorithm) (p. 1453)
- Data Wrangler (algorithm) (p. 1454)
- Debugger (algorithm) (p. 1454)
- DeepAR Forecasting (algorithm) (p. 1454)
- Factorization Machines (algorithm) (p. 1455)
- Hugging Face (algorithm) (p. 1455)
- IP Insights (algorithm) (p. 1458)
- Image classification (algorithm) (p. 1458)
AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='ap-southeast-2', image_scope='inference', version='0.4')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
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1451
<table>
<thead>
<tr>
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<th>Job types (image scope)</th>
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<td></td>
</tr>
</tbody>
</table>
BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='ap-southeast-2', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tbody>
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<td>520713654638.dkr.ecr.ap-southeast-2.amazonaws.com/sagemaker-chainer:&lt;tag&gt;</td>
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<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify', region='ap-southeast-2', version='1.0', image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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</tbody>
</table>
Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='ap-southeast-2')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
422173101802.dkr.ecr.ap-southeast-2.amazonaws.com/sagemaker-data-wrangler-container:<tag> | 1.x | processing

Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='ap-southeast-2')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
184798709955.dkr.ecr.ap-southeast-2.amazonaws.com/sagemaker-debugger-rules:<tag> | latest | debugger

DeepAR Forecasting (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='ap-southeast-2')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
514117268639.dkr.ecr.ap-southeast-2.amazonaws.com/forecasting-deepar:<tag> | 1 | inference, training
Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</tbody>
</table>

Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='ap-southeast-2', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
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### Amazon SageMaker Developer Guide

#### Use Built-in Algorithms

**Registry path** | **Version** | **Job types (image scope)**
---|---|---
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763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/huggingface-pytorch-training:tag | 4.6.0 | training

763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/huggingface-pytorch-training:tag | 4.5.0 | training

763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/huggingface-tensorflow-training:tag | 4.5.0 | training

763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/huggingface-tensorflow-training:tag | 4.4.2 | training

#### IP Insights (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='ap-southeast-2')
```

**Registry path** | **Version** | **Job types (image scope)**
---|---|---
712309505854.dkr.ecr.ap-southeast-2.amazonaws.com/ipinsights:tag | 1 | inference, training

#### Image classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='ap-southeast-2')
```
Inferentia MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='ap-southeast-2', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Inferentia PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='ap-southeast-2', version='1.9', py_version='py3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inf</td>
<td>py3</td>
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<td></td>
<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>
**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>712309505854.dkr.ecr.ap-southeast-2.amazonaws.com/kmeans:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**LDA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
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</table>

**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='ap-southeast-2')
```
**Registry path** | **Version** | **Job types (image scope)**<br>**Processor types** | **Python versions**
---|---|---|---
712309505854.dkr.ecr.ap-southeast-2.amazonaws.com/linear-learner:<tag> | | inference, training |<br>CPU, GPU | py38
763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/mxnet-training:<tag> | training | CPU, GPU | py38
763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/mxnet-inference:<tag> | inference | CPU, GPU | py38
763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/mxnet-training:<tag> | training | CPU, GPU | py37
763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/mxnet-inference:<tag> | inference | CPU, GPU | py37
763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/mxnet-training:<tag> | training | CPU, GPU | py3
763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/mxnet-inference:<tag> | inference | CPU, GPU | py3
763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/mxnet-inference-eia:<tag> | eia | CPU | py3
763104351884.dkr.ecr.ap-southeast-2.amazonaws.com/mxnet-training:<tag> | training | CPU, GPU | py2, py3

**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet',region='ap-southeast-2',version='1.4.1',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
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<td>CPU, GPU</td>
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<td>Version</td>
<td>Job types (image scope)</td>
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<td>Python versions</td>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
</tbody>
</table>
MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='ap-southeast-2', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
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<td>CPU, GPU</td>
<td>py3</td>
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<tr>
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<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>563025443158.dkr.ecr.ap-southeast-2.amazonaws.com/sagemaker-model-monitor-analyzer:&lt;tag&gt;</td>
<td>monitoring</td>
<td></td>
</tr>
</tbody>
</table>

NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>712309505854.dkr.ecr.ap-southeast-2.amazonaws.com/ntm:&lt;tag&gt;</td>
<td>inference, training</td>
<td></td>
</tr>
</tbody>
</table>
Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
<td>355873309152.dkr.ecr.ap-southeast-2.amazonaws.com/image-classification-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet', region='ap-southeast-2', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</thead>
<tbody>
<tr>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

Neo PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='ap-southeast-2', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td></td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>
### Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='ap-southeast-2', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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<tbody>
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<td>CPU, GPU</td>
<td>py3</td>
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<td>py3</td>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

### Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

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### Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>latest</td>
<td>inference</td>
</tr>
</tbody>
</table>

### Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td>inference, training</td>
</tr>
</tbody>
</table>

### PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='ap-southeast-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
<td>712309505854.dkr.ecr.ap-southeast-2.amazonaws.com/object2vec:&lt;tag&gt;</td>
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</tr>
</tbody>
</table>
**PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='ap-southeast-2', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</table>
### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='ap-southeast-2')
```

### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch', region='ap-southeast-2', version='0.8.5', instance_type='ml.c5.4xlarge')
```
Use Built-in Algorithms

### Scikit-learn (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='ap-southeast-2', version='0.23-1', image_scope='inference')
```

### Semantic Segmentation (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='ap-southeast-2')
```

### Seq2Seq (algorithm)
SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='ap-southeast-2')

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**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='ap-southeast-2', version='3.0', image_scope='processing')
```

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**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='ap-southeast-2', version='2.4')
```

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### Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='ap-southeast-2', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
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Use Built-in Algorithms

### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='ap-southeast-2',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```

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Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='ap-southeast-2',version='1.15.0',instance_type='ml.inf1.6xlarge')
```

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Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='ap-southeast-2', version='0.8.5', instance_type='ml.c5.4xlarge')
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VW (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='vw', region='ap-southeast-2', version='8.7.0', image_scope='training')

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XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='ap-southeast-2', version='1.5-1')

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Amazon SageMaker Developer Guide
Use Built-in Algorithms

Docker Registry Paths and Example Code for Asia Pacific (Jakarta) (ap-southeast-3)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**
- AutoGluon (algorithm) (p. 1486)
- BlazingText (algorithm) (p. 1488)
- Clarify (algorithm) (p. 1488)
- DeepAR Forecasting (algorithm) (p. 1488)
- Factorization Machines (algorithm) (p. 1489)
- Hugging Face (algorithm) (p. 1489)
- IP Insights (algorithm) (p. 1492)
- Image classification (algorithm) (p. 1492)
- K-Means (algorithm) (p. 1493)
- KNN (algorithm) (p. 1493)
- Linear Learner (algorithm) (p. 1493)
- MXNet (DLC) (p. 1494)
- NTM (algorithm) (p. 1495)
- Object Detection (algorithm) (p. 1495)
- Object2Vec (algorithm) (p. 1495)
- PCA (algorithm) (p. 1496)
- PyTorch (DLC) (p. 1496)
- Random Cut Forest (algorithm) (p. 1499)
- Scikit-learn (algorithm) (p. 1499)
- Semantic Segmentation (algorithm) (p. 1500)
- Seq2Seq (algorithm) (p. 1500)
- Spark (algorithm) (p. 1500)
- Tensorflow (DLC) (p. 1501)
- XGBoost (algorithm) (p. 1507)

**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='ap-southeast-3', image_scope='inference', version='0.4')
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Use Built-in Algorithms

### BlazingText (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='ap-southeast-3')
```

### Clarify (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify', region='ap-southeast-3', version='1.0', image_scope='processing')
```

### DeepAR Forecasting (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='ap-southeast-3')
```
Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='ap-southeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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</tbody>
</table>

Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='ap-southeast-3', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```

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</tbody>
</table>

**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
dpl = image_uris.retrieve(framework='ipinsights',region='ap-southeast-3')
```

<table>
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<td></td>
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</table>

**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
dpl = image_uris.retrieve(framework='image-classification',region='ap-southeast-3')
```
K-Means (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='ap-southeast-3')
```

KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='ap-southeast-3')
```

Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='ap-southeast-3')
```
**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet',region='ap-southeast-3',version='1.4.1',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
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</tbody>
</table>
## Use Built-in Algorithms

<table>
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<tr>
<th>Registry path</th>
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<td>eia</td>
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<td>py2, py3</td>
</tr>
</tbody>
</table>

### NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='ap-southeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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<td>inference, training</td>
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</table>

### Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='ap-southeast-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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</table>

### Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='object2vec', region='ap-southeast-3')

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
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</table>

PCA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='ap-southeast-3')
```

<table>
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<tr>
<th>Registry path</th>
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</table>

PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='ap-southeast-3', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
<th>Registry path</th>
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Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='ap-southeast-3')
```

<table>
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### Semantic Segmentation (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='ap-southeast-3')
```

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### Seq2Seq (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='ap-southeast-3')
```

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### Spark (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark',region='ap-southeast-3',version='3.0',image_scope='processing')
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### Use Built-in Algorithms

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### Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='ap-southeast-3',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='ap-southeast-3', version='1.5-1')
```

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Docker Registry Paths and Example Code for Asia Pacific (Tokyo) (ap-northeast-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics

- AutoGluon (algorithm) (p. 1509)
- BlazingText (algorithm) (p. 1510)
- Chainer (DLC) (p. 1511)
- Clarify (algorithm) (p. 1511)
- Data Wrangler (algorithm) (p. 1511)
- Debugger (algorithm) (p. 1512)
- DeepAR Forecasting (algorithm) (p. 1512)
- Factorization Machines (algorithm) (p. 1512)
- Hugging Face (algorithm) (p. 1513)
- IP Insights (algorithm) (p. 1516)
- Image classification (algorithm) (p. 1516)
- Inferentia MXNet (DLC) (p. 1516)
- Inferentia PyTorch (DLC) (p. 1517)
- K-Means (algorithm) (p. 1517)
- KNN (algorithm) (p. 1518)
- LDA (algorithm) (p. 1518)
- Linear Learner (algorithm) (p. 1518)
- MXNet (DLC) (p. 1519)
- MXNet Coach (DLC) (p. 1521)
- Model Monitor (algorithm) (p. 1522)
- NTM (algorithm) (p. 1522)
• Neo Image Classification (algorithm) (p. 1522)
• Neo MXNet (DLC) (p. 1523)
• Neo PyTorch (DLC) (p. 1523)
• Neo Tensorflow (DLC) (p. 1524)
• Neo XGBoost (algorithm) (p. 1524)
• Object Detection (algorithm) (p. 1525)
• Object2Vec (algorithm) (p. 1525)
• PCA (algorithm) (p. 1525)
• PyTorch (DLC) (p. 1525)
• Random Cut Forest (algorithm) (p. 1529)
• Ray PyTorch (DLC) (p. 1529)
• Scikit-learn (algorithm) (p. 1530)
• Semantic Segmentation (algorithm) (p. 1530)
• Seq2Seq (algorithm) (p. 1530)
• Spark (algorithm) (p. 1531)
• SparkML Serving (algorithm) (p. 1531)
• Tensorflow (DLC) (p. 1532)
• Tensorflow Coach (DLC) (p. 1540)
• Tensorflow Inferentia (DLC) (p. 1541)
• Tensorflow Ray (DLC) (p. 1541)
• VW (algorithm) (p. 1542)
• XGBoost (algorithm) (p. 1543)

**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='ap-northeast-1', image_scope='inference', version='0.4')
```

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## Registry path

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<td>BlazingText (algorithm)</td>
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</tr>
</tbody>
</table>

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
df = image_uris.retrieve(framework='blazingtext', region='ap-northeast-1')
```
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<td>CPU, GPU</td>
<td>py2, py3</td>
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</table>

Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='ap-northeast-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
<th>Registry path</th>
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<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py2, py3</td>
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</tbody>
</table>

Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='ap-northeast-1',version='1.0',image_scope='processing')
```

<table>
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<th>Registry path</th>
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Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='ap-northeast-1')

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**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='ap-northeast-1')

<table>
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**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='ap-northeast-1')

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**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='ap-northeast-1')
Use Built-in Algorithms

**Hugging Face (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='ap-northeast-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
```

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</table>

**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='ap-northeast-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</tr>
</tbody>
</table>

**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='ap-northeast-1')
```

<table>
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<th>Registry path</th>
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**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet',region='ap-northeast-1',version='1.5.1',instance_type='ml.inf1.6xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Processor types</th>
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<td>py3</td>
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</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='ap-northeast-1',version='1.9',py_version='py3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='ap-northeast-1')
```
### KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='ap-northeast-1')
```

### LDA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='ap-northeast-1')
```

### Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='ap-northeast-1')
```
MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet',region='ap-northeast-1',version='1.4.1',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
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Use Built-in Algorithms

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**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='ap-northeast-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```
### Registry path

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</table>

### Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor',region='ap-northeast-1')
```

### NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='ntm',region='ap-northeast-1')
```

### Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='ap-northeast-1')
```
### Neo MXNet (DLC)

**SageMaker Python SDK example to retrieve registry path.**

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='ap-northeast-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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</table>

### Neo PyTorch (DLC)

**SageMaker Python SDK example to retrieve registry path.**

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='ap-northeast-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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<td>py3</td>
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</table>

**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='ap-northeast-1',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

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**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='ap-northeast-1')
```

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</table>
Object Detection (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='ap-northeast-1')
```

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Object2Vec (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='ap-northeast-1')
```

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PCA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='ap-northeast-1')
```

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PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='ap-northeast-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
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</table>
### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='ap-northeast-1')
```

### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch', region='ap-northeast-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```
**Scikit-learn (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='ap-northeast-1',version='0.23-1',image_scope='inference')
```

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**Semantic Segmentation (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='ap-northeast-1')
```

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**Seq2Seq (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='ap-northeast-1')
```
### Use Built-in Algorithms

#### Registry path

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#### Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='ap-northeast-1', version='3.0', image_scope='processing')
```

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#### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uri.retrieve(framework='sparkml-serving', region='ap-northeast-1', version='2.4')
```

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</table>
Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='ap-northeast-1',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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## Registry path | Version | Job types (image scope) | Processor types | Python versions
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### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='ap-northeast-1',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```
<table>
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<th>Python versions</th>
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**Tensorflow Inferentia (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='ap-northeast-1',version='1.15.0',instance_type='ml.inf1.6xlarge')
```

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**Tensorflow Ray (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow',region='ap-northeast-1',version='0.8.5',instance_type='ml.c5.4xlarge')
```
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**VW (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='vw', region='ap-northeast-1', version='8.7.0', image_scope='training')
```
### Use Built-in Algorithms

**Registry path**

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**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='ap-northeast-1', version='1.5-1')
```
### Docker Registry Paths and Example Code for Canada (Central) (ca-central-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**
- AutoGluon (algorithm) (p. 1545)
- BlazingText (algorithm) (p. 1546)
- Chainer (DLC) (p. 1546)
- Clarify (algorithm) (p. 1547)
- Data Wrangler (algorithm) (p. 1547)
- Debugger (algorithm) (p. 1547)
- DeepAR Forecasting (algorithm) (p. 1548)
- Factorization Machines (algorithm) (p. 1548)
- Hugging Face (algorithm) (p. 1548)
- IP Insights (algorithm) (p. 1552)
- Image classification (algorithm) (p. 1552)
- Inferentia MXNet (DLC) (p. 1552)
- Inferentia PyTorch (DLC) (p. 1552)
- K-Means (algorithm) (p. 1553)
- KNN (algorithm) (p. 1553)
- LDA (algorithm) (p. 1554)
- Linear Learner (algorithm) (p. 1554)
- MXNet (DLC) (p. 1554)
- MXNet Coach (DLC) (p. 1557)
- Model Monitor (algorithm) (p. 1557)
- NTM (algorithm) (p. 1558)
- Neo Image Classification (algorithm) (p. 1558)
- Neo MXNet (DLC) (p. 1558)
- Neo PyTorch (DLC) (p. 1559)
- Neo Tensorflow (DLC) (p. 1559)
- Neo XGBoost (algorithm) (p. 1560)
- Object Detection (algorithm) (p. 1560)
- Object2Vec (algorithm) (p. 1560)
- PCA (algorithm) (p. 1561)
- PyTorch (DLC) (p. 1561)
- Random Cut Forest (algorithm) (p. 1564)
- Ray PyTorch (DLC) (p. 1565)
• Scikit-learn (algorithm) (p. 1565)
• Semantic Segmentation (algorithm) (p. 1566)
• Seq2Seq (algorithm) (p. 1566)
• Spark (algorithm) (p. 1566)
• SparkML Serving (algorithm) (p. 1567)
• Tensorflow (DLC) (p. 1567)
• Tensorflow Coach (DLC) (p. 1576)
• Tensorflow Inferentia (DLC) (p. 1577)
• Tensorflow Ray (DLC) (p. 1577)
• VW (algorithm) (p. 1578)
• XGBoost (algorithm) (p. 1578)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='ca-central-1', image_scope='inference', version='0.4')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>763104351884.dkr.ecr.ca-central-1.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td>0.5.2</td>
<td>training</td>
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<tr>
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<td>0.4.3</td>
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<td>763104351884.dkr.ecr.ca-central-1.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td>0.4.3</td>
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</tr>
<tr>
<td>Registry path</td>
<td>Version</td>
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</tr>
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</tr>
</tbody>
</table>

BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='ca-central-1')
```

Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='ca-central-1', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>520713654638.dkr.ecr.ca-central-1.amazonaws.com/sagemaker-chainer:&lt;tag&gt;</td>
<td>5.0.0</td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
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<td>4.0.0</td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

#### Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='ca-central-1',version='1.0',image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1.0</td>
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</tr>
</tbody>
</table>

#### Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='ca-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
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</table>

#### Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='ca-central-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>debugger</td>
</tr>
</tbody>
</table>

**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='ca-central-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1</td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='ca-central-1',base_framework_version='tensorflow2.4.1')

<table>
<thead>
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<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
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<td>inference, training</td>
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</table>

**Hugging Face (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='ca-central-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
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<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
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<td>4.4.2</td>
<td>training</td>
</tr>
</tbody>
</table>
IP Insights (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='ca-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>469771592824.dkr.ecr.ca-central-1.amazonaws.com/ipinsights:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Image classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='ca-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Inferentia MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet',region='ca-central-1',version='1.5.1',instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
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<tr>
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<td>py3</td>
</tr>
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<td>464438896020.dkr.eda-central-1.amazonaws.com/sagemaker-neo-mxnet:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

Inferentia PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='ca-central-1',version='1.9',py_version='py3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>464438896020.dkr.ecr.ca-central-1.amazonaws.com/sagemaker-neo-pytorch:&lt;tag&gt;</td>
<td>inference</td>
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<td>inference</td>
<td>inf</td>
<td></td>
<td>py3</td>
</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='ca-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>469771592824.dkr.ecr.ca-central-1.amazonaws.com/kmeans:&lt;tag&gt;</td>
<td>inference, training</td>
<td></td>
</tr>
</tbody>
</table>

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn',region='ca-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>469771592824.dkr.ecr.ca-central-1.amazonaws.com/knn:&lt;tag&gt;</td>
<td>inference, training</td>
<td></td>
</tr>
</tbody>
</table>
LDA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='ca-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>469771592824.dkr.ecr.ca-central-1.amazonaws.com/lda:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Linear Learner (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='ca-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
<td>469771592824.dkr.ecr.ca-central-1.amazonaws.com/linear-learner:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
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</tbody>
</table>

MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='ca-central-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tbody>
<tr>
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**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='ca-central-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

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<td>training</td>
<td>CPU, GPU</td>
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</table>

**Model Monitor (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor',region='ca-central-1')
```
<table>
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<th>Job types (image scope)</th>
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**NTM (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='ca-central-1')
```

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**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image.uris
image.uris.retrieve(framework='image-classification-neo', region='ca-central-1')
```

<table>
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<th>Version</th>
<th>Job types (image scope)</th>
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**Neo MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image.uris
image.uris.retrieve(framework='neo-mxnet', region='ca-central-1', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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### Use Built-in Algorithms

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**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='ca-central-1', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='ca-central-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```
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<td>py3</td>
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**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='ca-central-1')
```

**Object Detection (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='ca-central-1')
```

**Object2Vec (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='ca-central-1')
```
Use Built-in Algorithms

### Registry path | Version | Job types (image scope)
--- | --- | ---
469771592824.dkr.ecr.ca-central-1.amazonaws.com/object2vec:tag | 1 | inference, training

#### PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='ca-central-1')
```

### Registry path | Version | Job types (image scope)
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469771592824.dkr.ecr.ca-central-1.amazonaws.com/pca:tag | 1 | inference, training

#### PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='ca-central-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

### Registry path | Version | Job types (image scope) | Processor types | Python versions
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763104351884.dkr.ecr.ca-central-1.amazonaws.com/pytorch-inference:tag | 1.11.0 | inference | CPU, GPU | py38
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</table>

**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='ca-central-1')
```
### Registry path

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### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch',region='ca-central-1',version='0.8.5',instance_type='ml.c5.4xlarge')
```

### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='ca-central-1',version='0.23-1',image_scope='inference')
```
### Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='ca-central-1')
```

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### Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='ca-central-1')
```

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### Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark',region='ca-central-1',version='3.0',image_scope='processing')
```

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</table>
Use Built-in Algorithms

## SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving',region='ca-central-1',version='2.4')
```

## Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='ca-central-1',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```
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</table>
Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='ca-central-1',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```
Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='ca-central-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Processor types</th>
<th>Python versions</th>
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Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='ca-central-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

<table>
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<th>Processor types</th>
<th>Python versions</th>
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</table>
### VW (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='vw',region='ca-central-1',version='8.7.0',image_scope='training')
```

### XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost',region='ca-central-1',version='1.5-1')
```
### Registry path

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### Docker Registry Paths and Example Code for China (Beijing) (cn-north-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

#### Topics
- AutoGluon (algorithm) (p. 1580)
- BlazingText (algorithm) (p. 1581)
- Chainer (DLC) (p. 1581)
- Clarify (algorithm) (p. 1582)
- Data Wrangler (algorithm) (p. 1582)
- Debugger (algorithm) (p. 1582)
- DeepAR Forecasting (algorithm) (p. 1583)
- Factorization Machines (algorithm) (p. 1583)
- Hugging Face (algorithm) (p. 1583)
- IP Insights (algorithm) (p. 1587)
- Image classification (algorithm) (p. 1587)
• Inferentia MXNet (DLC) (p. 1587)
• Inferentia PyTorch (DLC) (p. 1587)
• K-Means (algorithm) (p. 1588)
• KNN (algorithm) (p. 1588)
• Linear Learner (algorithm) (p. 1589)
• MXNet (DLC) (p. 1589)
• MXNet Coach (DLC) (p. 1592)
• Model Monitor (algorithm) (p. 1592)
• NTM (algorithm) (p. 1592)
• Neo Image Classification (algorithm) (p. 1593)
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• Neo Tensorflow (DLC) (p. 1594)
• Neo XGBoost (algorithm) (p. 1595)
• Object Detection (algorithm) (p. 1595)
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• Semantic Segmentation (algorithm) (p. 1600)
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• Spark (algorithm) (p. 1600)
• SparkML Serving (algorithm) (p. 1601)
• Tensorflow (DLC) (p. 1601)
• Tensorflow Coach (DLC) (p. 1610)
• Tensorflow Inferentia (DLC) (p. 1611)
• Tensorflow Ray (DLC) (p. 1611)
• XGBoost (algorithm) (p. 1612)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='cn-north-1',image_scope='inference',version='0.4')
```

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**BlazingText (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext',region='cn-north-1')
```

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**Chainer (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='cn-north-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```
Use Built-in Algorithms

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<td>py2, py3</td>
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**Clarify (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify', region='cn-north-1', version='1.0', image_scope='processing')
```

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**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='cn-north-1')
```

<table>
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**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='cn-north-1')
```
<table>
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</table>

**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='cn-north-1')
```

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='cn-north-1')
```

**Hugging Face (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='cn-north-1', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```
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</table>
**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='cn-north-1')
```

<table>
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<th>Registry path</th>
<th>Version</th>
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**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification', region='cn-north-1')
```

<table>
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**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='cn-north-1', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

<table>
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**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='cn-north-1',version='1.9',py_version='py3')

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K-Means (algorithm)
SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='cn-north-1')

<table>
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KNN (algorithm)
SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='knn',region='cn-north-1')

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**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='cn-north-1')
```

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**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='cn-north-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
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## Use Built-in Algorithms

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</table>
Use Built-in Algorithms

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<td>py3</td>
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</tbody>
</table>

MXNet Coach (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='cn-north-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
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<th>Job types (image scope)</th>
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<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

Model Monitor (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor',region='cn-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td></td>
<td></td>
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</table>

NTM (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='ntm', region='cn-north-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
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</table>

**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='cn-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td>inference</td>
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</table>

**Neo MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet', region='cn-north-1', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='cn-north-1', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```
<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='cn-north-1',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>
Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='cn-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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</table>

Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='cn-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td>inference, training</td>
</tr>
</tbody>
</table>

Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='cn-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
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<td></td>
<td>inference, training</td>
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</tbody>
</table>

PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='cn-north-1')
```
Registry path | Version | Job types (image scope) |
---|---|---
390948362332.dkr.ecr.cn-north-1.amazonaws.com.cn/pca: *tag* | inference, training |

PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='cn-north-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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### Use Built-in Algorithms

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### Registry path

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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='cn-north-1')
```

### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='cn-north-1', version='0.23-1', image_scope='inference')
```
Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='cn-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>

Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='cn-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
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<td>inference, training</td>
</tr>
<tr>
<td>tag&gt;</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
<td>390948362332.dkr.ecr.cn-1 north-1.amazonaws.com.cn/seq2seq:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

|
Use Built-in Algorithms

```python
image_uris.retrieve(framework='spark', region='cn-north-1', version='3.0', image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tr>
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</table>

**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='cn-north-1', version='2.4')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='cn-north-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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## Use Built-in Algorithms

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#### Use Built-in Algorithms

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#### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow', region='cn-north-1', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
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### TensorFlow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='cn-north-1',version='1.15.0',instance_type='ml.inf1.6xlarge')
```

<table>
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### TensorFlow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow',region='cn-north-1',version='0.8.5',instance_type='ml.c5.4xlarge')
```

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Use Built-in Algorithms

XGBoost (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='cn-north-1', version='1.5-1')
```

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Docker Registry Paths and Example Code for China (Ningxia) (cn-northwest-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

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- BlazingText (algorithm) (p. 1614)
- Chainer (DLC) (p. 1615)
- Clarify (algorithm) (p. 1615)
- Data Wrangler (algorithm) (p. 1616)
- Debugger (algorithm) (p. 1616)
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- Hugging Face (algorithm) (p. 1617)
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- Inferentia MXNet (DLC) (p. 1620)
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- Neo Image Classification (algorithm) (p. 1626)
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- Neo XGBoost (algorithm) (p. 1628)
- Object Detection (algorithm) (p. 1628)
- Object2Vec (algorithm) (p. 1629)
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- Tensorflow Ray (DLC) (p. 1644)
- XGBoost (algorithm) (p. 1645)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='cn-northwest-1',image_scope='inference',version='0.4')
```

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BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext',region='cn-northwest-1')

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**Chainer (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='cn-northwest-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')

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<td>py2, py3</td>
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**Clarify (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='cn-northwest-1',version='1.0',image_scope='processing')

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**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='cn-northwest-1')
```

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**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='cn-northwest-1')
```

<table>
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**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='cn-northwest-1')
```

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**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='cn-northwest-1')
```
### Registry path

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#### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='cn-northwest-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
```
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<td>huggingface-pytorch-training:&lt;tag&gt;</td>
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</tr>
</tbody>
</table>
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--- | --- | ---
727897471807.dkr.ecr.cn-northwest-1.amazonaws.com.cn/huggingface-tensorflow-training:tag | 4.5.0 | training

### IP Insights (algorithm)
SageMaker Python SDK example to retrieve registry path.
```
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='cn-northwest-1')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
387376663083.dkr.ecr.cn-northwest-1.amazonaws.com.cn/ipinsights:tag | 1 | inference, training

### Image classification (algorithm)
SageMaker Python SDK example to retrieve registry path.
```
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='cn-northwest-1')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
387376663083.dkr.ecr.cn-northwest-1.amazonaws.com.cn/image-classification:tag | 1 | inference, training

### Inferentia MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='cn-northwest-1', version='1.5.1', instance_type='ml.inf1.6xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Processor types</th>
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<td>inf</td>
<td>py3</td>
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</tbody>
</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='cn-northwest-1', version='1.9', py_version='py3')
```

<table>
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<tr>
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<th>Python versions</th>
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<td>inf</td>
<td>py3</td>
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</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='cn-northwest-1')
```
Use Built-in Algorithms

KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn',region='cn-northwest-1')
```

Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner',region='cn-northwest-1')
```

MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet',region='cn-northwest-1',version='1.4.1',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```
<table>
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<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
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<th>Python versions</th>
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### Registry path | Version | Job types (image scope) | Processor types | Python versions
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### MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='cn-northwest-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

### Registry path | Version | Job types (image scope) | Processor types | Python versions
--- | --- | --- | --- | ---
423003514399.dkr.ecr-<tag> | training | CPU, GPU | py3
423003514399.dkr.ecr-<tag> | training | CPU, GPU | py3
Model Monitor (algorithm)
SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor',region='cn-northwest-1')
```

<table>
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NTM (algorithm)
SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='ntm',region='cn-northwest-1')
```

<table>
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Neo Image Classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='cn-northwest-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>inference</td>
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Neo MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
```
image_uris.retrieve(framework='neo-mxnet',region='cn-northwest-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='cn-northwest-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

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### Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
gcbs = image_uris.retrieve(framework='neo-tensorflow', region='cn-northwest-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

### Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
gcbs = image_uris.retrieve(framework='xgboost-neo', region='cn-northwest-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

### Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
gcbs = image_uris.retrieve(framework='object-detection', region='cn-northwest-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>387376663083.dkr.ecr-cn-northwest-1.amazonaws.com.cn/object-detection:&lt;tag&gt;</td>
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<td>inference, training</td>
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</tbody>
</table>
**Object2Vec (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='cn-northwest-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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**PCA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='cn-northwest-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<tbody>
<tr>
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<td></td>
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</table>

**PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='cn-northwest-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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<th>Processor types</th>
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**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='randomcutforest', region='cn-northwest-1')

<table>
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**Scikit-learn (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='cn-northwest-1', version='0.23-1', image_scope='inference')
```

<table>
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**Semantic Segmentation (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='cn-northwest-1')
```

<table>
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<th>Registry path</th>
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**Seq2Seq (algorithm)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='cn-northwest-1')

<table>
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**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='spark',region='cn-northwest-1',version='3.0',image_scope='processing')

<table>
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**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving',region='cn-northwest-1',version='2.4')

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Use Built-in Algorithms

**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='cn-northwest-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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**Tensorflow Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='cn-northwest-1',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```

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Tensorflow Inference (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='cn-northwest-1',version='1.15.0',instance_type='ml.inf1.6xlarge')
```

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Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow',region='cn-northwest-1',version='0.8.5',instance_type='ml.c5.4xlarge')
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**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

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from sagemaker import image_uris
image_uris.retrieve(framework='xgboost',region='cn-northwest-1',version='1.5-1')
```

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<td>Version</td>
<td>Package version</td>
<td>Job types (image scope)</td>
</tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Docker Registry Paths and Example Code for Europe (Frankfurt) (eu-central-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics
- AutoGluon (algorithm) (p. 1647)
- BlazingText (algorithm) (p. 1648)
- Chainer (DLC) (p. 1649)
- Clarify (algorithm) (p. 1649)
- Data Wrangler (algorithm) (p. 1649)
- Debugger (algorithm) (p. 1650)
- DeepAR Forecasting (algorithm) (p. 1650)
- Factorization Machines (algorithm) (p. 1650)
- Hugging Face (algorithm) (p. 1651)
- IP Insights (algorithm) (p. 1654)
- Image classification (algorithm) (p. 1654)
- Inferentia MXNet (DLC) (p. 1654)
- Inferentia PyTorch (DLC) (p. 1655)
- K-Means (algorithm) (p. 1655)
- KNN (algorithm) (p. 1656)
- LDA (algorithm) (p. 1656)
- Linear Learner (algorithm) (p. 1656)
- MXNet (DLC) (p. 1657)
- MXNet Coach (DLC) (p. 1659)
- Model Monitor (algorithm) (p. 1660)
- NTM (algorithm) (p. 1660)
- Neo Image Classification (algorithm) (p. 1660)
- Neo MXNet (DLC) (p. 1661)
AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='eu-central-1',image_scope='inference',version='0.4')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td>0.5.2</td>
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</tr>
<tr>
<td>763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td>0.5.2</td>
<td>inference</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
<td>0.4.3</td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
<td>0.4.3</td>
<td>inference</td>
</tr>
</tbody>
</table>
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--- | --- | ---
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763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-inference:<tag> | 0.4.2 | inference
763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-training:<tag> | 0.4.0 | training
763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-inference:<tag> | 0.4.0 | inference
763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-training:<tag> | 0.3.2 | training
763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-inference:<tag> | 0.3.2 | inference
763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-training:<tag> | 0.3.1 | training
763104351884.dkr.ecr.eu-central-1.amazonaws.com/autogluon-inference:<tag> | 0.3.1 | inference

**BlazingText (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='eu-central-1')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
813361260812.dkr.ecr.eu-central-1.amazonaws.com/blazingtext:<tag> | | inference, training
Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
ing image_uris.retrieve(framework='chainer', region='eu-central-1', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
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<tr>
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<td>py2, py3</td>
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<tr>
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<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
<tr>
<td>520713654638.dkr.ecr.eu-central-1.amazonaws.com/sagemaker-chainer:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
ing image_uris.retrieve(framework='clarify', region='eu-central-1', version='1.0', image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>processing</td>
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</tbody>
</table>

Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
ing image_uris.retrieve(framework='data-wrangler', region='eu-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>024640144536.dkr.ecr.eu-central-1.amazonaws.com/</td>
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<td>processing</td>
</tr>
<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
</tr>
<tr>
<td>---------------</td>
<td>---------</td>
<td>-------------------------</td>
</tr>
<tr>
<td>sagemaker-data-wrangler-container:</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='eu-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>482524230118.dkr.ecr.eu-central-1.amazonaws.com/sagemaker-debugger-rules:</td>
<td>latest</td>
<td>debugger</td>
</tr>
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</table>

**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='eu-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>inference, training</td>
</tr>
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</table>

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='eu-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>664544806723.dkr.ecr.eu-central-1.amazonaws.com/</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>
### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='eu-central-1', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<tbody>
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### Registry path examples

<table>
<thead>
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<tr>
<td>763104351884.dkr.ecr.eu-central-1.amazonaws.com/huggingface-tensorflow-inference</td>
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</tr>
<tr>
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<td>Registry path</td>
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<td>inference</td>
</tr>
<tr>
<td>Registry path</td>
<td>Version</td>
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<tr>
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<tr>
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<td>training</td>
</tr>
<tr>
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<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.eu-4.6.1central-1.amazonaws.com/huggingface-pytorchtraining:&lt;tag&gt;</td>
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<td>763104351884.dkr.ecr.eu-4.6.1central-1.amazonaws.com/huggingface-pytorchtraining:&lt;tag&gt;</td>
<td></td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.eu-4.5.0central-1.amazonaws.com/huggingface-pytorchtraining:&lt;tag&gt;</td>
<td></td>
<td>training</td>
</tr>
</tbody>
</table>
# Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>763104351884.dkr.ecr.eu-central-1.amazonaws.com/huggingface-tensorflow-training:&lt;tag&gt;</td>
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<tr>
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<td>4.4.2</td>
<td>training</td>
</tr>
<tr>
<td>763104351884.dkr.ecr.eu-central-1.amazonaws.com/huggingface-tensorflow-training:&lt;tag&gt;</td>
<td>4.4.2</td>
<td>training</td>
</tr>
</tbody>
</table>

**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='eu-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>664544806723.dkr.ecr.eu-central-1.amazonaws.com/ ipinsights:&lt;tag&gt;</td>
<td>1</td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='eu-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>813361260812.dkr.ecr.eu-central-1.amazonaws.com/image-classification:&lt;tag&gt;</td>
<td>1</td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python

```
from sagemaker import image_uris
text = image_uris.retrieve(framework='inferentia-mxnet',region='eu-central-1',version='1.5.1',instance_type='ml.inf1.6xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>746233611703.dkr.ecr.eu-central-1.amazonaws.com/sagemaker-neo-mxnet:&lt;tag&gt;</td>
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<tr>
<td>746233611703.dkr.ecr.eu-central-1.amazonaws.com/sagemaker-neo-mxnet:&lt;tag&gt;</td>
<td></td>
<td></td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

Inferentia PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
text = image_uris.retrieve(framework='inferentia-pytorch',region='eu-central-1',version='1.9',py_version='py3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>746233611703.dkr.ecr.eu-central-1.amazonaws.com/sagemaker-neo-pytorch:&lt;tag&gt;</td>
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<tr>
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<td>inf</td>
<td>py3</td>
</tr>
<tr>
<td>746233611703.dkr.ecr.eu-central-1.amazonaws.com/sagemaker-neo-pytorch:&lt;tag&gt;</td>
<td></td>
<td></td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

K-Means (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
text = image_uris.retrieve(framework='kmeans',region='eu-central-1')
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>664544806723.dkr.ecr.eu-central-1.amazonaws.com/kmeans:&lt;tag&gt;</td>
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<td>inference, training</td>
</tr>
<tr>
<td>664544806723.dkr.ecr.eu-central-1.amazonaws.com/knn:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
<tr>
<td>353608530281.dkr.ecr.eu-central-1.amazonaws.com/lda:&lt;tag&gt;</td>
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<td>inference, training</td>
</tr>
<tr>
<td>664544806723.dkr.ecr.eu-central-1.amazonaws.com/linear-learner:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='eu-central-1')
```

**LDA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='eu-central-1')
```

**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='eu-central-1')
```
MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='eu-central-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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520713654638.dkr.ecr.central-1.amazonaws.com/sagemaker-mxnet:tag | 1.2.1 | inference | CPU, GPU | py2, py3 |
520713654638.dkr.ecr.central-1.amazonaws.com/sagemaker-mxnet:tag | 1.1.0 | training | CPU, GPU | py2, py3 |
520713654638.dkr.ecr.central-1.amazonaws.com/sagemaker-mxnet:tag | 1.1.0 | inference | CPU, GPU | py2, py3 |
520713654638.dkr.ecr.central-1.amazonaws.com/sagemaker-mxnet:tag | 1.0.0 | training | CPU, GPU | py2, py3 |
520713654638.dkr.ecr.central-1.amazonaws.com/sagemaker-mxnet:tag | 1.0.0 | inference | CPU, GPU | py2, py3 |
520713654638.dkr.ecr.central-1.amazonaws.com/sagemaker-mxnet:tag | 0.12.1 | training | CPU, GPU | py2, py3 |
520713654638.dkr.ecr.central-1.amazonaws.com/sagemaker-mxnet:tag | 0.12.1 | inference | CPU, GPU | py2, py3 |

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
dl = image_uris.retrieve(framework='coach-mxnet', region='eu-central-1', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```
<table>
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<td>CPU, GPU</td>
<td>py3</td>
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</tbody>
</table>

**Model Monitor (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='eu-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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</table>

**NTM (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='eu-central-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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</table>

**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='eu-central-1')
```
<table>
<thead>
<tr>
<th>Registry path</th>
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<td>inference</td>
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</tr>
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</table>

**Neo MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet', region='eu-central-1', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
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<td></td>
<td>CPU, GPU</td>
<td>py3</td>
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</tbody>
</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='eu-central-1', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
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<th>Python versions</th>
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<td>py3</td>
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</tbody>
</table>
### Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='eu-central-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
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<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

### Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='eu-central-1')
```

<table>
<thead>
<tr>
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<td>py3</td>
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</table>
Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='eu-central-1')
```

<table>
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<tr>
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Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='eu-central-1')
```

<table>
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</table>

PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca',region='eu-central-1')
```

<table>
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PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch',region='eu-central-1',version='1.8.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```
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</table>
### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='eu-central-1')
```

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### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch', region='eu-central-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

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</table>

### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='eu-central-1',version='0.23-1',image_scope='inference')

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### Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='eu-central-1')
```

<table>
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### Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='eu-central-1')
```

<table>
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</table>
**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='eu-central-1', version='3.0', image_scope='processing')
```

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**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='eu-central-1', version='2.4')
```

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**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='eu-central-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```
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### Use Built-in Algorithms

#### Registry path

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#### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uri = image_uris.retrieve(framework='coach-tensorflow', region='eu-central-1', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```

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```
Use Built-in Algorithms

### Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='eu-central-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

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### Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='eu-central-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

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</table>

### TensorFlow Inference (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='eu-central-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</table>
### Use Built-in Algorithms

#### VW (algorithm)

**SageMaker Python SDK example to retrieve registry path.**

```python
g
from sagemaker import image_uris
g
image_uris.retrieve(framework='vw', region='eu-central-1', version='8.7.0', image_scope='training')
```

<table>
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<th>Python versions</th>
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#### XGBoost (algorithm)

**SageMaker Python SDK example to retrieve registry path.**

```python
g
from sagemaker import image_uris
g
image_uris.retrieve(framework='xgboost', region='eu-central-1', version='1.0.1', image_scope='training')
```
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost',region='eu-central-1',version='1.5-1')

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Docker Registry Paths and Example Code for Europe (Ireland) (eu-west-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**
- AutoGluon (algorithm) (p. 1682)
- BlazingText (algorithm) (p. 1684)
- Chainer (DLC) (p. 1684)
- Clarify (algorithm) (p. 1684)
• Data Wrangler (algorithm) (p. 1685)
• Debugger (algorithm) (p. 1685)
• DeepAR Forecasting (algorithm) (p. 1685)
• Factorization Machines (algorithm) (p. 1686)
• Hugging Face (algorithm) (p. 1686)
• IP Insights (algorithm) (p. 1689)
• Image classification (algorithm) (p. 1689)
• Inferentia MXNet (DLC) (p. 1690)
• Inferentia PyTorch (DLC) (p. 1690)
• K-Means (algorithm) (p. 1691)
• KNN (algorithm) (p. 1691)
• LDA (algorithm) (p. 1691)
• Linear Learner (algorithm) (p. 1691)
• MXNet (DLC) (p. 1692)
• MXNet Coach (DLC) (p. 1695)
• Model Monitor (algorithm) (p. 1695)
• NTM (algorithm) (p. 1695)
• Neo Image Classification (algorithm) (p. 1696)
• Neo MXNet (DLC) (p. 1696)
• Neo PyTorch (DLC) (p. 1696)
• Neo Tensorflow (DLC) (p. 1697)
• Neo XGBoost (algorithm) (p. 1698)
• Object Detection (algorithm) (p. 1698)
• Object2Vec (algorithm) (p. 1698)
• PCA (algorithm) (p. 1698)
• PyTorch (DLC) (p. 1699)
• Random Cut Forest (algorithm) (p. 1702)
• Ray PyTorch (DLC) (p. 1702)
• Scikit-learn (algorithm) (p. 1703)
• Semantic Segmentation (algorithm) (p. 1703)
• Seq2Seq (algorithm) (p. 1704)
• Spark (algorithm) (p. 1704)
• SparkML Serving (algorithm) (p. 1704)
• Tensorflow (DLC) (p. 1705)
• Tensorflow Coach (DLC) (p. 1713)
• Tensorflow Inferentia (DLC) (p. 1714)
• Tensorflow Ray (DLC) (p. 1715)
• VW (algorithm) (p. 1715)
• XGBoost (algorithm) (p. 1716)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
```python
image_uris.retrieve(framework='autogluon',region='eu-west-1',image_scope='inference',version='0.4')
```

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</tr>
</tbody>
</table>

**BlazingText (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>inference, training</td>
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</tbody>
</table>

**Chainer (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='eu-west-1', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Python versions</th>
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<td>py2, py3</td>
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</table>

**Clarify (algorithm)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='eu-west-1',version='1.0',image_scope='processing')

<table>
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<th>Job types (image scope)</th>
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</table>

**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='eu-west-1')

<table>
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</table>

**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='debugger',region='eu-west-1')

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar',region='eu-west-1')
## Registry path | Version | Job types (image scope)
---|---|---
224300973850.dkr.ecr.eu-west-1.amazonaws.com/forecasting-deepar:<tag> | | inference, training

### Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines',region='eu-west-1')
```

### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='eu-west-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
```
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**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='eu-west-1')
```

<table>
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<td>ipinsights:&lt;tag&gt;</td>
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<td>inference, training</td>
</tr>
</tbody>
</table>

**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='image-classification',region='eu-west-1')

## Registry path | Version | Job types (image scope) | Processor types | Python versions
---|---|---|---|---
685385470294.dkr.ecr.eu-west-1.amazonaws.com/image-classification:<tag> | | inference, training | |

### Inferentia MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet',region='eu-west-1',version='1.5.1',instance_type='ml.inf1.6xlarge')
```

## Registry path | Version | Job types (image scope) | Processor types | Python versions
---|---|---|---|---
802834080501.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-neo-mxnet:<tag> | inference | inf | py3
802834080501.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-neo-mxnet:<tag> | inference | inf | py3

### Inferentia PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='eu-west-1',version='1.9',py_version='py3')
```

## Registry path | Version | Job types (image scope) | Processor types | Python versions
---|---|---|---|---
802834080501.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-neo-pytorch:<tag> | inference | inf | py3
802834080501.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-neo-pytorch:<tag> | inference | inf | py3
802834080501.dkr.ecr.eu-west-1.amazonaws.com/ | inference | inf | py3
## Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>sagemaker-neo-pytorch:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### K-Means (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>438346466558.dkr.ecr.eu-west-1.amazonaws.com/kmeans:</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

### KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn',region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

### LDA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda',region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>999678624901.dkr.ecr.eu-west-1.amazonaws.com/lda:</td>
<td></td>
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</tr>
</tbody>
</table>

### Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner',region='eu-west-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet',region='eu-west-1',version='1.4.1',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</thead>
<tbody>
<tr>
<td>763104351884.dkr.ecr.eu-west-1.amazonaws.com/mxnet-training:&lt;tag&gt;</td>
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<td>CPU, GPU</td>
<td>py38</td>
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<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
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<td>Python versions</td>
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</tr>
<tr>
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<td>py2, py3</td>
</tr>
<tr>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
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<tr>
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</tr>
<tr>
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<td>py2, py3</td>
</tr>
<tr>
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<tr>
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<td>CPU, GPU</td>
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</tr>
</tbody>
</table>
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>520713654638.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-mxnet:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='eu-west-1', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>520713654638.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-rl-mxnet:coach0.11.0-&lt;tag&gt;</td>
<td></td>
<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
<tr>
<td>520713654638.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-rl-mxnet:coach0.11-&lt;tag&gt;</td>
<td></td>
<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>468650794304.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-model-monitor-analyzer:&lt;tag&gt;</td>
<td></td>
<td>monitoring</td>
</tr>
</tbody>
</table>

NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='ntm',region='eu-west-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>438346466558.dkr.ecr.eu-west-1.amazonaws.com/ntm:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>802834080501.dkr.ecr.eu-west-1.amazonaws.com/image-classification-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

**Neo MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='eu-west-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>802834080501.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-inference-mxnet:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='eu-west-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>802834080501.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-inference-pytorch:&lt;tag&gt;</td>
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<td>CPU, GPU</td>
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<td>py3</td>
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<td>CPU, GPU</td>
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<td></td>
<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

### Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='eu-west-1',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>
**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>802834080501.dkr.ecr.eu-west-1.amazonaws.com/xgboost-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

**Object Detection (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Object2Vec (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='eu-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>438346466558.dkr.ecr.eu-west-1.amazonaws.com/object2vec:&lt;tag&gt;</td>
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</table>

**PCA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca',region='eu-west-1')
```
### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>

#### PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='eu-west-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

### Registry path

<table>
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<tr>
<th>Registry path</th>
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520713654638.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-pytorch:<tag> | training | CPU, GPU | py2, py3

#### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest',region='eu-west-1')
```

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<tr>
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#### Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
ing_image_uris.retrieve(framework='ray-pytorch', region='eu-west-1', version='0.8.5', instance_type='ml.c5.4xlarge')

<table>
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</table>

**Scikit-learn (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='eu-west-1', version='0.23-1', image_scope='inference')
```

<table>
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**Semantic Segmentation (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='eu-west-1')
```
### Registry path | Version | Job types (image scope)
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685385470294.dkr.ecr.eu-west-1.amazonaws.com/semantic-segmentation: | 1 | inference, training

**Seq2Seq (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='eu-west-1')
```

### Registry path | Version | Job types (image scope)
--- | --- | ---
685385470294.dkr.ecr.eu-west-1.amazonaws.com/seq2seq: | 1 | inference, training

**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='eu-west-1', version='3.0', image_scope='processing')
```

### Registry path | Version | Job types (image scope)
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571004829621.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-spark-processing: | 3.0 | processing
571004829621.dkr.ecr.eu-west-1.amazonaws.com/sagemaker-spark-processing: | 2.4 | processing

**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='sparkml-serving',region='eu-west-1',version='2.4')

<table>
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**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='eu-west-1',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='eu-west-1',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```

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## Use Built-in Algorithms

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### Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uri = image_uris.retrieve(framework='inferentia-tensorflow', region='eu-west-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

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Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow',region='eu-west-1',version='0.8.5',instance_type='ml.c5.4xlarge')
```

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</table>

VW (algorithm)

SageMaker Python SDK example to retrieve registry path.
Use Built-in Algorithms

from sagemaker import image_uris
image_uris.retrieve(framework='vw', region='eu-west-1', version='8.7.0', image_scope='training')

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**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='eu-west-1', version='1.5-1')

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Docker Registry Paths and Example Code for Europe (London) (eu-west-2)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics
- AutoGluon (algorithm) (p. 1718)
- BlazingText (algorithm) (p. 1719)
- Chainer (DLC) (p. 1719)
- Clarify (algorithm) (p. 1720)
- Data Wrangler (algorithm) (p. 1720)
- Debugger (algorithm) (p. 1720)
- DeepAR Forecasting (algorithm) (p. 1721)
- Factorization Machines (algorithm) (p. 1721)
- Hugging Face (algorithm) (p. 1721)
- IP Insights (algorithm) (p. 1725)
- Image classification (algorithm) (p. 1725)
- Inferentia MXNet (DLC) (p. 1725)
- Inferentia PyTorch (DLC) (p. 1725)
- K-Means (algorithm) (p. 1726)
- KNN (algorithm) (p. 1726)
- LDA (algorithm) (p. 1727)
- Linear Learner (algorithm) (p. 1727)
- MXNet (DLC) (p. 1727)
- MXNet Coach (DLC) (p. 1730)
- Model Monitor (algorithm) (p. 1730)
- NTM (algorithm) (p. 1731)
- Neo Image Classification (algorithm) (p. 1731)
- Neo MXNet (DLC) (p. 1731)
- Neo PyTorch (DLC) (p. 1732)
- Neo Tensorflow (DLC) (p. 1732)
- Neo XGBoost (algorithm) (p. 1733)
- Object Detection (algorithm) (p. 1733)
- Object2Vec (algorithm) (p. 1733)
- PCA (algorithm) (p. 1734)
- PyTorch (DLC) (p. 1734)
- Random Cut Forest (algorithm) (p. 1737)

<table>
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</table>
Use Built-in Algorithms

- Ray PyTorch (DLC) (p. 1738)
- Scikit-learn (algorithm) (p. 1738)
- Semantic Segmentation (algorithm) (p. 1738)
- Seq2Seq (algorithm) (p. 1739)
- Spark (algorithm) (p. 1739)
- SparkML Serving (algorithm) (p. 1739)
- Tensorflow (DLC) (p. 1740)
- Tensorflow Coach (DLC) (p. 1748)
- Tensorflow Inferentia (DLC) (p. 1749)
- Tensorflow Ray (DLC) (p. 1750)
- VW (algorithm) (p. 1750)
- XGBoost (algorithm) (p. 1751)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon', region='eu-west-2', image_scope='inference', version='0.4')
```

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</table>
### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='eu-west-2')
```

### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='eu-west-2', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
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<td>py2, py3</td>
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</table>

**Clarify (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='eu-west-2',version='1.0',image_scope='processing')
```

<table>
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</table>

**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='eu-west-2')
```

<table>
<thead>
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<tbody>
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</table>

**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='debugger',region='eu-west-2')

<table>
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<tr>
<th>Registry path</th>
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**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar',region='eu-west-2')

<table>
<thead>
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<tbody>
<tr>
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</table>

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines',region='eu-west-2')

<table>
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<th>Version</th>
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**Hugging Face (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='eu-west-2',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
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IP Insights (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='eu-west-2')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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</table>

Image classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification', region='eu-west-2')
```

<table>
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<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td></td>
<td>inference, training</td>
</tr>
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</table>

Inferentia MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='eu-west-2', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
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<th>Version</th>
<th>Processor types</th>
<th>Python versions</th>
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</thead>
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</table>

Inferentia PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='eu-west-2',version='1.9',py_version='py3')

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Processor types</th>
<th>Python versions</th>
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<td></td>
<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='eu-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td>inference, training</td>
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</tbody>
</table>

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn',region='eu-west-2')
```

<table>
<thead>
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<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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</tr>
</tbody>
</table>
## LDA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='lda', region='eu-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td></td>
<td>inference, training</td>
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</tbody>
</table>

## Linear Learner (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='eu-west-2')
```

<table>
<thead>
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<th>Registry path</th>
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<th>Job types (image scope)</th>
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</table>

## MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='eu-west-2', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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## Use Built-in Algorithms

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<td>py2, py3</td>
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</table>

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='eu-west-2',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
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<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Model Monitor (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor',region='eu-west-2')
```
### NTM (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve('framework='ntm','region='eu-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<table>
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<td></td>
<td>inference, training</td>
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</tbody>
</table>

### Neo Image Classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve('framework='image-classification-neo','region='eu-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>205493899709.dkr.ecr.eu-west-2.amazonaws.com/image-classification-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

### Neo MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve('framework='neo-mxnet','region='eu-west-2',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>SageMaker Python SDK example to retrieve registry path.</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>from sagemaker import image_uris</td>
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<tr>
<td>image_uris.retrieve(framework='neo-pytorch',region='eu-west-2',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')</td>
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<tr>
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<td>image_uris.retrieve(framework='neo-tensorflow',region='eu-west-2',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')</td>
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</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
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<td>py3</td>
<td></td>
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</table>

#### Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='eu-west-2')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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</table>

#### Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='eu-west-2')
```

<table>
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</table>

#### Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='eu-west-2')
```
### PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='eu-west-2')
```

### PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='eu-west-2', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
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**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest',region='eu-west-2')
```

<table>
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Ray PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-pytorch', region='eu-west-2', version='0.8.5', instance_type='ml.c5.4xlarge')
```

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</table>

Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='eu-west-2', version='0.23-1', image_scope='inference')
```

<table>
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Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
Use Built-in Algorithms

```python
image_uris.retrieve(framework='semantic-segmentation', region='eu-west-2')
```

<table>
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<th>Version</th>
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### Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='eu-west-2')
```

<table>
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### Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='eu-west-2', version='3.0', image_scope='processing')
```

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### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.
```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving',region='eu-west-2',version='2.4')
```

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**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='eu-west-2',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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**Tensorflow Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
tensorflow urgently retrieve(framework='coach-tensorflow', region='eu-west-2', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```
### Use Built-in Algorithms

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### Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='eu-west-2', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

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Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='eu-west-2', version='0.8.5', instance_type='ml.c5.4xlarge')
```

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VW (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='vw', region='eu-west-2', version='8.7.0', image_scope='training')

<table>
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  <tag> |-training |

**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='eu-west-2', version='1.5-1')

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Docker Registry Paths and Example Code for Europe (Paris) (eu-west-3)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics

- AutoGluon (algorithm) (p. 1753)
- BlazingText (algorithm) (p. 1754)
- Chainer (DLC) (p. 1754)
- Clarify (algorithm) (p. 1755)
- Data Wrangler (algorithm) (p. 1755)
- Debugger (algorithm) (p. 1755)
- DeepAR Forecasting (algorithm) (p. 1756)
- Factorization Machines (algorithm) (p. 1756)
- Hugging Face (algorithm) (p. 1756)
- IP Insights (algorithm) (p. 1760)
- Image classification (algorithm) (p. 1760)
- Inferentia MXNet (DLC) (p. 1760)
- Inferentia PyTorch (DLC) (p. 1760)
- K-Means (algorithm) (p. 1761)
- KNN (algorithm) (p. 1761)
- Linear Learner (algorithm) (p. 1762)
- MXNet (DLC) (p. 1762)
- MXNet Coach (DLC) (p. 1765)
- Model Monitor (algorithm) (p. 1765)
- NTM (algorithm) (p. 1765)
- Neo Image Classification (algorithm) (p. 1766)
- Neo MXNet (DLC) (p. 1766)
- Neo PyTorch (DLC) (p. 1766)
- Neo Tensorflow (DLC) (p. 1767)
- Neo XGBoost (algorithm) (p. 1768)
- Object Detection (algorithm) (p. 1768)
- Object2Vec (algorithm) (p. 1768)
- PCA (algorithm) (p. 1768)
- PyTorch (DLC) (p. 1769)
• Random Cut Forest (algorithm) (p. 1772)
• Scikit-learn (algorithm) (p. 1772)
• Semantic Segmentation (algorithm) (p. 1773)
• Seq2Seq (algorithm) (p. 1773)
• Spark (algorithm) (p. 1773)
• SparkML Serving (algorithm) (p. 1774)
• Tensorflow (DLC) (p. 1774)
• Tensorflow Coach (DLC) (p. 1783)
• Tensorflow Inferentia (DLC) (p. 1784)
• Tensorflow Ray (DLC) (p. 1784)
• XGBoost (algorithm) (p. 1785)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='eu-west-3',image_scope='inference',version='0.4')
```

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</table>
### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext',region='eu-west-3')
```

<table>
<thead>
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<th>Job types (image scope)</th>
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</table>

### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='eu-west-3',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
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<th>Job types (image scope)</th>
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</table>

1754
<table>
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<td>py2, py3</td>
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<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
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</tbody>
</table>

**Clarify (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
debugger_image = image_uris.retrieve(framework='clarify',region='eu-west-3',version='1.0',image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>

**Data Wrangler (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
debugger_image = image_uris.retrieve(framework='data-wrangler',region='eu-west-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='debugger',region='eu-west-3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar',region='eu-west-3')

<table>
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<th>Version</th>
<th>Job types (image scope)</th>
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</table>

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines',region='eu-west-3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td>1</td>
<td>inference, training</td>
</tr>
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</table>

**Hugging Face (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='eu-west-3',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
<table>
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</table>
IP Insights (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='eu-west-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>

Image classification (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='eu-west-3')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<td>inference, training</td>
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</table>

Inferentia MXNet (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet',region='eu-west-3',version='1.5.1',instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>254080097072.dkr.ecr.eu-west-3.amazonaws.com/sagemaker-neo-mxnet:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
<td>inf</td>
<td>py3</td>
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<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

Inferentia PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='eu-west-3', version='1.9', py_version='py3')

<table>
<thead>
<tr>
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<th>Python versions</th>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

K-Means (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='eu-west-3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>inference, training</td>
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</table>

KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='eu-west-3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>
Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='eu-west-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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<td>inference, training</td>
</tr>
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</table>

MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='eu-west-3', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>py2, py3</td>
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</tbody>
</table>
Use Built-in Algorithms

<table>
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<td></td>
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<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='eu-west-3', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
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<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
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<td>520713654638.dkr.ecr.eu-west-3.amazonaws.com/sagemaker-rl-mxnet:coach0.11:&lt;tag&gt;</td>
<td></td>
<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Model Monitor (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='eu-west-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
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<tr>
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<td>monitoring</td>
<td></td>
<td></td>
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</table>

**NTM (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='ntm',region='eu-west-3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='eu-west-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>254080097072.dkr.ecr.eu-west-3.amazonaws.com/image-classification-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='eu-west-3',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Python versions</th>
</tr>
</thead>
</table>

Neo PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='eu-west-3',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```
### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>

### Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='eu-west-3', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
</table>
Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='eu-west-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
<td>254080097072.dkr.ecr.eu-west-3.amazonaws.com/xgboost-neo:&lt;tag&gt;</td>
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<td>inference</td>
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</tbody>
</table>

Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='eu-west-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<td>inference, training</td>
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</tbody>
</table>

Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='eu-west-3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tr>
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<td>inference, training</td>
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</table>

PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca',region='eu-west-3')
```
Use Built-in Algorithms

#### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<tr>
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</table>

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**PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='eu-west-3', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
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### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest',region='eu-west-3')
```

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### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='eu-west-3',version='0.23-1',image_scope='inference')
```

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**Semantic Segmentation (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='eu-west-3')
```

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**Seq2Seq (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='eu-west-3')
```

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**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='eu-west-3', version='3.0', image_scope='processing')
```
### Use Built-in Algorithms

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#### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='eu-west-3', version='2.4')
```

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#### Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='eu-west-3', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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<td>py2</td>
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</table>
### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow', region='eu-west-3', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
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<th>Python versions</th>
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**Tensorflow Inferentia (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='eu-west-3', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

<table>
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**Tensorflow Ray (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='eu-west-3', version='0.8.5', instance_type='ml.c5.4xlarge')
```

<table>
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</table>
XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='eu-west-3', version='1.5-1')
```

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Docker Registry Paths and Example Code for Europe (Stockholm) (eu-north-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**
- AutoGluon (algorithm) (p. 1786)
- BlazingText (algorithm) (p. 1788)
• Chainer (DLC) (p. 1788)
• Clarify (algorithm) (p. 1788)
• Data Wrangler (algorithm) (p. 1789)
• Debugger (algorithm) (p. 1789)
• DeepAR Forecasting (algorithm) (p. 1789)
• Factorization Machines (algorithm) (p. 1790)
• Hugging Face (algorithm) (p. 1790)
• IP Insights (algorithm) (p. 1793)
• Image classification (algorithm) (p. 1793)
• Inferentia MXNet (DLC) (p. 1794)
• Inferentia PyTorch (DLC) (p. 1794)
• K-Means (algorithm) (p. 1795)
• KNN (algorithm) (p. 1795)
• Linear Learner (algorithm) (p. 1795)
• MXNet (DLC) (p. 1795)
• MXNet Coach (DLC) (p. 1798)
• Model Monitor (algorithm) (p. 1799)
• NTM (algorithm) (p. 1799)
• Neo Image Classification (algorithm) (p. 1799)
• Neo MXNet (DLC) (p. 1800)
• Neo PyTorch (DLC) (p. 1800)
• Neo Tensorflow (DLC) (p. 1801)
• Neo XGBoost (algorithm) (p. 1801)
• Object Detection (algorithm) (p. 1802)
• Object2Vec (algorithm) (p. 1802)
• PCA (algorithm) (p. 1802)
• PyTorch (DLC) (p. 1802)
• Random Cut Forest (algorithm) (p. 1806)
• Scikit-learn (algorithm) (p. 1806)
• Semantic Segmentation (algorithm) (p. 1807)
• Seq2Seq (algorithm) (p. 1807)
• Spark (algorithm) (p. 1807)
• SparkML Serving (algorithm) (p. 1808)
• Tensorflow (DLC) (p. 1808)
• Tensorflow Coach (DLC) (p. 1816)
• Tensorflow Inferentia (DLC) (p. 1817)
• Tensorflow Ray (DLC) (p. 1818)
• XGBoost (algorithm) (p. 1818)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='eu-north-1',image_scope='inference',version='0.4')
```
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Use Built-in Algorithms

### Registry path

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</table>

### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='eu-north-1')
```

### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer', region='eu-north-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

### Processor types

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<td>py2, py3</td>
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### Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='clarify', region='eu-north-1', version='1.0', image_scope='processing')

<table>
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Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='eu-north-1')

<table>
<thead>
<tr>
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<th>Job types (image scope)</th>
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Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='eu-north-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
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</tr>
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DeepAR Forecasting (algorithm)

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='eu-north-1')
### Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines',region='eu-north-1')
```

### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='eu-north-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
```
<table>
<thead>
<tr>
<th>Registry path</th>
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<tbody>
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**Registry path** | **Version** | **Job types (image scope)**
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763104351884.dkr.ecr.eu-north-1.amazonaws.com/huggingface-tensorflow-inference:tag | 4.6.1 | inference
763104351884.dkr.ecr.eu-north-1.amazonaws.com/huggingface-pytorch-training:tag | 4.5.0 | training
763104351884.dkr.ecr.eu-north-1.amazonaws.com/huggingface-tensorflow-training:tag | 4.5.0 | training
763104351884.dkr.ecr.eu-north-1.amazonaws.com/huggingface-pytorch-training:tag | 4.4.2 | training
763104351884.dkr.ecr.eu-north-1.amazonaws.com/huggingface-tensorflow-training:tag | 4.4.2 | training

**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='eu-north-1')
```

**Registry path** | **Version** | **Job types (image scope)**
--- | --- | ---
669576153137.dkr.ecr.eu-north-1.amazonaws.com/ipinsights:tag | | inference, training

**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='image-classification', region='eu-north-1')

<table>
<thead>
<tr>
<th>Registry path</th>
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<tbody>
<tr>
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</tbody>
</table>

**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='eu-north-1', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>py3</td>
</tr>
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</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='eu-north-1', version='1.9', py_version='py3')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</tbody>
</table>
### K-Means (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>sagemaker-neo-pytorch:</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
<td>669576153137.dkr.ecr.eu-north-1.amazonaws.com/kmeans:</td>
<td></td>
<td>inference, training</td>
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</table>

### Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
<td>669576153137.dkr.ecr.eu-north-1.amazonaws.com/linear-learner:</td>
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<td>inference, training</td>
</tr>
</tbody>
</table>

### MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>mxnet:</td>
<td></td>
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</tr>
</tbody>
</table>
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='eu-north-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tbody>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='eu-north-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</tbody>
</table>

**Model Monitor (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>monitoring</td>
</tr>
</tbody>
</table>

**NTM (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='eu-north-1')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Neo MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet',region='eu-north-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='eu-north-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='eu-north-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<tr>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>
Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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<td>object-detection:&lt;tag&gt;</td>
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<tr>
<td></td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>669576153137.dkr.ecr.eu-north-1.amazonaws.com/</td>
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<td></td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<tr>
<td></td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='eu-north-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<th>Python versions</th>
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<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
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<tr>
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<tr>
<td>Registry path</td>
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</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>py2, py3</td>
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<td></td>
<td>training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

#### Random Cut Forest (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
<td>669576153137.dkr.ecr.eu-north-1.amazonaws.com/randomcutforest:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

#### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='eu-north-1', version='0.23-1', image_scope='inference')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
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</tr>
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<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>
## Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>669576153137.dkr.ecr.eu-north-1.amazonaws.com/semantic-segmentation:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

## Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq',region='eu-north-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
<td>669576153137.dkr.ecr.eu-north-1.amazonaws.com/seq2seq:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

## Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark',region='eu-north-1',version='3.0',image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='eu-north-1', version='2.4')
```

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### Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='eu-north-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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## Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='coach-tensorflow', region='eu-north-1', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')

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</tr>
</tbody>
</table>

Tensorflow Inferentia (DLC)
SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow', region='eu-north-1', version='1.15.0', instance_type='ml.inf1.6xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
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</tr>
</tbody>
</table>
Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='eu-north-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>training</td>
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<td>py3</td>
</tr>
</tbody>
</table>

XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='eu-north-1', version='1.5-1')
```

<table>
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<th>Version</th>
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<td>Package version</td>
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</table>

Docker Registry Paths and Example Code for Europe (Milan) (eu-south-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics
- AutoGluon (algorithm) (p. 1820)
- BlazingText (algorithm) (p. 1821)
- Chainer (DLC) (p. 1822)
- Clarify (algorithm) (p. 1822)
- Data Wrangler (algorithm) (p. 1823)
- Debugger (algorithm) (p. 1823)
- DeepAR Forecasting (algorithm) (p. 1823)
- Factorization Machines (algorithm) (p. 1823)
- Hugging Face (algorithm) (p. 1824)
- IP Insights (algorithm) (p. 1827)
- Image classification (algorithm) (p. 1827)
- Inferentia MXNet (DLC) (p. 1827)
- Inferentia PyTorch (DLC) (p. 1828)
- K-Means (algorithm) (p. 1828)
- KNN (algorithm) (p. 1829)
• Linear Learner (algorithm) (p. 1829)
• MXNet (DLC) (p. 1829)
• MXNet Coach (DLC) (p. 1832)
• Model Monitor (algorithm) (p. 1833)
• NTM (algorithm) (p. 1833)
• Neo Image Classification (algorithm) (p. 1833)
• Neo MXNet (DLC) (p. 1833)
• Neo PyTorch (DLC) (p. 1834)
• Neo Tensorflow (DLC) (p. 1835)
• Neo XGBoost (algorithm) (p. 1835)
• Object Detection (algorithm) (p. 1835)
• Object2Vec (algorithm) (p. 1836)
• PCA (algorithm) (p. 1836)
• PyTorch (DLC) (p. 1836)
• Random Cut Forest (algorithm) (p. 1839)
• Scikit-learn (algorithm) (p. 1840)
• Semantic Segmentation (algorithm) (p. 1840)
• Seq2Seq (algorithm) (p. 1840)
• Spark (algorithm) (p. 1841)
• SparkML Serving (algorithm) (p. 1841)
• Tensorflow (DLC) (p. 1842)
• Tensorflow Coach (DLC) (p. 1850)
• Tensorflow Inference (DLC) (p. 1851)
• Tensorflow Ray (DLC) (p. 1851)
• XGBoost (algorithm) (p. 1852)

AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='eu-south-1',image_scope='inference',version='0.4')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

**BlazingText (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
### Use Built-in Algorithms

```python
image_uris.retrieve(framework='blazingtext',region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>257386234256.dkr.ecr.eu-south-1.amazonaws.com/blazingtext:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

#### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
dl = image_uris.retrieve(framework='chainer',region='eu-south-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
<tr>
<td>048378556238.dkr.ecr.eu-south-1.amazonaws.com/sagemaker-chainer:&lt;tag&gt;</td>
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<tr>
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<td></td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

#### Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
dl = image_uris.retrieve(framework='clarify',region='eu-south-1',version='1.0',image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>processing</td>
</tr>
</tbody>
</table>
Data Wrangler (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler', region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td></td>
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</tr>
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</table>

Debugger (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>debugger</td>
</tr>
</tbody>
</table>

DeepAR Forecasting (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
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</table>

Factorization Machines (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='eu-south-1')
```
### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='eu-south-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</tbody>
</table>
### IP Insights (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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</tbody>
</table>

### Image classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification', region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td>257386234256.dkr.ecr.eu-south-1.amazonaws.com/ipinsights: &lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

### Inferentia MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet',region='eu-south-1',version='1.5.1',instance_type='ml.inf1.6xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>966458181534.dkr.ecr.eu-south-1.amazonaws.com/sagemaker-neo-mxnet:&lt;tag&gt;</td>
<td>inference</td>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='eu-south-1',version='1.9',py_version='py3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<th>Python versions</th>
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<td>inf</td>
<td>py3</td>
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</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='eu-south-1')
### KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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</table>

### Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td>inference, training</td>
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</table>

### MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='eu-south-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>Python versions</td>
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<tr>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
<td></td>
</tr>
</tbody>
</table>

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='eu-south-1', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
<td>048378556238.dkr.ecr.eu-south-1.amazonaws.com/sagemaker-rl-mxnet:coach0.11.0-&lt;tag&gt;</td>
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<td>CPU, GPU</td>
<td>py3</td>
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<tr>
<td>048378556238.dkr.ecr.eu-south-1.amazonaws.com/sagemaker-rl-mxnet:coach0.11-&lt;tag&gt;</td>
<td>training</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>
Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor',region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>933208885752.dkr.ecr.eu-south-1.amazonaws.com/sagemaker-model-monitor-analyzer:&lt;tag&gt;</td>
<td></td>
<td>monitoring</td>
</tr>
</tbody>
</table>

NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm',region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>257386234256.dkr.ecr.eu-south-1.amazonaws.com/ntm:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>966458181534.dkr.ecr.eu-latest south-1.amazonaws.com/image-classification-neo:&lt;tag&gt;</td>
<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```

image_uris.retrieve(framework='neo-mxnet', region='eu-south-1', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<th>Python versions</th>
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<tr>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='eu-south-1', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
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</table>
Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='eu-south-1',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
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</table>

Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
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</table>
Object2Vec (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='eu-south-1')
```

<table>
<thead>
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<th>Registry path</th>
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</table>

PCA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='eu-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='eu-south-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
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<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest',region='eu-south-1')
```
**Scikit-learn (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='eu-south-1', version='0.23-1', image_scope='inference')
```

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**Semantic Segmentation (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='eu-south-1')
```

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**Seq2Seq (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```

1840
image_uris.retrieve(framework='seq2seq', region='eu-south-1')

<table>
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**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='eu-south-1', version='3.0', image_scope='processing')
```

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**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='eu-south-1', version='2.4')
```

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Use Built-in Algorithms

### Registry path

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#### Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='eu-south-1',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```
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</table>
### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow', region='eu-south-1', version='1.0.0', image_scope='training', instance_type='ml.c5.4xlarge')
```

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### Use Built-in Algorithms

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Tensorflow Inferentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='eu-south-1',version='1.15.0',instance_type='ml.inf1.6xlarge')
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Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow',region='eu-south-1',version='0.8.5',instance_type='ml.c5.4xlarge')
```
## XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='eu-south-1', version='1.5-1')
```

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978288397137.dkr.ecr.eu-south-1.amazonaws.com/sagemaker-xgboost:<tag> | 0.90 | inference, training

Docker Registry Paths and Example Code for Middle East (Bahrain) (me-south-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics
- AutoGluon (algorithm) (p. 1854)
- BlazingText (algorithm) (p. 1855)
- Chainer (DLC) (p. 1856)
- Clarify (algorithm) (p. 1856)
- Data Wrangler (algorithm) (p. 1856)
- Debugger (algorithm) (p. 1857)
- DeepAR Forecasting (algorithm) (p. 1857)
- Factorization Machines (algorithm) (p. 1857)
- Hugging Face (algorithm) (p. 1858)
- IP Insights (algorithm) (p. 1861)
- Image classification (algorithm) (p. 1861)
- Inferentia MXNet (DLC) (p. 1861)
- Inferentia PyTorch (DLC) (p. 1862)
- K-Means (algorithm) (p. 1862)
- KNN (algorithm) (p. 1863)
- Linear Learner (algorithm) (p. 1863)
- MXNet (DLC) (p. 1863)
- MXNet Coach (DLC) (p. 1866)
- Model Monitor (algorithm) (p. 1867)
- NTM (algorithm) (p. 1867)
- Neo Image Classification (algorithm) (p. 1867)
- Neo MXNet (DLC) (p. 1867)
AutoGluon (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='me-south-1',image_scope='inference',version='0.4')
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1854
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<td>217643126080.dkr.ecr.me0.3.2 south-1.amazonaws.com/autogluon-inference:&lt;tag&gt;</td>
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</tr>
<tr>
<td>217643126080.dkr.ecr.me0.3.1 south-1.amazonaws.com/autogluon-training:&lt;tag&gt;</td>
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<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

**BlazingText (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='me-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>249704162688.dkr.ecr.me1 south-1.amazonaws.com/blazingtext:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>
Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```py
from sagemaker import image_uris
e_image_uris.retrieve(framework='chainer', region='me-south-1', version='5.0.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
</thead>
<tbody>
<tr>
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<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
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<td>py2, py3</td>
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<td>version</td>
<td>inference, training</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```py
from sagemaker import image_uris
e_image_uris.retrieve(framework='clarify', region='me-south-1', version='1.0', image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
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<td>processing</td>
</tr>
</tbody>
</table>

Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```py
from sagemaker import image_uris
e_image_uris.retrieve(framework='data-wrangler', region='me-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
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<tr>
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<tr>
<td>sagemaker-data-wrangler-container:&lt;tag&gt;</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='me-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>latest</td>
<td>debugger</td>
</tr>
</tbody>
</table>

**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='me-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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</table>

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='me-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
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<tbody>
<tr>
<td>factorization-machines:&lt;tag&gt;</td>
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</table>

### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface', region='me-south-1', version='4.4.2', image_scope='training', base_framework_version='tensorflow2.4.1')
```

<table>
<thead>
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<tr>
<td>Registry path</td>
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<td>Job types (image scope)</td>
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<tr>
<td>Registry path</td>
<td>Version</td>
<td>Job types (image scope)</td>
</tr>
<tr>
<td>------------------------------------------------------------------------------</td>
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<tr>
<td>217643126080.dkr.ecr.me-south-1.amazonaws.com/huggingface-tensorflow-training:&lt;tag&gt;</td>
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<tr>
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<tr>
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<td></td>
<td>training</td>
</tr>
</tbody>
</table>

**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights', region='me-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>249704162688.dkr.ecr.me-south-1.amazonaws.com/ipinsights:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification', region='me-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>249704162688.dkr.ecr.me-south-1.amazonaws.com/image-classification:&lt;tag&gt;</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet', region='me-south-1', version='1.5.1', instance_type='ml.inf1.6xlarge')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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<tr>
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<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch', region='me-south-1', version='1.9', py_version='py3')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
</tr>
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<tbody>
<tr>
<td>836785723513.dkr.ecr.me-south-1.amazonaws.com/sagemaker-neo-pytorch:&lt;tag&gt;</td>
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<td>inference</td>
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<tr>
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<td></td>
<td>inference</td>
<td>inf</td>
<td>py3</td>
</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='me-south-1')
### Use Built-in Algorithms

#### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<td>training</td>
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</tbody>
</table>

#### KNN (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='me-south-1')
```

#### Linear Learner (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='me-south-1')
```

#### MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='me-south-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```
<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>Processor types</td>
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</table>
Use Built-in Algorithms

### Registry path

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<td>py2, py3</td>
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</table>

### MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet',region='me-south-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

---

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Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='me-south-1')
```

<table>
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NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='me-south-1')
```

<table>
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</table>

Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='me-south-1')
```

<table>
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Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='me-south-1')
```
image_uris.retrieve(framework='neo-mxnet',region='me-south-1',version='1.8',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')

<table>
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<th>Processor types</th>
<th>Python versions</th>
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<td>py3</td>
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</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch',region='me-south-1',version='1.6',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
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<td>py3</td>
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</tbody>
</table>

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Neo Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='me-south-1',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
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Neo XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='me-south-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection',region='me-south-1')
```

<table>
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Use Built-in Algorithms

Object2Vec (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='me-south-1')
```

<table>
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<th>Registry path</th>
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PCA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='me-south-1')
```

<table>
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PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch', region='me-south-1', version='1.8.0', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
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</table>

**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='me-south-1')
```
### Use Built-in Algorithms

#### Registry path

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>inference, training</td>
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</table>

**Scikit-learn (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='me-south-1', version='0.23-1', image_scope='inference')
```

<table>
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<th>Package version</th>
<th>Job types (image scope)</th>
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**Semantic Segmentation (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='me-south-1')
```

<table>
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**Seq2Seq (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
### Use Built-in Algorithms

#### Registry path

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#### Spark (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='me-south-1', version='3.0', image_scope='processing')
```

#### SparkML Serving (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='me-south-1', version='2.4')
```
Registry path | Version | Job types (image scope) | Processor types | Python versions
--- | --- | --- | --- | ---
sagemaker-sparkml-serving: | | | | 

**Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='me-south-1',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

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## Use Built-in Algorithms

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724002660598.dkr.ecr-me-south-1.amazonaws.com/sagemaker-tensorflow:<tag> | | inference | CPU, GPU | py2
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724002660598.dkr.ecr-me-south-1.amazonaws.com/sagemaker-tensorflow:<tag> | | training | CPU, GPU | py2
724002660598.dkr.ecr-me-south-1.amazonaws.com/sagemaker-tensorflow:<tag> | | inference | CPU, GPU | py2
724002660598.dkr.ecr-me-south-1.amazonaws.com/sagemaker-tensorflow:<tag> | | training | CPU, GPU | py2

### Tensorflow Coach (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='me-south-1',version='0.11.1',image_scope='training',instance_type='ml.c5.4xlarge',image_type='docker')
```

### Registry path | Version | Job types (image scope) | Processor types | Python versions
--- | --- | --- | --- | ---
724002660598.dkr.ecr-me-south-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.11.1-<tag> | | training | CPU, GPU | py3
724002660598.dkr.ecr-me-south-1.amazonaws.com/sagemaker-rl-tensorflow:coach0.11.0-<tag> | | training | CPU, GPU | py3
### Tensorflow Inherentia (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inherentia-tensorflow', region='me-south-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inf</td>
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</table>

### Tensorflow Ray (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow', region='me-south-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```
Use Built-in Algorithms

Registry path | Version | Job types (image scope) | Processor types | Python versions
---|---|---|---|---
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724002660598.dkr.ecr.me-south-1.amazonaws.com/sagemaker-rl-tensorflow:ray0.6-<tag> | training | CPU, GPU | py3
724002660598.dkr.ecr.me-south-1.amazonaws.com/sagemaker-rl-tensorflow:ray0.5.3-<tag> | training | CPU, GPU | py3
724002660598.dkr.ecr.me-south-1.amazonaws.com/sagemaker-rl-tensorflow:ray0.5-<tag> | training | CPU, GPU | py3

XGBoost (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='me-south-1', version='1.5-1')
```

Registry path | Version | Package version | Job types (image scope)
---|---|---|---
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801668240914.dkr.ecr.hn-1south-1.amazonaws.com/sagemaker-xgboost:<tag> | 1.3.3 | inference, training
801668240914.dkr.ecr.hn-2south-1.amazonaws.com/sagemaker-xgboost:<tag> | 1.2.0 | inference, training
801668240914.dkr.ecr.hn-1south-1.amazonaws.com/sagemaker-xgboost:<tag> | 1.2.0 | inference, training
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Docker Registry Paths and Example Code for South America (São Paulo) (sa-east-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

Topics
- AutoGluon (algorithm) (p. 1888)
- BlazingText (algorithm) (p. 1889)
- Chainer (DLC) (p. 1890)
- Clarify (algorithm) (p. 1890)
- Data Wrangler (algorithm) (p. 1890)
- Debugger (algorithm) (p. 1891)
- DeepAR Forecasting (algorithm) (p. 1891)
- Factorization Machines (algorithm) (p. 1891)
- Hugging Face (algorithm) (p. 1892)
- IP Insights (algorithm) (p. 1895)
- Image classification (algorithm) (p. 1895)
- Inferentia MXNet (DLC) (p. 1895)
- Inferentia PyTorch (DLC) (p. 1896)
- K-Means (algorithm) (p. 1896)
- KNN (algorithm) (p. 1897)
- Linear Learner (algorithm) (p. 1897)
- MXNet (DLC) (p. 1897)
- MXNet Coach (DLC) (p. 1900)
- Model Monitor (algorithm) (p. 1901)
- NTM (algorithm) (p. 1901)
- Neo Image Classification (algorithm) (p. 1901)
- Neo MXNet (DLC) (p. 1901)
- Neo PyTorch (DLC) (p. 1902)
- Neo Tensorflow (DLC) (p. 1903)
- Neo XGBoost (algorithm) (p. 1903)
- Object Detection (algorithm) (p. 1903)
- Object2Vec (algorithm) (p. 1904)
- PCA (algorithm) (p. 1904)
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- Random Cut Forest (algorithm) (p. 1907)
- Scikit-learn (algorithm) (p. 1908)
- Semantic Segmentation (algorithm) (p. 1908)
- Seq2Seq (algorithm) (p. 1908)
- Spark (algorithm) (p. 1909)
- SparkML Serving (algorithm) (p. 1909)
- Tensorflow (DLC) (p. 1910)
- Tensorflow Coach (DLC) (p. 1918)
- Tensorflow Inferentia (DLC) (p. 1919)
- Tensorflow Ray (DLC) (p. 1919)
- XGBoost (algorithm) (p. 1920)

**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='sa-east-1',image_scope='inference',version='0.4')
```

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<td>inference, training</td>
</tr>
</tbody>
</table>

### BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
going from sagemaker import image_uris
df = image尿quis.retrieve(framework='blazingtext', region='sa-east-1')
```
Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='sa-east-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='sa-east-1',version='1.0',image_scope='processing')
```

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Data Wrangler (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='data-wrangler',region='sa-east-1')
```

<table>
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Use Built-in Algorithms

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</tbody>
</table>

**Debugger (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='sa-east-1')
```

<table>
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<th>Registry path and Version</th>
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</table>

**DeepAR Forecasting (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='sa-east-1')
```

<table>
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<th>Registry path</th>
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<th>Job types (image scope)</th>
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</table>

**Factorization Machines (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='sa-east-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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### Use Built-in Algorithms

**Registry path**

<table>
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<th>Registry path</th>
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<tr>
<td>factorization-machines:&lt;tag&gt;</td>
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<td></td>
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</table>

**Hugging Face (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='sa-east-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')
```

<table>
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**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='sa-east-1')
```

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**Image classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification',region='sa-east-1')
```

<table>
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**Inferentia MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-mxnet',region='sa-east-1',version='1.5.1',instance_type='ml.inf1.6xlarge')

<table>
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**Inferentia PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-pytorch',region='sa-east-1',version='1.9',py_version='py3')

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**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

from sagemaker import image_uris
image_uris.retrieve(framework='kmeans',region='sa-east-1')
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**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='sa-east-1')
```

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**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='sa-east-1')
```

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**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='sa-east-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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### MXNet Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-mxnet', region='sa-east-1', version='0.11', py_version='py3', image_scope='training', instance_type='ml.c5.4xlarge')
```

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Model Monitor (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='model-monitor', region='sa-east-1')
```

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<th>Version</th>
<th>Job types (image scope)</th>
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<td>monitoring</td>
</tr>
</tbody>
</table>

NTM (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm', region='sa-east-1')
```

<table>
<thead>
<tr>
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<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>inference, training</td>
</tr>
</tbody>
</table>

Neo Image Classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo', region='sa-east-1')
```

<table>
<thead>
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<th>Registry path</th>
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<td>inference</td>
</tr>
</tbody>
</table>

Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='neo-mxnet', region='sa-east-1', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')

<table>
<thead>
<tr>
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<th>Processor types</th>
<th>Python versions</th>
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<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Neo PyTorch (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='sa-east-1', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>
**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow', region='sa-east-1', version='1.15.3', py_version='py3', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo', region='sa-east-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference</td>
</tr>
</tbody>
</table>

**Object Detection (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='sa-east-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td>inference, training</td>
</tr>
</tbody>
</table>
Object2Vec (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec',region='sa-east-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

PCA (algorithm)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca',region='sa-east-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
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<tbody>
<tr>
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<td>inference, training</td>
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</tbody>
</table>

PyTorch (DLC)
SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pytorch',region='sa-east-1',version='1.8.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py2, py3</td>
</tr>
</tbody>
</table>

**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest', region='sa-east-1')```

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### Use Built-in Algorithms

#### Registry path

**Scikit-learn (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn', region='sa-east-1', version='0.23-1', image_scope='inference')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
<th>Job types (image scope)</th>
</tr>
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<tr>
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<td></td>
</tr>
</tbody>
</table>

#### Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation', region='sa-east-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>855470959533.dkr.ecr.sa-east-1.amazonaws.com/</td>
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<td>semantic-segmentation:&lt;tag&gt;</td>
<td></td>
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</tr>
</tbody>
</table>

#### Seq2Seq (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
<tr>
<td>855470959533.dkr.ecr.sa-east-1.amazonaws.com/</td>
<td></td>
</tr>
<tr>
<td>semantic-segmentation:&lt;tag&gt;</td>
<td></td>
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</tbody>
</table>
image_uris.retrieve(framework='seq2seq', region='sa-east-1')

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td></td>
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</tbody>
</table>

**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='sa-east-1', version='3.0', image_scope='processing')
```

<table>
<thead>
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<th>Registry path</th>
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</table>

**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='sa-east-1', version='2.4')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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### Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow', region='sa-east-1', version='1.12.0', image_scope='inference', instance_type='ml.c5.4xlarge')
```

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### Use Built-in Algorithms

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<td>py2</td>
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</table>

#### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
def image_uris.retrieve(framework='coach-tensorflow',region='sa-east-1',version='0.11.0',image_scope='training',instance_type='ml.c4.xlarge')
```

<table>
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<tr>
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<th>Python versions</th>
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**Tensorflow Inferredia (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
g naive_tensorflow = image_uris.retrieve(framework='inferredia-tensorflow', region='saaeast-1', version='1.15.0', instance_type='ml.inf1.6xlarge')
```

<table>
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<th>Python versions</th>
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**Tensorflow Ray (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
g ray_tensorflow = image_uris.retrieve(framework='ray-tensorflow', region='saaeast-1', version='0.8.5', instance_type='ml.c5.4xlarge')
```
### Amazon SageMaker Developer Guide

#### Use Built-in Algorithms

<table>
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<tr>
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</table>

**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost',region='sa-east-1',version='1.5-1')
```

<table>
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Docker Registry Paths and Example Code for AWS GovCloud (US-West) (us-gov-west-1)

The following topics list parameters for each of the algorithms and deep learning containers in this region provided by Amazon SageMaker.

**Topics**

- AutoGluon (algorithm) (p. 1922)
- BlazingText (algorithm) (p. 1923)
- Chainer (DLC) (p. 1924)
- Clarify (algorithm) (p. 1924)
- Debugger (algorithm) (p. 1925)
- DeepAR Forecasting (algorithm) (p. 1925)
- Factorization Machines (algorithm) (p. 1925)
- Hugging Face (algorithm) (p. 1925)
- IP Insights (algorithm) (p. 1929)
- Image classification (algorithm) (p. 1930)
- Inferentia MXNet (DLC) (p. 1930)
- Inferentia PyTorch (DLC) (p. 1930)
- K-Means (algorithm) (p. 1931)
- KNN (algorithm) (p. 1931)
- LDA (algorithm) (p. 1931)
- Linear Learner (algorithm) (p. 1932)
- MXNet (DLC) (p. 1932)
- MXNet Coach (DLC) (p. 1935)
- NTM (algorithm) (p. 1936)
- Neo Image Classification (algorithm) (p. 1936)
- Neo MXNet (DLC) (p. 1937)
- Neo PyTorch (DLC) (p. 1937)
- Neo Tensorflow (DLC) (p. 1938)
- Neo XGBoost (algorithm) (p. 1938)
- Object Detection (algorithm) (p. 1939)
- Object2Vec (algorithm) (p. 1939)
- PCA (algorithm) (p. 1939)
- PyTorch (DLC) (p. 1939)
- Random Cut Forest (algorithm) (p. 1943)
- Scikit-learn (algorithm) (p. 1944)
- Semantic Segmentation (algorithm) (p. 1944)
- Seq2Seq (algorithm) (p. 1945)
- Spark (algorithm) (p. 1945)
- SparkML Serving (algorithm) (p. 1945)
- Tensorflow (DLC) (p. 1946)
- Tensorflow Coach (DLC) (p. 1956)
- Tensorflow Inference (DLC) (p. 1957)
- Tensorflow Ray (DLC) (p. 1957)
- XGBoost (algorithm) (p. 1958)

**AutoGluon (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='autogluon',region='us-gov-west-1',image_scope='inference',version='0.4')
```

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</table>
## BlazingText (algorithm)

SageMaker Python SDK example to retrieve registry path.

```
from sagemaker import image_uris
image_uris.retrieve(framework='blazingtext', region='us-gov-west-1')
```
### Chainer (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='chainer',region='us-gov-west-1',version='5.0.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')
```

### Clarify (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='clarify',region='us-gov-west-1',version='1.0',image_scope='processing')
```

---

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Processor types</th>
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---
### Debugger (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='debugger', region='us-gov-west-1')
```

<table>
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</table>

### DeepAR Forecasting (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='forecasting-deepar', region='us-gov-west-1')
```

<table>
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### Factorization Machines (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='factorization-machines', region='us-gov-west-1')
```

<table>
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### Hugging Face (algorithm)

SageMaker Python SDK example to retrieve registry path.
from sagemaker import image_uris
image_uris.retrieve(framework='huggingface',region='us-gov-west-1',version='4.4.2',image_scope='training',base_framework_version='tensorflow2.4.1')

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</tbody>
</table>

**IP Insights (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ipinsights',region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td>inference, training</td>
</tr>
</tbody>
</table>
Image classification (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uri = image_uris.retrieve(framework='image-classification', region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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</table>

Inferentia MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uri = image_uris.retrieve(framework='inferentia-mxnet', region='us-gov-west-1', version='1.5.1', instance_type='ml.inf1.6xlarge')
```

<table>
<thead>
<tr>
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<th>Python versions</th>
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<td>py3</td>
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</table>

Inferentia PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uri = image_uris.retrieve(framework='inferentia-pytorch', region='us-gov-west-1', version='1.9', py_version='py3')
```

<table>
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<tr>
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<th>Version</th>
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<th>Python versions</th>
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</table>
Use Built-in Algorithms

<table>
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<td>inf</td>
<td>py3</td>
<td></td>
</tr>
</tbody>
</table>

**K-Means (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='kmeans', region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
<td>226302683700.dkr.ecr.us-gov-west-1.amazonaws.com/kmeans:tag</td>
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</tbody>
</table>

**KNN (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='knn', region='us-gov-west-1')
```

<table>
<thead>
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<th>Registry path</th>
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<tbody>
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</table>

**LDA (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
Use Built-in Algorithms

```python
image_uris.retrieve(framework='lda', region='us-gov-west-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td></td>
<td>inference, training</td>
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</table>

**Linear Learner (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='linear-learner', region='us-gov-west-1')
```

<table>
<thead>
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<th>Registry path</th>
<th>Version</th>
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<tbody>
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**MXNet (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='mxnet', region='us-gov-west-1', version='1.4.1', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
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<td>py2, py3</td>
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</tbody>
</table>

**MXNet Coach (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
Use Built-in Algorithms

```
image_uris.retrieve(framework='coach-mxnet',region='us-gov-west-1',version='0.11',py_version='py3',image_scope='training',instance_type='ml.c5.4xlarge')
```

<table>
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<th>Registry path</th>
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<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**NTM (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ntm',region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</thead>
<tbody>
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<td></td>
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</table>

**Neo Image Classification (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='image-classification-neo',region='us-gov-west-1')
```

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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<td></td>
<td>inference</td>
</tr>
</tbody>
</table>
### Neo MXNet (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-mxnet', region='us-gov-west-1', version='1.8', py_version='py3', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
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<th>Registry path</th>
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<th>Python versions</th>
</tr>
</thead>
</table>

### Neo PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-pytorch', region='us-gov-west-1', version='1.6', image_scope='inference', instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
<th>Python versions</th>
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<td>Job types (image scope)</td>
<td>Processor types</td>
<td>Python versions</td>
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<td>CPU, GPU</td>
<td>py3</td>
</tr>
</tbody>
</table>

**Neo Tensorflow (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='neo-tensorflow',region='us-gov-west-1',version='1.15.3',py_version='py3',instance_type='ml.c5.4xlarge')
```

<table>
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<tr>
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<th>Version</th>
<th>Job types (image scope)</th>
<th>Processor types</th>
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<td>inference</td>
<td>CPU, GPU</td>
<td>py3</td>
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</tbody>
</table>

**Neo XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost-neo',region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<td></td>
<td>latest inference</td>
</tr>
</tbody>
</table>
### Object Detection (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object-detection', region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
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<th>Job types (image scope)</th>
</tr>
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<tbody>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

### Object2Vec (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='object2vec', region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
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</table>

### PCA (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='pca', region='us-gov-west-1')
```

<table>
<thead>
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<th>Version</th>
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</table>

### PyTorch (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
```
image_uris.retrieve(framework='pytorch',region='us-gov-west-1',version='1.8.0',py_version='py3',image_scope='inference',instance_type='ml.c5.4xlarge')

<table>
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<th>Processor types</th>
<th>Python versions</th>
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246785580436.dkr.ecr.us-gov-west-1.amazonaws.com/sagemaker-pytorch:<tag> | | training | CPU, GPU | py2, py3
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246785580436.dkr.ecr.us-gov-west-1.amazonaws.com/sagemaker-pytorch:<tag> | | training | CPU, GPU | py2, py3

**Random Cut Forest (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='randomcutforest',region='us-gov-west-1')
```
### Scikit-learn (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sklearn',region='us-gov-west-1',version='0.23-1',image_scope='inference')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Package version</th>
<th>Job types (image scope)</th>
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</tbody>
</table>

### Semantic Segmentation (algorithm)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='semantic-segmentation',region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>226302683700.dkr.ecr.us-west-1.amazonaws.com/...</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>
**Seq2Seq (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='seq2seq', region='us-gov-west-1')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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<tbody>
<tr>
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<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

**Spark (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='spark', region='us-gov-west-1', version='3.0', image_scope='processing')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
<th>Job types (image scope)</th>
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</table>

**SparkML Serving (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='sparkml-serving', region='us-gov-west-1', version='2.4')
```
<table>
<thead>
<tr>
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<th>Processor types</th>
<th>Python versions</th>
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<td>2.2</td>
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<td></td>
<td></td>
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</tbody>
</table>

Tensorflow (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='tensorflow',region='us-gov-west-1',version='1.12.0',image_scope='inference',instance_type='ml.c5.4xlarge')
```

<table>
<thead>
<tr>
<th>Registry path</th>
<th>Version</th>
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<th>Python versions</th>
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### Registry path | Version | Job types (image scope) | Processor types | Python versions
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246785580436.dkr.ecr.us-gov-west-1.amazonaws.com/sagemaker-tensorflow:tag | training | CPU, GPU | py2

#### Tensorflow Coach (DLC)

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='coach-tensorflow',region='us-gov-west-1',version='1.0.0',image_scope='training',instance_type='ml.c5.4xlarge')
```

### Registry path | Version | Job types (image scope) | Processor types | Python versions
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**Tensorflow Inferentia (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='inferentia-tensorflow',region='us-gov-west-1',version='1.15.0',instance_type='ml.inf1.6xlarge')
```

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**Tensorflow Ray (DLC)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='ray-tensorflow',region='us-gov-west-1',version='0.8.5',instance_type='ml.c5.4xlarge')
```
Use Built-in Algorithms

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**XGBoost (algorithm)**

SageMaker Python SDK example to retrieve registry path.

```python
from sagemaker import image_uris
image_uris.retrieve(framework='xgboost', region='us-gov-west-1', version='1.5-1')
```

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<td>1.3.3</td>
<td>inference, training</td>
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<td>1.2.0</td>
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<td></td>
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<tr>
<td>Registry path</td>
<td>Version</td>
<td>Package version</td>
<td>Job types (image scope)</td>
</tr>
<tr>
<td>------------------------------------------------------------------------------</td>
<td>---------</td>
<td>-----------------</td>
<td>-------------------------</td>
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<tr>
<td>west-1.amazonaws.com/sagemaker-xgboost:&lt;tag&gt;</td>
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<td></td>
</tr>
<tr>
<td>414596584902.dkr.ecr.ds2-1.gov-west-1.amazonaws.com/sagemaker-xgboost:&lt;tag&gt;</td>
<td>1.2.0</td>
<td></td>
<td>inference, training</td>
</tr>
<tr>
<td>414596584902.dkr.ecr.ds0-1.gov-west-1.amazonaws.com/sagemaker-xgboost:&lt;tag&gt;</td>
<td>1.0</td>
<td></td>
<td>inference, training</td>
</tr>
<tr>
<td>226302683700.dkr.ecr.ds-gov-west-1.amazonaws.com/xgboost:&lt;tag&gt;</td>
<td>0.72</td>
<td></td>
<td>inference, training</td>
</tr>
<tr>
<td>414596584902.dkr.ecr.ds90-2.gov-west-1.amazonaws.com/sagemaker-xgboost:&lt;tag&gt;</td>
<td>0.90</td>
<td></td>
<td>inference, training</td>
</tr>
<tr>
<td>414596584902.dkr.ecr.ds90-1.gov-west-1.amazonaws.com/sagemaker-xgboost:&lt;tag&gt;</td>
<td>0.90</td>
<td></td>
<td>inference, training</td>
</tr>
</tbody>
</table>

Common Data Formats for Built-in Algorithms

The following topics explain the data formats for the algorithms provided by Amazon SageMaker.

Topics
- Common Data Formats for Training (p. 1959)
- Common Data Formats for Inference (p. 1963)

Common Data Formats for Training

To prepare for training, you can preprocess your data using a variety of AWS services, including AWS Glue, Amazon EMR, Amazon Redshift, Amazon Relational Database Service, and Amazon Athena. After preprocessing, publish the data to an Amazon S3 bucket. For training, the data need to go through a series of conversions and transformations, including:

- Training data serialization (handled by you)
- Training data deserialization (handled by the algorithm)
- Training model serialization (handled by the algorithm)
- Trained model deserialization (optional, handled by you)
When using Amazon SageMaker in the training portion of the algorithm, make sure to upload all data at once. If more data is added to that location, a new training call would need to be made to construct a brand new model.

Topics
- Content Types Supported by Built-In Algorithms (p. 1960)
- Using Pipe Mode (p. 1960)
- Using CSV Format (p. 1960)
- Using RecordIO Format (p. 1961)
- Trained Model Deserialization (p. 1963)

Content Types Supported by Built-In Algorithms

The following table lists some of the commonly supported ContentType values and the algorithms that use them:

<table>
<thead>
<tr>
<th>ContentType</th>
<th>Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>application/x-image</td>
<td>Object Detection Algorithm, Semantic Segmentation</td>
</tr>
<tr>
<td>application/x-recordio</td>
<td>Object Detection Algorithm</td>
</tr>
<tr>
<td>application/x-recordio-protobuf</td>
<td>Factorization Machines, K-Means, k-NN, Latent Dirichlet Allocation, Linear Learner, NTM, PCA, RCF, Sequence-to-Sequence</td>
</tr>
<tr>
<td>application/jsonlines</td>
<td>BlazingText, DeepAR</td>
</tr>
<tr>
<td>image/jpeg</td>
<td>Object Detection Algorithm, Semantic Segmentation</td>
</tr>
<tr>
<td>image/png</td>
<td>Object Detection Algorithm, Semantic Segmentation</td>
</tr>
<tr>
<td>text/libsvm</td>
<td>XGBoost</td>
</tr>
</tbody>
</table>

For a summary of the parameters used by each algorithm, see the documentation for the individual algorithms or this table.

Using Pipe Mode

In Pipe mode, your training job streams data directly from Amazon Simple Storage Service (Amazon S3). Streaming can provide faster start times for training jobs and better throughput. This is in contrast to File mode, in which your data from Amazon S3 is stored on the training instance volumes. File mode uses disk space to store both your final model artifacts and your full training dataset. By streaming in your data directly from Amazon S3 in Pipe mode, you reduce the size of Amazon Elastic Block Store volumes of your training instances. Pipe mode needs only enough disk space to store your final model artifacts. See the AlgorithmSpecification for additional details on the training input mode.

Using CSV Format

Many Amazon SageMaker algorithms support training with data in CSV format. To use data in CSV format for training, in the input data channel specification, specify text/csv as the ContentType. Amazon SageMaker requires that a CSV file does not have a header record and that the target variable
is in the first column. To run unsupervised learning algorithms that don’t have a target, specify the number of label columns in the content type. For example, in this case `content_type=text/csv;label_size=0`. For a notebook example that uses CSV format, see Breast Cancer Prediction. For more information, see Now use Pipe mode with CSV datasets for faster training on Amazon SageMaker built-in algorithms.

Using RecordIO Format

In the protobuf recordIO format, SageMaker converts each observation in the dataset into a binary representation as a set of 4-byte floats, then loads it in the protobuf values field. If you are using Python for your data preparation, we strongly recommend that you use these existing transformations. However, if you are using another language, the protobuf definition file below provides the schema that you use to convert your data into SageMaker protobuf format.

**Note**
For an example that shows how to convert the commonly used numPy array into the protobuf recordIO format, see An Introduction to Factorization Machines with MNIST.

```proto
syntax = "proto2";

package aialgs.data;

option java_package = "com.amazonaws.aialgorithms.proto";
option java_outer_classname = "RecordProtos";

// A sparse or dense rank-R tensor that stores data as doubles (float64).
message Float32Tensor {
  // Each value in the vector. If keys is empty, this is treated as a dense vector.
  repeated float values = 1 [packed = true];

  // If key is not empty, the vector is treated as sparse, with each key specifying the location of the value in the sparse vector.
  repeated uint64 keys = 2 [packed = true];

  // An optional shape that allows the vector to represent a matrix.
  // For example, if shape = [10, 20], floor(keys[i] / 20) gives the row, and keys[i] % 20 gives the column.
  // This also supports n-dimensional tensors.
  // Note: If the tensor is sparse, you must specify this value.
  repeated uint64 shape = 3 [packed = true];
}

// A sparse or dense rank-R tensor that stores data as doubles (float64).
message Float64Tensor {
  // Each value in the vector. If keys is empty, this is treated as a dense vector.
  repeated double values = 1 [packed = true];

  // If key is not empty, the vector is treated as sparse, with each key specifying the location of the value in the sparse vector.
  repeated uint64 keys = 2 [packed = true];

  // An optional shape that allows the vector to represent a matrix.
  // For example, if shape = [10, 20], floor(keys[i] / 20) gives the row, and keys[i] % 20 gives the column.
  // This also supports n-dimensional tensors.
  // Note: If the tensor is sparse, you must specify this value.
  repeated uint64 shape = 3 [packed = true];
}

// A sparse or dense rank-R tensor that stores data as 32-bit ints (int32).
message Int32Tensor {
  // Each value in the vector. If keys is empty, this is treated as a
  repeated int32 values = 1 [packed = true];

  // If key is not empty, the vector is treated as sparse, with each key specifying the location of the value in the sparse vector.
  repeated uint64 keys = 2 [packed = true];

  // An optional shape that allows the vector to represent a matrix.
  // For example, if shape = [10, 20], floor(keys[i] / 20) gives the row, and keys[i] % 20 gives the column.
  // This also supports n-dimensional tensors.
  // Note: If the tensor is sparse, you must specify this value.
  repeated uint64 shape = 3 [packed = true];
}
```
// dense vector.
repeated int32 values = 1 [packed = true];

// If this is not empty, the vector is treated as sparse with
// each key specifying the location of the value in the sparse vector.
repeated uint64 keys = 2 [packed = true];

// An optional shape that allows the vector to represent a matrix.
// For example, if shape = [10, 20], floor(keys[i] / 10) gives the row,
// and keys[i] % 20 gives the column.
// This also supports n-dimensional tensors.
// Note: If the tensor is sparse, you must specify this value.
repeated uint64 shape = 3 [packed = true];

} // Support for storing binary data for parsing in other ways (such as JPEG/etc).
// This is an example of another type of value and may not immediately be supported.
message Bytes {
    repeated bytes value = 1;

    // If the content type of the data is known, stores it.
    // This allows for the possibility of using decoders for common formats
    // in the future.
    optional string content_type = 2;
}

message Value {
    oneof value {
        // The numbering assumes the possible use of:
        // - float16, float128
        // - int8, int16, int32
        Float32Tensor float32_tensor = 2;
        Float64Tensor float64_tensor = 3;
        Int32Tensor int32_tensor = 7;
        Bytes bytes = 9;
    }
}

message Record {
    // Map from the name of the feature to the value.
    // For vectors and libsvm-like datasets,
    // a single feature with the name 'values'
    // should be specified.
    map<string, Value> features = 1;

    // An optional set of labels for this record.
    // Similar to the features field above, the key used for
    // generic scalar / vector labels should be 'values'.
    map<string, Value> label = 2;

    // A unique identifier for this record in the dataset.
    // Whilst not necessary, this allows better
    // debugging where there are data issues.
    // This is not used by the algorithm directly.
    optional string uid = 3;

    // Textual metadata describing the record.
    // This may include JSON-serialized information
    // about the source of the record.
    // This is not used by the algorithm directly.
    optional string metadata = 4;
}
After creating the protocol buffer, store it in an Amazon S3 location that Amazon SageMaker can access and that can be passed as part of InputDataConfig in create_training_job.

Note

For all Amazon SageMaker algorithms, the ChannelName in InputDataConfig must be set to train. Some algorithms also support a validation or test input channel. These are typically used to evaluate the model's performance by using a hold-out dataset. Hold-out datasets are not used in the initial training but can be used to further tune the model.

Trained Model Deserialization

Amazon SageMaker models are stored as model.tar.gz in the S3 bucket specified in OutputDataConfig S3OutputPath parameter of the create_training_job call. You can specify most of these model artifacts when creating a hosting model. You can also open and review them in your notebook instance. When model.tar.gz is unarred, it contains model_algo-1, which is a serialized Apache MXNet object. For example, you use the following to load the k-means model into memory and view it:

```python
import mxnet as mx
print(mx.ndarray.load('model_algo-1'))
```

Common Data Formats for Inference

Amazon SageMaker algorithms accept and produce several different MIME types for the HTTP payloads used in retrieving online and mini-batch predictions. You can use various AWS services to transform or preprocess records prior to running inference. At a minimum, you need to convert the data for the following:

- Inference request serialization (handled by you)
- Inference request deserialization (handled by the algorithm)
- Inference response serialization (handled by the algorithm)
- Inference response deserialization (handled by you)

Topics

- Convert Data for Inference Request Serialization (p. 1963)
- Convert Data for Inference Response Deserialization (p. 1965)
- Common Request Formats for All Algorithms (p. 1966)
- Use Batch Transform with Built-in Algorithms (p. 1967)

Convert Data for Inference Request Serialization

Content type options for Amazon SageMaker algorithm inference requests include: text/csv, application/json, and application/x-recordio-protobuf. Algorithms that don't support all of
these types can support other types. XGBoost, for example, only supports text/csv from this list, but also supports text/libsvm.

For text/csv, the value for the Body argument to invoke_endpoint should be a string with commas separating the values for each feature. For example, a record for a model with four features might look like 1.5, 16.0, 14, 23.0. Any transformations performed on the training data should also be performed on the data before obtaining inference. The order of the features matters and must remain unchanged.

application/json is significantly more flexible and provides multiple possible formats for developers to use in their applications. At a high level, in JavaScript, the payload might look like the following:

```javascript
let request = {
  // Instances might contain multiple rows that predictions are sought for.
  "instances": [
    // Request and algorithm specific inference parameters.
    "configuration": {},
    // Data in the specific format required by the algorithm.
    "data": {
      "<field name>": dataElement
    }
  ]
}
```

You have the following options for specifying the dataElement:

**Protocol buffers equivalent**

```javascript
// Has the same format as the protocol buffers implementation described for training.
let dataElement = {
  "keys": [],
  "values": [],
  "shape": []
}
```

**Simple numeric vector**

```javascript
// An array containing numeric values is treated as an instance containing a
// single dense vector.
let dataElement = [1.5, 16.0, 14.0, 23.0]

// It will be converted to the following representation by the SDK.
let converted = {
  "features": dataElement
}
```

**For multiple records**

```javascript
let request = {
  "instances": [
    // First instance.
    {
      "features": [1.5, 16.0, 14.0, 23.0]
    },
    // Second instance.
    {
      "features": [-2.0, 100.2, 15.2, 9.2]
    }
  ]
}
```
Convert Data for Inference Response Deserialization

Amazon SageMaker algorithms return JSON in several layouts. At a high level, the structure is:

```json
let response = {
  "predictions": [{
      // Fields in the response object are defined on a per algorithm-basis.
  }]
}
```

The fields that are included in predictions differ across algorithms. The following are examples of output for the k-means algorithm.

**Single-record inference**

```json
let response = {
  "predictions": [
      {"closest_cluster": 5,
       "distance_to_cluster": 36.5}
  ]
}
```

**Multi-record inference**

```json
let response = {
  "predictions": [
      // First instance prediction.
      {"closest_cluster": 5,
       "distance_to_cluster": 36.5},
      // Second instance prediction.
      {"closest_cluster": 2,
       "distance_to_cluster": 90.3}
  ]
}
```

**Multi-record inference with protobuf input**

```json
{
  "features": [],
  "label": {
    "closest_cluster": {
      "values": [5.0] // e.g. the closest centroid/cluster was 1.0
    },
    "distance_to_cluster": {
      "values": [36.5]
    }
  },
  "uid": "abc123",
  "metadata": "{ "created_at": '2017-06-03' }"
}
```

SageMaker algorithms also support the JSONLINES format, where the per-record response content is same as that in JSON format. The multi-record structure is a concatenation of per-record response
Use Built-in Algorithms

objects separated by newline characters. The response content for the built-in KMeans algorithm for 2 input data points is:

```json
[{
  "distance_to_cluster": 23.40593910217285,
  "closest_cluster": 0.0
},
{
  "distance_to_cluster": 27.250282287597656,
  "closest_cluster": 0.0
}]
```

While running batch transform, we recommended using the jsonlines response type by setting the `Accept` field in the `CreateTransformJobRequest` to `application/jsonlines`.

**Common Request Formats for All Algorithms**

Most algorithms use several of the following inference request formats.

**JSON Request Format**

**Content type:** application/JSON

**Dense format**

```json
let request = {
  "instances": [
    {
      "features": [1.5, 16.0, 14.0, 23.0]
    }
  ]
}
```

```json
let request = {
  "instances": [
    {
      "data": {
        "features": [1.5, 16.0, 14.0, 23.0]
      }
    }
  ]
}
```

**Sparse format**

```json
{
  "instances": [
    {
      "data": {
        "features": {
          "keys": [26, 182, 232, 243, 431],
          "shape": [2000],
          "values": [1, 1, 1, 4, 1]
        }
      }
    },
    {
      "data": {
        "features": {
          "keys": [0, 182, 232, 243, 431],
          "shape": [2000],
          "values": [13, 1, 1, 4, 1]
        }
      }
    }
  ]
}
```
JSONLINES Request Format

**Content type:** application/JSONLINES

**Dense format**

A single record in dense format can be represented as either:

```json
{ "features": [1.5, 16.0, 14.0, 23.0] }
```

or:

```json
{ "data": { "features": [1.5, 16.0, 14.0, 23.0] } }
```

**Sparse Format**

A single record in sparse format is represented as:

```json
{"data": {"features": {"keys": [26, 182, 232, 243, 431], "shape": [2000], "values": [1, 1, 1, 4, 1] } }}
```

Multiple records are represented as a concatenation of the above single-record representations, separated by newline characters:

```json
{"data": {"features": {"keys": [0, 1, 3], "shape": [4], "values": [1, 4, 1] } }}
{"data": { "features": { "values": [1.5, 16.0, 14.0, 23.0] } } }
{"features": [1.5, 16.0, 14.0, 23.0] }
```

CSV Request Format

**Content type:** text/CSV; label_size=0

**Note**

CSV support is not available for factorization machines.

RECORDIO Request Format

**Content type:** application/x-recordio-protobuf

**Use Batch Transform with Built-in Algorithms**

While running batch transform, we recommended using the JSONLINES response type instead of JSON, if supported by the algorithm. This is accomplished by setting the `Accept` field in the `CreateTransformJobRequest` to `application/jsonlines`.

When you create a transform job, the `SplitType` must be set according to the `ContentType` of the input data. Similarly, depending on the `Accept` field in the `CreateTransformJobRequest`, `AssembleWith` must be set accordingly. Please use the following table to help appropriately set these fields:

<table>
<thead>
<tr>
<th><strong>ContentType</strong></th>
<th><strong>Recommended SplitType</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>application/x-recordio-protobuf</td>
<td>RecordIO</td>
</tr>
<tr>
<td>text/csv</td>
<td>Line</td>
</tr>
<tr>
<td>ContentType</td>
<td>Recommended SplitType</td>
</tr>
<tr>
<td>-------------------------------------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>application/jsonlines</td>
<td>Line</td>
</tr>
<tr>
<td>application/json</td>
<td>None</td>
</tr>
<tr>
<td>application/x-image</td>
<td>None</td>
</tr>
<tr>
<td>image/*</td>
<td>None</td>
</tr>
<tr>
<td><strong>Accept</strong></td>
<td><strong>Recommended AssembleWith</strong></td>
</tr>
<tr>
<td>application/x-recordio-protobuf</td>
<td>None</td>
</tr>
<tr>
<td>application/json</td>
<td>None</td>
</tr>
<tr>
<td>application/jsonlines</td>
<td>Line</td>
</tr>
</tbody>
</table>

For more information on response formats for specific algorithms, see the following:

- DeepAR Inference Formats (p. 2138)
- Factorization Machines Response Formats (p. 1995)
- IP Insights Inference Data Formats (p. 2149)
- K-Means Response Formats (p. 2158)
- k-NN Request and Response Formats (p. 2002)
- Linear learner response formats (p. 2029)
- NTM Response Formats (p. 2086)
- Data Formats for Object2Vec Inference (p. 2101)
- Encoder Embeddings for Object2Vec (p. 2102)
- PCA Response Formats (p. 2162)
- RCF Response Formats (p. 2169)

**Instance Types for Built-in Algorithms**

For training and hosting Amazon SageMaker algorithms, we recommend using the following Amazon EC2 instance types:

- ml.m5.xlarge, ml.m5.4xlarge, and ml.m5.12xlarge
- ml.c5.xlarge, ml.c5.2xlarge, and ml.c5.8xlarge
- ml.p3.xlarge, ml.p3.8xlarge, and ml.p3.16xlarge

Most Amazon SageMaker algorithms have been engineered to take advantage of GPU computing for training. For most algorithm training, we support P2, P3, G4dn, and G5 GPU instances. Despite higher per-instance costs, GPUs train more quickly, making them more cost-effective. Exceptions are noted in this guide.

The size and type of data can have a great effect on which hardware configuration is most effective. When the same model is trained on a recurring basis, initial testing across a spectrum of instance types can discover configurations that are more cost-effective in the long run. Additionally, algorithms that train most efficiently on GPUs might not require GPUs for efficient inference. Experiment to determine the most cost-effectiveness solution. To get an automatic instance recommendation or conduct custom load tests, use Amazon SageMaker Inference Recommender.

For more information on SageMaker hardware specifications, see Amazon SageMaker ML Instance Types.
Logs for Built-in Algorithms

Amazon SageMaker algorithms produce Amazon CloudWatch logs, which provide detailed information on the training process. To see the logs, in the AWS management console, choose **CloudWatch**, choose **Logs**, and then choose the /aws/sagemaker/TrainingJobs log group. Each training job has one log stream per node on which it was trained. The log stream's name begins with the value specified in the TrainingJobName parameter when the job was created.

**Note**

If a job fails and logs do not appear in CloudWatch, it's likely that an error occurred before the start of training. Reasons include specifying the wrong training image or S3 location.

The contents of logs vary by algorithms. However, you can typically find the following information:

- Confirmation of arguments provided at the beginning of the log
- Errors that occurred during training
- Measurement of an algorithm's accuracy or numerical performance
- Timings for the algorithm and any major stages within the algorithm

Common Errors

If a training job fails, some details about the failure are provided by the FailureReason return value in the training job description, as follows:

```python
sage = boto3.client('sagemaker')
sage.describe_training_job(TrainingJobName=job_name)['FailureReason']
```

Others are reported only in the CloudWatch logs. Common errors include the following:

1. Misspecifying a hyperparameter or specifying a hyperparameter that is invalid for the algorithm.

   **From the CloudWatch Log**

   ```plaintext
   [10/16/2017 23:45:17 ERROR 139623806805824 train.py:48]
   Additional properties are not allowed (u'mini_batch_siz' was unexpected)
   ```

2. Specifying an invalid value for a hyperparameter.

   **FailureReason**

   ```plaintext
   AlgorithmError: u'abc' is not valid under any of the given schemas\n   Failed validating u'oneOf' in schema[u'properties'][u'feature_dim']:
   [u'oneOf':
    [u'pattern': u'^([1-9][0-9]*)$', u'type': u'string'],
    {u'minimum': 1, u'type': u'integer'}]
   ```

3. Inaccurate protobuf file format.

   **From the CloudWatch log**

   ```plaintext
   [10/16/2017 23:57:17 ERROR 140373086025536 train.py:48] u'abc'
   is not valid under any of the given schemas
   ```

   ```plaintext
   [10/17/2017 18:01:04 ERROR 140234860816192 train.py:48] cannot
   ```
Built-in SageMaker Algorithms for Tabular Data

Amazon SageMaker provides built-in algorithms that are tailored to the analysis of tabular data. The built-in SageMaker algorithms for tabular data can be used for either classification or regression problems.

- **AutoGluon-Tabular (p. 1971)**—an open-source AutoML framework that succeeds by ensembling models and stacking them in multiple layers.
- **CatBoost (p. 1978)**—an implementation of the gradient-boosted trees algorithm that introduces ordered boosting and an innovative algorithm for processing categorical features.
- **Factorization Machines Algorithm (p. 1986)**—an extension of a linear model that is designed to economically capture interactions between features within high-dimensional sparse datasets.
- **K-Nearest Neighbors (k-NN) Algorithm (p. 1996)**—a non-parametric method that uses the k nearest labeled points to assign a label to a new data point for classification or a predicted target value from the average of the k nearest points for regression.
- **LightGBM (p. 2005)**—an implementation of the gradient-boosted trees algorithm that adds two novel techniques for improved efficiency and scalability: Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB).
- **Linear Learner Algorithm (p. 2014)**—learns a linear function for regression or a linear threshold function for classification.
- **TabTransformer (p. 2031)**—a novel deep tabular data modeling architecture built on self-attention-based Transformers.
- **XGBoost Algorithm (p. 2038)**—an implementation of the gradient-boosted trees algorithm that combines an ensemble of estimates from a set of simpler and weaker models.

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>AutoGluon-Tabular</td>
<td>training and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU or GPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>CatBoost</td>
<td>training and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>Factorization Machines</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf</td>
<td>CPU (GPU for dense data)</td>
<td>Yes</td>
</tr>
<tr>
<td>K-Nearest-Neighbors (k-NN)</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU or GPU (single GPU device on one or more instances)</td>
<td>Yes</td>
</tr>
<tr>
<td>LightGBM</td>
<td>training and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU (single instance only)</td>
<td>No</td>
</tr>
</tbody>
</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear Learner</td>
<td>train and (optionally) validation, test, or both</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU or GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>TabTransformer training and (optionally) validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU or GPU (single instance only)</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td>XGBoost (0.90-1, 0.90-2, 1.0-1, 1.2-1, 1.2-21)</td>
<td>train and (optionally) validation</td>
<td>File or Pipe</td>
<td>CSV, LibSVM, or Parquet</td>
<td>CPU (or GPU for 1.2-1)</td>
<td>Yes</td>
</tr>
</tbody>
</table>

### AutoGluon-Tabular

AutoGluon-Tabular is a popular open-source AutoML framework that trains highly accurate machine learning models on an unprocessed tabular dataset. Unlike existing AutoML frameworks that primarily focus on model and hyperparameter selection, AutoGluon-Tabular succeeds by ensembling multiple models and stacking them in multiple layers.

**How to use SageMaker AutoGluon-Tabular**

You can use AutoGluon-Tabular as an Amazon SageMaker built-in algorithm. The following section describes how to use AutoGluon-Tabular with the SageMaker Python SDK. For information on how to use AutoGluon-Tabular from the Amazon SageMaker Studio UI, see SageMaker JumpStart (p. 45).

- **Use AutoGluon-Tabular as a built-in algorithm**

  Use the AutoGluon-Tabular built-in algorithm to build an AutoGluon-Tabular training container as shown in the following code example. You can automatically spot the AutoGluon-Tabular built-in algorithm image URI using the SageMaker image_uris.retrieve API (or the get_image_uri API if using Amazon SageMaker Python SDK version 2).

  After specifying the AutoGluon-Tabular image URI, you can use the AutoGluon-Tabular container to construct an estimator using the SageMaker Estimator API and initiate a training job. The AutoGluon-Tabular built-in algorithm runs in script mode, but the training script is provided for you and there is no need to replace it. If you have extensive experience using script mode to create a SageMaker training job, then you can incorporate your own AutoGluon-Tabular training scripts.

```python
from sagemaker import image_uris, model_uris, script_uris

train_model_id, train_model_version, train_scope = "autogluon-regression-ensemble", "*", "training"
training_instance_type = "ml.p3.2xlarge"

# Retrieve the docker image
train_image_uri = image_uris.retrieve(  
    region=None,  
    framework=None,  
    model_id=train_model_id,  
    model_version=train_model_version,  
    image_scope=train_scope,  
    instance_type=training_instance_type
```
# Retrieve the training script
train_source_uri = script_uri.retrieve(
    model_id=train_model_id, model_version=train_model_version, script_scope=train_scope
)

train_model_uri = model_uri.retrieve(
    model_id=train_model_id, model_version=train_model_version, model_scope=train_scope
)

# Sample training data is available in this bucket
training_data_bucket = f"jumpstart-cache-prod-{aws_region}"
training_data_prefix = "training-datasets/tabular_multiclass/"
training_dataset_s3_path = f"s3://{training_data_bucket}/{training_data_prefix}"
output_bucket = sess.default_bucket()
output_prefix = "jumpstart-example-tabular-training"
s3_output_location = f"s3://{output_bucket}/{output_prefix}/output"

from sagemaker import hyperparameters

# Retrieve the default hyper-parameters for training the model
hyperparameters = hyperparameters.retrieve_default(
    model_id=train_model_id, model_version=train_model_version
)

# [Optional] Override default hyperparameters with custom values
hyperparameters["auto_stack"] = "True"
print(hyperparameters)

from sagemaker.estimator import Estimator
from sagemaker.utils import name_from_base

training_job_name = name_from_base(f"built-in-algo-{train_model_id}-training")

# Create SageMaker Estimator instance

# Create a SageMaker Estimator instance

# Launch a SageMaker Training job by passing the S3 path of the training data

For more information about how to set up the AutoGluon-Tabular as a built-in algorithm, see the following notebook examples.

- Tabular classification with Amazon SageMaker AutoGluon-Tabular algorithm
- Tabular regression with Amazon SageMaker AutoGluon-Tabular algorithm
Input and Output interface for the AutoGluon-Tabular algorithm

Gradient boosting operates on tabular data, with the rows representing observations, one column representing the target variable or label, and the remaining columns representing features.

The SageMaker implementation of AutoGluon-Tabular supports CSV for training and inference:

- For **Training ContentType**, valid inputs must be `text/csv`.
- For **Inference ContentType**, valid inputs must be `text/csv`.

**Note**
For CSV training, the algorithm assumes that the target variable is in the first column and that the CSV does not have a header record.
For CSV inference, the algorithm assumes that CSV input does not have the label column.

Be mindful of how to format your training data for input to the AutoGluon-Tabular model. You must provide the path to an Amazon S3 bucket containing subdirectories for your training and optional validation data.

- **Training data input format**: Your training data should be in a subdirectory named `train/` that contains a `data.csv` file. The target variables should be in the first column of `data.csv`. The predictor variables (features) should be in the remaining columns.
- **Validation data input format**: You can optionally include another directory called `validation/` that also has a `data.csv` file. The validation data is used to compute a validation score at the end of each boosting iteration. Early stopping is applied when the validation score stops improving. If the validation data is not provided, then a fraction of your training data is randomly sampled to serve as the validation data. This fraction is selected based on the number of rows in your training data. For more information see Tabular Prediction in the AutoGluon documentation.

For CSV training input mode, the total memory available to the algorithm (instance count multiplied by the memory available in the `InstanceType`) must be able to hold the training dataset.

SageMaker AutoGluon-Tabular uses the `autogluon.tabular.TabularPredictor` module to serialize or deserialize the model, which can be used for saving or loading the model.

**To use a model trained with SageMaker AutoGluon-Tabular with the AutoGluon framework**

- Use the following Python code:

```python
import tarfile
from autogluon.tabular import TabularPredictor
t = tarfile.open('model.tar.gz', 'r:gz')
t.extractall()
model = TabularPredictor.load(model_file_path)

# prediction with test data
# dtest should be a pandas DataFrame with column names 'feature_0', 'feature_1', ..., 'feature_d'
pred = model.predict(dtest)
```

Amazon EC2 instance recommendation for the AutoGluon-Tabular algorithm

SageMaker AutoGluon-Tabular supports single-instance CPU and single-instance GPU training. Despite higher per-instance costs, GPUs train more quickly, making them more cost effective. To take advantage
of GPU training, specify the instance type as one of the GPU instances (for example, P3). SageMaker AutoGluon-Tabular currently does not support multi-GPU training.

AutoGluon-Tabular sample notebooks

The following table outlines a variety of sample notebooks that address different use cases of Amazon SageMaker AutoGluon-Tabular algorithm.

<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabular classification with Amazon SageMaker AutoGluon-Tabular algorithm</td>
<td>This notebook demonstrates the use of the Amazon SageMaker AutoGluon-Tabular algorithm to train and host a tabular classification model.</td>
</tr>
<tr>
<td>Tabular regression with Amazon SageMaker AutoGluon-Tabular algorithm</td>
<td>This notebook demonstrates the use of the Amazon SageMaker AutoGluon-Tabular algorithm to train and host a tabular regression model.</td>
</tr>
</tbody>
</table>

For instructions on how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, choose the SageMaker Examples tab to see a list of all of the SageMaker samples. To open a notebook, choose its Use tab and choose Create copy.

How AutoGluon-Tabular works

AutoGluon-Tabular performs advanced data processing, deep learning, and multi-layer model ensemble methods. It automatically recognizes the data type in each column for robust data preprocessing, including special handling of text fields.

AutoGluon fits various models ranging from off-the-shelf boosted trees to customized neural networks. These models are assembled in a novel way: models are stacked in multiple layers and trained in a layer-wise manner that guarantees raw data can be translated into high-quality predictions within a given time constraint. This process mitigates overfitting by splitting the data in various ways with careful tracking of out-of-fold examples.

The AutoGluon-Tabular algorithm performs well in machine learning competitions because of its robust handling of a variety of data types, relationships, and distributions. You can use AutoGluon-Tabular for regression, classification (binary and multiclass), and ranking problems.

Refer to the following diagram illustrating how the multi-layer stacking strategy works.
Use Built-in Algorithms

For more information, see *AutoGluon-Tabular: Robust and Accurate AutoML for Structured Data*.

### AutoGluon-Tabular hyperparameters

The following table contains the subset of hyperparameters that are required or most commonly used for the Amazon SageMaker AutoGluon-Tabular algorithm. Users set these parameters to facilitate the estimation of model parameters from data. The SageMaker AutoGluon-Tabular algorithm is an implementation of the open-source *AutoGluon-Tabular* package.

**Note**

The default hyperparameters are based on example datasets in the *AutoGluon-Tabular sample notebooks* (p. 1974).

By default, the SageMaker AutoGluon-Tabular algorithm automatically chooses an evaluation metric based on the type of classification problem. The algorithm detects the type of classification problem based on the number of labels in your data. For regression problems, the evaluation metric is root mean squared error. For binary classification problems, the evaluation metric is area under the receiver operating characteristic curve (AUC). For multiclass classification problems, the evaluation metric is accuracy. You can use the `eval_metric` hyperparameter to change the default evaluation metric. Refer to the following table for more information on LightGBM hyperparameters, including descriptions, valid values, and default values.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| eval_metric    | The evaluation metric for validation data. If `eval_metric` is set to the default "auto" value, then the algorithm automatically chooses an evaluation metric based on the type of classification problem:  
  - "root_mean_squared_error" for regression  
  - "roc_auc" for binary classification  
  - "accuracy" for multi-class classification |
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Valid values:</td>
<td>string, refer to the AutoGluon documentation for valid values.</td>
</tr>
<tr>
<td>Default value:</td>
<td>&quot;auto&quot;.</td>
</tr>
<tr>
<td>presets</td>
<td>List of preset configurations for various arguments in fit().</td>
</tr>
</tbody>
</table>
|                   | - "best_quality": high predictive accuracy, slower inference times and higher disk usage  
|                   | - "high_quality": high predictive accuracy and fast inference  
|                   | - "good_quality": good predictive accuracy and very fast inference  
|                   | - "medium_quality": medium predictive accuracy, very fast inference and training time  
|                   | - "optimize_for_deployment": delete unused models and remove training artifacts  
|                   | - "interpretable": fits only interpretable rule-based models from the imodels package  
|                   | For more details, see AutoGluon Predictors.                                                                                                                                                                                                                                                                                                                    |
| Valid values:     | string, any of the following: ("best_quality", "high_quality", "good_quality", "medium_quality", "optimize_for_deployment", or "interpretable").                                                                                                                                                                                                                         |
| Default value:    | "medium_quality".                                                                                                                                                                                                                                                                                                                                                 |
| auto_stack        | Whether AutoGluon should automatically utilize bagging and multi-layer stack ensembling to boost predictive accuracy. Set auto_stack to "True" if you are willing to tolerate longer training times in order to maximize predictive accuracy. This automatically sets the num_bag_folds and num_stack_levels arguments based on dataset properties.  
|                   | Valid values: string, "True" or "False".                                                                                                                                                                                                                                                                                                                        |
| Default value:    | "False".                                                                                                                                                                                                                                                                                                                                                         |
| num_bag_folds     | Number of folds used for bagging of models. When num_bag_folds is equal to k, training time is roughly increased by a factor of k. Set num_bag_folds to 0 to deactivate bagging. This is disabled by default, but we recommend using values between 5 and 10 to maximize predictive performance. Increasing num_bag_folds results in models with lower bias, but that are more prone to overfitting. One is an invalid value for this parameter, and will raise a ValueError. Values greater than 10 may produce diminishing returns and can even harm overall results due to overfitting. To further improve predictions, avoid increasing num_bag_folds and instead increase num_bag_sets.  
<p>|                   | Valid values: string, any integer between (and including) &quot;0&quot; and &quot;10&quot;.                                                                                                                                                                                                                                                                                              |
| Default value:    | &quot;0&quot;.                                                                                                                                                                                                                                                                                                                                                             |</p>
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_bag_sets</td>
<td>Number of repeats of kfold bagging to perform (values must be greater than or equal to 1). The total number of models trained during bagging is equal to num_bag_folds * num_bag_sets. This parameter defaults to one if time_limit is not specified. This parameters is disabled if num_bag_folds is not specified. Values greater than one result in superior predictive performance, especially on smaller problems and with stacking enabled. Valid values: integer, range: [1, 20]. Default value: 1.</td>
</tr>
<tr>
<td>num_stack_levels</td>
<td>Number of stacking levels to use in stack ensemble. Roughly increases model training time by factor of num_stack_levels + 1. Set this parameter to 0 to deactivate stack ensembling. This parameter is deactivated by default, but we recommend using values between 1 and 3 to maximize predictive performance. To prevent overfitting and a ValueError, num_bag_folds must be greater than or equal to 2. Valid values: float, range: [0, 3]. Default value: 0.</td>
</tr>
<tr>
<td>refit_full</td>
<td>Whether or not to retrain all models on all of the data (training and validation) after the normal training procedure. For more details, see AutoGluon Predictors. Valid values: string, &quot;True&quot; or &quot;False&quot;. Default value: &quot;False&quot;.</td>
</tr>
<tr>
<td>set_best_to_refit_full</td>
<td>Whether or not to change the default model that the predictor uses for prediction. If set_best_to_refit_full is set to &quot;True&quot;, the default model changes to the model that exhibited the highest validation score as a result of refitting (activated by refit_full). Only valid if refit_full is set. Valid values: string, &quot;True&quot; or &quot;False&quot;. Default value: &quot;False&quot;.</td>
</tr>
<tr>
<td>save_space</td>
<td>Whether or note to reduce the memory and disk size of predictor by deleting auxiliary model files that aren't needed for prediction on new data. This has no impact on inference accuracy. We recommend setting save_space to &quot;True&quot; if the only goal is to use the trained model for prediction. Certain advanced functionality may no longer be available if save_space is set to &quot;True&quot;. Refer to the predictor.save_space() documentation for more details. Valid values: string, &quot;True&quot; or &quot;False&quot;. Default value: &quot;False&quot;.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td>verbosity</td>
<td>The verbosity of print messages. <code>verbosity</code> levels range from 0 to 4, with higher levels corresponding to more detailed print statements. A <code>verbosity</code> of 0 suppresses warnings. Valid values: integer, any of the following: (0, 1, 2, 3, or 4). Default value: 2.</td>
</tr>
</tbody>
</table>

### Tuning an AutoGluon-Tabular model

Although AutoGluon-Tabular can be used with model tuning, its design can deliver good performance using stacking and ensemble methods, meaning hyperparameter optimization is not necessary. Rather than focusing on model tuning, AutoGluon-Tabular succeeds by stacking models in multiple layers and training in a layer-wise manner.

For more information about AutoGluon-Tabular hyperparameters, see AutoGluon-Tabular hyperparameters (p. 1975).

### CatBoost

**CatBoost** is a popular and high-performance open-source implementation of the Gradient Boosting Decision Tree (GBDT) algorithm. GBDT is a supervised learning algorithm that attempts to accurately predict a target variable by combining an ensemble of estimates from a set of simpler and weaker models.

CatBoost introduces two critical algorithmic advances to GBDT:

1. The implementation of ordered boosting, a permutation-driven alternative to the classic algorithm
2. An innovative algorithm for processing categorical features

Both techniques were created to fight a prediction shift caused by a special kind of target leakage present in all currently existing implementations of gradient boosting algorithms.

### How to use SageMaker CatBoost

You can use CatBoost as an Amazon SageMaker built-in algorithm. The following section describes how to use CatBoost with the SageMaker Python SDK. For information on how to use CatBoost from the Amazon SageMaker Studio UI, see SageMaker JumpStart (p. 45).

**Use CatBoost as a built-in algorithm**

Use the CatBoost built-in algorithm to build a CatBoost training container as shown in the following code example. You can automatically spot the CatBoost built-in algorithm image URI using the SageMaker `image_uris.retrieve` API (or the `get_image_uri` API if using Amazon SageMaker Python SDK version 2).

After specifying the CatBoost image URI, you can use the CatBoost container to construct an estimator using the SageMaker Estimator API and initiate a training job. The CatBoost built-in algorithm runs in script mode, but the training script is provided for you and there is no need to replace it. If you have extensive experience using script mode to create a SageMaker training job, then you can incorporate your own CatBoost training scripts.

```python
from sagemaker import image_uris, model_uris, script_uris

train_model_id, train_model_version, train_scope = "catboost-classification-model", "*", "training"
```
training_instance_type = "ml.m5.xlarge"

# Retrieve the docker image
train_image_uri = image_uris.retrieve(
    region=None,
    framework=None,
    model_id=train_model_id,
    model_version=train_model_version,
    instance_type=training_instance_type
)

# Retrieve the training script
train_source_uri = script_uris.retrieve(
    model_id=train_model_id, model_version=train_model_version, script_scope=train_scope
)

train_model_uri = model_uris.retrieve(
    model_id=train_model_id, model_version=train_model_version, model_scope=train_scope
)

# Sample training data is available in this bucket
training_data_bucket = f"jumpstart-cache-prod-{aws_region}"
training_data_prefix = "training-datasets/tabular_multiclass/"
training_dataset_s3_path = f"s3://{training_data_bucket}/{training_data_prefix}"

output_bucket = sess.default_bucket()
output_prefix = "jumpstart-example-tabular-training"
s3_output_location = f"s3://{output_bucket}/{output_prefix}/output"

from sagemaker import hyperparameters

# Retrieve the default hyper-parameters for training the model
hyperparameters = hyperparameters.retrieve_default(
    model_id=train_model_id, model_version=train_model_version
)

# [Optional] Override default hyperparameters with custom values
hyperparameters["iterations"] = "500"
print(hyperparameters)

from sagemaker import Estimator
from sagemaker import utils

training_job_name = name_from_base(f"built-in-algo-{train_model_id}-training")

# Create SageMaker Estimator instance
tabular_estimator = Estimator(
    role=aws_role,
    image_uri=train_image_uri,
    source_dir=train_source_uri,
    model_uri=train_model_uri,
    entry_point="transfer_learning.py",
    instance_count=1,
    instance_type=training_instance_type,
    max_run=360000,
    hyperparameters=hyperparameters,
    output_path=s3_output_location
)

# Launch a SageMaker Training job by passing the S3 path of the training data
tabular_estimator.fit(train_dataset_s3_path)
For more information about how to set up CatBoost as a built-in algorithm, see the following notebook examples.
- Tabular classification with Amazon SageMaker LightGBM and CatBoost algorithm
- Tabular regression with Amazon SageMaker LightGBM and CatBoost algorithm

Input and Output interface for the CatBoost algorithm

Gradient boosting operates on tabular data, with the rows representing observations, one column representing the target variable or label, and the remaining columns representing features.

The SageMaker implementation of CatBoost supports CSV for training and inference:
- For **Training ContentType**, valid inputs must be `text/csv`.
- For **Inference ContentType**, valid inputs must be `text/csv`.

**Note**
For CSV training, the algorithm assumes that the target variable is in the first column and that the CSV does not have a header record.
For CSV inference, the algorithm assumes that CSV input does not have the label column.

Be mindful of how to format your training data for input to the CatBoost model. You must provide the path to an Amazon S3 bucket containing subdirectories for your training and optional validation data. You can also include a list of categorical features.

- **Training data input format**: Your training data should be in a subdirectory named `train/` that contains a `data.csv` file. The target variables should be in the first column of `data.csv`. The predictor variables (features) should be in the remaining columns.
- **Validation data input format**: You can optionally include another directory called `validation/` that also has a `data.csv` file. The validation data is used to compute a validation score at the end of each boosting iteration. Early stopping is applied when the validation score stops improving. If the validation data is not provided, then 20% of your training data is randomly sampled to serve as the validation data.
- **Categorical features input format**: If your predictors include categorical features, you can provide a JSON file named `categorical_index.json` in the same location as your data directories. This file should contain a Python dictionary where the key is the string “cat_index_list” and the value is a list of unique integers. Each integer in the value list should indicate the column index of the corresponding categorical features in your training data CSV file. Each value should be a positive integer (greater than zero because zero represents the target value), less than the `Int32.MaxValue` (2147483647), and less than the total number of columns. There should only be one categorical index JSON file.

For CSV training input mode, the total memory available to the algorithm (instance count multiplied by the memory available in the `InstanceType`) must be able to hold the training dataset.

SageMaker CatBoost uses the `catboost.CatBoostClassifier` and `catboost.CatBoostRegressor` modules to serialize or deserialize the model, which can be used for saving or loading the model.

**To use a model trained with SageMaker CatBoost with catboost**

- Use the following Python code:
import tarfile
from catboost import CatBoostClassifier

t = tarfile.open('model.tar.gz', 'r:gz')
t.extractall()

file_path = os.path.join(model_file_path, "model")
model = CatBoostClassifier()
model.load_model(file_path)

# prediction with test data
# dtest should be a pandas DataFrame with column names feature_0, feature_1, ..., feature_d
pred = model.predict(dtest)

Amazon EC2 instance recommendation for the CatBoost algorithm

SageMaker CatBoost currently only trains using CPUs. CatBoost is a memory-bound (as opposed to compute-bound) algorithm. So, a general-purpose compute instance (for example, M5) is a better choice than a compute-optimized instance (for example, C5). Further, we recommend that you have enough total memory in selected instances to hold the training data.

CatBoost sample notebooks

The following table outlines a variety of sample notebooks that address different use cases of Amazon SageMaker CatBoost algorithm.

<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabular classification with Amazon SageMaker LightGBM and CatBoost algorithm</td>
<td>This notebook demonstrates the use of the Amazon SageMaker CatBoost algorithm to train and host a tabular classification model.</td>
</tr>
<tr>
<td>Tabular regression with Amazon SageMaker LightGBM and CatBoost algorithm</td>
<td>This notebook demonstrates the use of the Amazon SageMaker CatBoost algorithm to train and host a tabular regression model.</td>
</tr>
</tbody>
</table>

For instructions on how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, choose the SageMaker Examples tab to see a list of all of the SageMaker samples. To open a notebook, choose its Use tab and choose Create copy.

How CatBoost Works

CatBoost implements a conventional Gradient Boosting Decision Tree (GBDT) algorithm with the addition of two critical algorithmic advances:

1. The implementation of ordered boosting, a permutation-driven alternative to the classic algorithm
2. An innovative algorithm for processing categorical features

Both techniques were created to fight a prediction shift caused by a special kind of target leakage present in all currently existing implementations of gradient boosting algorithms.

The CatBoost algorithm performs well in machine learning competitions because of its robust handling of a variety of data types, relationships, distributions, and the diversity of hyperparameters that you
You can use CatBoost for regression, classification (binary and multiclass), and ranking problems.

For more information on gradient boosting, see How XGBoost Works (p. 2043). For in-depth details about the additional GOSS and EFB techniques used in the CatBoost method, see CatBoost: unbiased boosting with categorical features.

CatBoost hyperparameters

The following table contains the subset of hyperparameters that are required or most commonly used for the Amazon SageMaker CatBoost algorithm. Users set these parameters to facilitate the estimation of model parameters from data. The SageMaker CatBoost algorithm is an implementation of the open-source CatBoost package.

**Note**
The default hyperparameters are based on example datasets in the CatBoost sample notebooks (p. 1981).

By default, the SageMaker CatBoost algorithm automatically chooses an evaluation metric and loss function based on the type of classification problem. The CatBoost algorithm detects the type of classification problem based on the number of labels in your data. For regression problems, the evaluation metric and loss functions are both root mean squared error. For binary classification problems, the evaluation metric is Area Under the Curve (AUC) and the loss function is log loss. For multiclass classification problems, the evaluation metric and loss functions are multiclass cross entropy. You can use the `eval_metric` hyperparameter to change the default evaluation metric. Refer to the following table for more information on LightGBM hyperparameters, including descriptions, valid values, and default values.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>iterations</td>
<td>The maximum number of trees that can be built. Valid values: integer, range: Positive integer. Default value: 500.</td>
</tr>
<tr>
<td>early_stopping_rounds</td>
<td>The training will stop if one metric of one validation data point does not improve in the last <code>early_stopping_rounds</code> round. If <code>early_stopping_rounds</code> is less than or equal to zero, this hyperparameter is ignored. Valid values: integer. Default value: 5.</td>
</tr>
</tbody>
</table>
| eval_metric             | The evaluation metric for validation data. If `eval_metric` is set to the default "auto" value, then the algorithm automatically chooses an evaluation metric based on the type of classification problem:  
  - "RMSE" for regression  
  - "AUC" for binary classification  
  - "MultiClass" for multi-class classification  
  Valid values: string, refer to the CatBoost documentation for valid values. Default value: "auto". |
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>learning_rate</td>
<td>The rate at which the model weights are updated after working through each batch of training examples. Valid values: float, range: (0.0, 1.0). Default value: 0.009.</td>
</tr>
<tr>
<td>depth</td>
<td>Depth of the tree. Valid values: integer, range: (1, 16). Default value: 6.</td>
</tr>
<tr>
<td>random_strength</td>
<td>The amount of randomness to use for scoring splits when the tree structure is selected. Use this parameter to avoid overfitting the model. Valid values: float, range: Positive floating point number. Default value: 1.0.</td>
</tr>
<tr>
<td>max_leaves</td>
<td>The maximum number of leaves in the resulting tree. Can only be used with the &quot;Lossguide&quot; growing policy. Valid values: integer, range: [2, 64]. Default value: 31.</td>
</tr>
<tr>
<td>rsm</td>
<td>Random subspace method. The percentage of features to use at each split selection, when features are selected over again at random. Valid values: float, range: (0.0, 1.0]. Default value: 1.0.</td>
</tr>
<tr>
<td>sampling_frequency</td>
<td>Frequency to sample weights and objects when building trees. Valid values: string, either: (&quot;PerTreeLevel&quot; or &quot;PerTree&quot;). Default value: &quot;PerTreeLevel&quot;.</td>
</tr>
<tr>
<td>min_data_in_leaf</td>
<td>The minimum number of training samples in a leaf. CatBoost does not search for new splits in leaves with a sample count less than the specified value. Can only be used with the &quot;Lossguide&quot; and &quot;Depthwise&quot; growing policies. Valid values: integer, range: (1 or (\infty)). Default value: 1.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>bagging_temperature</td>
<td>Defines the settings of the Bayesian bootstrap. Use the Bayesian bootstrap to assign random weights to objects. If bagging_temperature is set to 1.0, then the weights are sampled from an exponential distribution. If bagging_temperature is set to 0.0, then all weights are 1.0. Valid values: float, range: Non-negative float. Default value: 1.0.</td>
</tr>
<tr>
<td>boosting_type</td>
<td>The boosting scheme. &quot;Auto&quot; means that the boosting_type is selected based on processing unit type, the number of objects in the training dataset, and the selected learning mode. Valid values: string, any of the following: (&quot;Auto&quot;, &quot;Ordered&quot;, &quot;Plain&quot;). Default value: &quot;Auto&quot;.</td>
</tr>
<tr>
<td>scale_pos_weight</td>
<td>The weight for positive class in binary classification. The value is used as a multiplier for the weights of objects from positive class. Valid values: float, range: Positive float. Default value: 1.0.</td>
</tr>
<tr>
<td>max_bin</td>
<td>The number of splits for numerical features. &quot;Auto&quot; means that max_bin is selected based on the processing unit type and other parameters. For details, see the CatBoost documentation. Valid values: string, either: (&quot;Auto&quot; or string of integer from &quot;1&quot; to &quot;65535&quot; inclusively). Default value: &quot;Auto&quot;.</td>
</tr>
<tr>
<td>grow_policy</td>
<td>The tree growing policy. Defines how to perform greedy tree construction. Valid values: string, any of the following: (&quot;SymmetricTree&quot;, &quot;Depthwise&quot;, or &quot;Lossguide&quot;). Default value: &quot;SymmetricTree&quot;.</td>
</tr>
<tr>
<td>random_seed</td>
<td>The random seed used for training. Valid values: integer, range: Non-negative integer. Default value: 1,0.</td>
</tr>
<tr>
<td>thread_count</td>
<td>The number of threads to use during the training. If thread_count is -1, then the number of threads is equal to the number of processor cores. thread_count cannot be 0. Valid values: integer, either: (-1 or positive integer). Default value: -1.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td>verbose</td>
<td>The verbosity of print messages, with higher levels corresponding to more detailed print statements. Valid values: integer, range: Positive integer. Default value: 1.</td>
</tr>
</tbody>
</table>

**Tune a CatBoost model**

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your training and validation datasets. Model tuning focuses on the following hyperparameters:

- A learning loss function to optimize during model training
- An evaluation metric that is used to evaluate model performance during validation
- A set of hyperparameters and a range of values for each to use when tuning the model automatically

Automatic model tuning searches your chosen hyperparameters to find the combination of values that results in a model that optimizes the chosen evaluation metric.

**Note**

Automatic model tuning for CatBoost is only available from the Amazon SageMaker SDKs, not from the SageMaker console.

For more information about model tuning, see [Perform Automatic Model Tuning with SageMaker](p. 2436).

**Evaluation metrics computed by the CatBoost algorithm**

The SageMaker CatBoost algorithm computes the following metrics to use for model validation. The evaluation metric is automatically assigned based on the type of classification task, which is determined by the number of unique integers in the label column. For a

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
<th>Regex Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>root mean square error</td>
<td>minimize</td>
<td>&quot;bestTest = ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>MAE</td>
<td>mean absolute error</td>
<td>minimize</td>
<td>&quot;bestTest = ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>MedianAbsoluteError</td>
<td>median absolute error</td>
<td>minimize</td>
<td>&quot;bestTest = ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>R2</td>
<td>r2 score</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>Logloss</td>
<td>binary cross entropy</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9.]+)&quot;</td>
</tr>
</tbody>
</table>

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Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
<th>Regex Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precision</td>
<td>precision</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9]+)&quot;</td>
</tr>
<tr>
<td>Recall</td>
<td>recall</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9]+)&quot;</td>
</tr>
<tr>
<td>F1</td>
<td>f1 score</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9]+)&quot;</td>
</tr>
<tr>
<td>AUC</td>
<td>auc score</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9]+)&quot;</td>
</tr>
<tr>
<td>MultiClass</td>
<td>multiclass cross entropy</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9]+)&quot;</td>
</tr>
<tr>
<td>Accuracy</td>
<td>accuracy</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9]+)&quot;</td>
</tr>
<tr>
<td>BalancedAccuracy</td>
<td>balanced accuracy</td>
<td>maximize</td>
<td>&quot;bestTest = ([0-9]+)&quot;</td>
</tr>
</tbody>
</table>

### Tunable CatBoost hyperparameters

Tune the CatBoost model with the following hyperparameters. The hyperparameters that have the greatest effect on optimizing the CatBoost evaluation metrics are: learning_rate, depth, l2_leaf_reg, and random_strength. For a list of all the CatBoost hyperparameters, see CatBoost hyperparameters (p. 1982).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.001, MaxValue: 0.01</td>
</tr>
<tr>
<td>depth</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 4, MaxValue: 10</td>
</tr>
<tr>
<td>l2_leaf_reg</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 2, MaxValue: 10</td>
</tr>
<tr>
<td>random_strength</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 10</td>
</tr>
</tbody>
</table>

### Factorization Machines Algorithm

The Factorization Machines algorithm is a general-purpose supervised learning algorithm that you can use for both classification and regression tasks. It is an extension of a linear model that is designed to capture interactions between features within high dimensional sparse datasets economically. For example, in a click prediction system, the Factorization Machines model can capture click rate patterns observed when ads from a certain ad-category are placed on pages from a certain page-category. Factorization machines are a good choice for tasks dealing with high dimensional sparse datasets, such as click prediction and item recommendation.
Note
The Amazon SageMaker implementation of the Factorization Machines algorithm considers only pair-wise (2nd order) interactions between features.

Topics
- Input/Output Interface for the Factorization Machines Algorithm (p. 1987)
- EC2 Instance Recommendation for the Factorization Machines Algorithm (p. 1987)
- Factorization Machines Sample Notebooks (p. 1987)
- How Factorization Machines Work (p. 1988)
- Factorization Machines Hyperparameters (p. 1988)
- Tune a Factorization Machines Model (p. 1993)
- Factorization Machines Response Formats (p. 1995)

Input/Output Interface for the Factorization Machines Algorithm

The Factorization Machines algorithm can be run in either in binary classification mode or regression mode. In each mode, a dataset can be provided to the test channel along with the train channel dataset. The scoring depends on the mode used. In regression mode, the testing dataset is scored using Root Mean Square Error (RMSE). In binary classification mode, the test dataset is scored using Binary Cross Entropy (Log Loss), Accuracy (at threshold=0.5) and F1 Score (at threshold =0.5).

For training, the Factorization Machines algorithm currently supports only the recordIO-protobuf format with Float32 tensors. Because their use case is predominantly on sparse data, CSV is not a good candidate. Both File and Pipe mode training are supported for recordIO-wrapped protobuf.

For inference, the Factorization Machines algorithm supports the application/json and x-recordio-protobuf formats.

- For the binary classification problem, the algorithm predicts a score and a label. The label is a number and can be either 0 or 1. The score is a number that indicates how strongly the algorithm believes that the label should be 1. The algorithm computes score first and then derives the label from the score value. If the score is greater than or equal to 0.5, the label is 1.
- For the regression problem, just a score is returned and it is the predicted value. For example, if Factorization Machines is used to predict a movie rating, score is the predicted rating value.

Please see Factorization Machines Sample Notebooks (p. 1987) for more details on training and inference file formats.

EC2 Instance Recommendation for the Factorization Machines Algorithm

The Amazon SageMaker Factorization Machines algorithm is highly scalable and can train across distributed instances. We recommend training and inference with CPU instances for both sparse and dense datasets. In some circumstances, training with one or more GPUs on dense data might provide some benefit. Training with GPUs is available only on dense data. Use CPU instances for sparse data. The Factorization Machines algorithm supports P2, P3, G4dn, and G5 instances for training and inference.

Factorization Machines Sample Notebooks

For a sample notebook that uses the SageMaker Factorization Machines algorithm to analyze the images of handwritten digits from zero to nine in the MNIST dataset, see An Introduction to Factorization Machines with MNIST. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. Example notebooks that use Factorization Machines algorithm are located in the Introduction to Amazon algorithms section. To open a notebook, click on its Use tab and select Create copy.
How Factorization Machines Work

The prediction task for a Factorization Machines model is to estimate a function \( \hat{y} \) from a feature set \( x_i \) to a target domain. This domain is real-valued for regression and binary for classification. The Factorization Machines model is supervised and so has a training dataset \((x_i, y_j)\) available. The advantages this model presents lie in the way it uses a factorized parametrization to capture the pairwise feature interactions. It can be represented mathematically as follows:

\[
\hat{y} = w_0 + \sum_i w_i x_i + \sum_i \sum_{j > i} <v_i, v_j> x_i x_j
\]

The three terms in this equation correspond respectively to the three components of the model:

- The \( w_0 \) term represents the global bias.
- The \( w_i \) linear terms model the strength of the \( i^{th} \) variable.
- The \( <v_i, v_j> \) factorization terms model the pairwise interaction between the \( i^{th} \) and \( j^{th} \) variable.

The global bias and linear terms are the same as in a linear model. The pairwise feature interactions are modeled in the third term as the inner product of the corresponding factors learned for each feature. Learned factors can also be considered as embedding vectors for each feature. For example, in a classification task, if a pair of features tends to co-occur more often in positive labeled samples, then the inner product of their factors would be large. In other words, their embedding vectors would be close to each other in cosine similarity. For more information about the Factorization Machines model, see Factorization Machines.

For regression tasks, the model is trained by minimizing the squared error between the model prediction \( \hat{y}_n \) and the target value \( y_n \). This is known as the square loss:

\[
L = \frac{1}{N} \sum_n (y_n - \hat{y}_n)^2
\]

For a classification task, the model is trained by minimizing the cross entropy loss, also known as the log loss:

\[
L = \frac{1}{N} \sum_n [y_n \log \hat{p}_n + (1 - y_n) \log (1 - \hat{p}_n)]
\]

where:

\[
\hat{p}_n = \frac{1}{1 + e^{-\hat{y}_n}}
\]

For more information about loss functions for classification, see Loss functions for classification.

Factorization Machines Hyperparameters

The following table contains the hyperparameters for the Factorization Machines algorithm. These are parameters that are set by users to facilitate the estimation of model parameters from data. The required hyperparameters that must be set are listed first, in alphabetical order. The optional hyperparameters that can be set are listed next, also in alphabetical order.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>feature_dim</td>
<td>The dimension of the input feature space. This could be very high with sparse input.</td>
</tr>
<tr>
<td>Required</td>
<td></td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td>num_factors</td>
<td>The dimensionality of factorization. Required. Valid values: Positive integer. Suggested value range: [10000,10000000].</td>
</tr>
<tr>
<td>predictor_type</td>
<td>The type of predictor. Required. Valid values: String: binary_classifier or regressor.</td>
</tr>
<tr>
<td>bias_init_method</td>
<td>The initialization method for the bias term: Optional. Valid values: uniform, normal, or constant. Default value: normal.</td>
</tr>
<tr>
<td>bias_init_scale</td>
<td>Range for initialization of the bias term. Takes effect if bias_init_method is set to uniform. Optional. Valid values: Non-negative float. Suggested value range: [1e-8, 512]. Default value: None.</td>
</tr>
<tr>
<td>bias_init_sigma</td>
<td>The standard deviation for initialization of the bias term. Takes effect if bias_init_method is set to normal. Optional. Valid values: Non-negative float. Suggested value range: [1e-8, 512]. Default value: 0.01</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>bias_init_value</td>
<td>The initial value of the bias term. Takes effect if bias_init_method is set to constant.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Suggested value range: [1e-8, 512].</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>bias_lr</td>
<td>The learning rate for the bias term.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Non-negative float. Suggested value range: [1e-8, 512].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.1</td>
</tr>
<tr>
<td>bias_wd</td>
<td>The weight decay for the bias term.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Non-negative float. Suggested value range: [1e-8, 512].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.01</td>
</tr>
<tr>
<td>clip_gradient</td>
<td>Gradient clipping optimizer parameter. Clips the gradient by projecting onto the interval ([-\text{clip_gradient}, +\text{clip_gradient}]).</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>epochs</td>
<td>The number of training epochs to run.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>eps</td>
<td>Epsilon parameter to avoid division by 0.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Suggested value: small.</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| factors_init_method | The initialization method for factorization terms:  
  - normal: Initializes weights with random values sampled from a normal distribution with a mean of zero and standard deviation specified by factors_init_sigma.  
  - uniform: Initializes weights with random values uniformly sampled from a range specified by [-factors_init_scale, +factors_init_scale].  
  - constant: Initializes the weights to a scalar value specified by factors_init_value. |
| factors_init_scale | The range for initialization of factorization terms. Takes effect if factors_init_method is set to uniform.  
  **Optional**  
  Valid values: Non-negative float. Suggested value range: [1e-8, 512].  
  Default value: None |
| factors_init_sigma | The standard deviation for initialization of factorization terms. Takes effect if factors_init_method is set to normal.  
  **Optional**  
  Valid values: Non-negative float. Suggested value range: [1e-8, 512].  
  Default value: 0.001 |
| factors_init_value | The initial value of factorization terms. Takes effect if factors_init_method is set to constant.  
  **Optional**  
  Valid values: Float. Suggested value range: [1e-8, 512].  
  Default value: None |
| factors_lr       | The learning rate for factorization terms.  
  **Optional**  
  Valid values: Non-negative float. Suggested value range: [1e-8, 512].  
  Default value: 0.0001 |
<p>| Parameter Name   | Description | |
|------------------|-------------||
| factors_wd      | The weight decay for factorization terms. | |
|                  | <strong>Optional</strong> | |
|                  | Valid values: Non-negative float. Suggested value range: [1e-8, 512]. | |
|                  | Default value: 0.00001 | |
| linear_lr       | The learning rate for linear terms. | |
|                  | <strong>Optional</strong> | |
|                  | Valid values: Non-negative float. Suggested value range: [1e-8, 512]. | |
|                  | Default value: 0.001 | |
| linear_init_method | The initialization method for linear terms: | |
|                  | • <strong>normal</strong> Initializes weights with random values sampled from a normal distribution with a mean of zero and standard deviation specified by linear_init_sigma. | |
|                  | • <strong>uniform</strong> Initializes weights with random values uniformly sampled from a range specified by [-linear_init_scale, +linear_init_scale]. | |
|                  | • <strong>constant</strong> Initializes the weights to a scalar value specified by linear_init_value. | |
|                  | <strong>Optional</strong> | |
|                  | Valid values: uniform, normal, or constant. | |
|                  | Default value: normal | |
| linear_init_scale | Range for initialization of linear terms. Takes effect if linear_init_method is set to uniform. | |
|                  | <strong>Optional</strong> | |
|                  | Valid values: Non-negative float. Suggested value range: [1e-8, 512]. | |
|                  | Default value: None | |
| linear_init_sigma | The standard deviation for initialization of linear terms. Takes effect if linear_init_method is set to normal. | |
|                  | <strong>Optional</strong> | |
|                  | Valid values: Non-negative float. Suggested value range: [1e-8, 512]. | |
|                  | Default value: 0.01 | |</p>
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>linear_init_value</td>
<td>The initial value of linear terms. Takes effect if linear_init_method is set to constant.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Suggested value range: [1e-8, 512].</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>linear_wd</td>
<td>The weight decay for linear terms.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Non-negative float. Suggested value range: [1e-8, 512].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.001</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The size of mini-batch used for training.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 1000</td>
</tr>
<tr>
<td>rescale_grad</td>
<td>Gradient rescaling optimizer parameter. If set, multiplies the gradient with rescale_grad before updating. Often choose to be 1.0/batch_size.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
</tbody>
</table>

**Tune a Factorization Machines Model**

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see *Perform Automatic Model Tuning with SageMaker* (p. 2436).

**Metrics Computed by the Factorization Machines Algorithm**

The Factorization Machines algorithm has both binary classification and regression predictor types. The predictor type determines which metric you can use for automatic model tuning. The algorithm reports a test:rmse regressor metric, which is computed during training. When tuning the model for regression tasks, choose this metric as the objective.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test:rmse</td>
<td>Root Mean Square Error</td>
<td>Minimize</td>
</tr>
</tbody>
</table>
The Factorization Machines algorithm reports three binary classification metrics, which are computed during training. When tuning the model for binary classification tasks, choose one of these as the objective.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test:binary_classification_accuracy</td>
<td>Accuracy</td>
<td>Maximize</td>
</tr>
<tr>
<td>test:binary_classification_cross_entropy</td>
<td>Cross Entropy</td>
<td>Minimize</td>
</tr>
<tr>
<td>test:binary_f_beta</td>
<td>Beta</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

### Tunable Factorization Machines Hyperparameters

You can tune the following hyperparameters for the Factorization Machines algorithm. The initialization parameters that contain the terms bias, linear, and factorization depend on their initialization method. There are three initialization methods: uniform, normal, and constant. These initialization methods are not themselves tunable. The parameters that are tunable are dependent on this choice of the initialization method. For example, if the initialization method is uniform, then only the scale parameters are tunable. Specifically, if `bias_init_method==uniform`, then only `bias_init_scale`, `linear_init_scale`, and `factors_init_scale` are tunable. Similarly, if the initialization method is normal, then only `sigma` parameters are tunable. If the initialization method is constant, then only `value` parameters are tunable. These dependencies are listed in the following table.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
<th>Dependency</th>
</tr>
</thead>
<tbody>
<tr>
<td>bias_init_scale</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td><code>bias_init_method==uniform</code></td>
</tr>
<tr>
<td>bias_init_sigma</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td><code>bias_init_method==normal</code></td>
</tr>
<tr>
<td>bias_init_value</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td><code>bias_init_method==constant</code></td>
</tr>
<tr>
<td>bias_lr</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>None</td>
</tr>
<tr>
<td>bias_wd</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>None</td>
</tr>
<tr>
<td>epoch</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 1000</td>
<td>None</td>
</tr>
<tr>
<td>factors_init_scale</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td><code>bias_init_method==uniform</code></td>
</tr>
<tr>
<td>factors_init_sigma</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td><code>bias_init_method==normal</code></td>
</tr>
<tr>
<td>factors_init_value</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td><code>bias_init_method==constant</code></td>
</tr>
<tr>
<td>factors_lr</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>None</td>
</tr>
</tbody>
</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
<th>Dependency</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>factors_wd</code></td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>None</td>
</tr>
<tr>
<td><code>linear_init_scale</code></td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>bias_init_method==uniform</td>
</tr>
<tr>
<td><code>linear_init_sigma</code></td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>bias_init_method==normal</td>
</tr>
<tr>
<td><code>linear_init_value</code></td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>bias_init_method==constant</td>
</tr>
<tr>
<td><code>linear_lr</code></td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>None</td>
</tr>
<tr>
<td><code>linear_wd</code></td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-8, MaxValue: 512</td>
<td>None</td>
</tr>
<tr>
<td><code>mini_batch_size</code></td>
<td>IntegerParameterRange</td>
<td>MinValue: 100, MaxValue: 10000</td>
<td>None</td>
</tr>
</tbody>
</table>

#### Factorization Machines Response Formats

**JSON Response Format**

**Binary classification**

```json
let response = {
  "predictions": [
    {
      "score": 0.4,
      "predicted_label": 0
    }
  ]
}
```

**Regression**

```json
let response = {
  "predictions": [
    {
      "score": 0.4
    }
  ]
}
```

**JSONLINES Response Format**

**Binary classification**

```json
{"score": 0.4, "predicted_label": 0}
```

**Regression**

```json
{"score": 0.4}
```
**RECORDIO Response Format**

Binary classification

```
[ Record = {  
    features = {},  
    label = {  
        'score': {  
            keys: [],  
            values: [0.4]  # float32  
        },  
        'predicted_label': {  
            keys: [],  
            values: [0.0]  # float32  
        }  
    }  
}  
]
```

Regression

```
[ Record = {  
    features = {},  
    label = {  
        'score': {  
            keys: [],  
            values: [0.4]  # float32  
        }  
    }  
}  
]
```

**K-Nearest Neighbors (k-NN) Algorithm**

Amazon SageMaker k-nearest neighbors (k-NN) algorithm is an index-based algorithm. It uses a non-parametric method for classification or regression. For classification problems, the algorithm queries the \( k \) points that are closest to the sample point and returns the most frequently used label of their class as the predicted label. For regression problems, the algorithm queries the \( k \) closest points to the sample point and returns the average of their feature values as the predicted value.

Training with the k-NN algorithm has three steps: sampling, dimension reduction, and index building. Sampling reduces the size of the initial dataset so that it fits into memory. For dimension reduction, the algorithm decreases the feature dimension of the data to reduce the footprint of the k-NN model in memory and inference latency. We provide two methods of dimension reduction methods: random projection and the fast Johnson-Lindenstrauss transform. Typically, you use dimension reduction for high-dimensional (\( d >1000 \)) datasets to avoid the “curse of dimensionality” that troubles the statistical analysis of data that becomes sparse as dimensionality increases. The main objective of k-NN’s training is to construct the index. The index enables efficient lookups of distances between points whose values or class labels have not yet been determined and the k nearest points to use for inference.

**Topics**
- Input/Output Interface for the k-NN Algorithm (p. 1997)
- k-NN Sample Notebooks (p. 1997)
- How the k-NN Algorithm Works (p. 1998)
- EC2 Instance Recommendation for the k-NN Algorithm (p. 1998)
- k-NN Hyperparameters (p. 1999)
Input/Output Interface for the k-NN Algorithm

SageMaker k-NN supports train and test data channels.

- Use a **train channel** for data that you want to sample and construct into the k-NN index.
- Use a **test channel** to emit scores in log files. Scores are listed as one line per mini-batch: accuracy for classifier, mean-squared error (mse) for regressor for score.

For training inputs, k-NN supports *text/csv* and *application/x-recordio-protobuf* data formats. For input type *text/csv*, the first *label_size* columns are interpreted as the label vector for that row. You can use either File mode or Pipe mode to train models on data that is formatted as recordIO-wrapped-protobuf or as *CSV*.

For inference inputs, k-NN supports the *application/json*, *application/x-recordio-protobuf*, and *text/csv* data formats. The *text/csv* format accepts a *label_size* and encoding parameter. It assumes a *label_size* of 0 and a UTF-8 encoding.

For inference outputs, k-NN supports the *application/json* and *application/x-recordio-protobuf* data formats. These two data formats also support a verbose output mode. In verbose output mode, the API provides the search results with the distances vector sorted from smallest to largest, and corresponding elements in the labels vector.

For batch transform, k-NN supports the *application/jsonlines* data format for both input and output. An example input is as follows:

```
content-type: application/jsonlines
{"features": [1.5, 16.0, 14.0, 23.0]}
{"data": {"features": {"values": [1.5, 16.0, 14.0, 23.0]}}}
```

An example output is as follows:

```
accept: application/jsonlines
{"predicted_label": 0.0}
{"predicted_label": 2.0}
```

For more information on input and output file formats, see Data Formats for k-NN Training Input (p. 2001) for training, k-NN Request and Response Formats (p. 2002) for inference, and the k-NN Sample Notebooks (p. 1997).

k-NN Sample Notebooks

For a sample notebook that uses the SageMaker k-nearest neighbor algorithm to predict wilderness cover types from geological and forest service data, see the K-Nearest Neighbor Covertype.

Use a Jupyter notebook instance to run the example in SageMaker. To learn how to create and open a Jupyter notebook instance in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker example notebooks. Find K-Nearest Neighbor notebooks in the Introduction to Amazon algorithms section. To open a notebook, click on its Use tab and select Create copy.
How the k-NN Algorithm Works

Step 1: Sample

To specify the total number of data points to be sampled from the training dataset, use the `sample_size` parameter. For example, if the initial dataset has 1,000 data points and the `sample_size` is set to 100, where the total number of instances is 2, each worker would sample 50 points. A total set of 100 data points would be collected. Sampling runs in linear time with respect to the number of data points.

Step 2: Perform Dimension Reduction

The current implementation of the k-NN algorithm has two methods of dimension reduction. You specify the method in the `dimension_reduction_type` hyperparameter. The `sign` method specifies a random projection, which uses a linear projection using a matrix of random signs, and the `fjlt` method specifies a fast Johnson-Lindenstrauss transform, a method based on the Fourier transform. Both methods preserve the L2 and inner product distances. The `fjlt` method should be used when the target dimension is large and has better performance with CPU inference. The methods differ in their computational complexity. The `sign` method requires $O(ndk)$ time to reduce the dimension of a batch of $n$ points of dimension $d$ into a target dimension $k$. The `fjlt` method requires $O(nd \log(d))$ time, but the constants involved are larger. Using dimension reduction introduces noise into the data and this noise can reduce prediction accuracy.

Step 3: Build an Index

During inference, the algorithm queries the index for the k-nearest-neighbors of a sample point. Based on the references to the points, the algorithm makes the classification or regression prediction. It makes the prediction based on the class labels or values provided. k-NN provides three different types of indexes: a flat index, an inverted index, and an inverted index with product quantization. You specify the type with the `index_type` parameter.

Serialize the Model

When the k-NN algorithm finishes training, it serializes three files to prepare for inference.

- `model_algo-1`: Contains the serialized index for computing the nearest neighbors.
- `model_algo-1.labels`: Contains serialized labels (np.float32 binary format) for computing the predicted label based on the query result from the index.
- `model_algo-1.json`: Contains the JSON-formatted model metadata which stores the $k$ and `predictor_type` hyper-parameters from training for inference along with other relevant state.

With the current implementation of k-NN, you can modify the metadata file to change the way predictions are computed. For example, you can change $k$ to 10 or change `predictor_type` to `regressor`.

```json
{
    "k": 5,
    "predictor_type": "classifier",
    "dimension_reduction": {
        "type": "sign",
        "seed": 3,
        "target_dim": 10,
        "input_dim": 20,
        "normalize": false,
        "version": "1.0"
    }
}
```

EC2 Instance Recommendation for the k-NN Algorithm

We recommend training on a CPU instance (such as ml.m5.2xlarge) or on a GPU instance. The k-NN algorithm supports P2, P3, G4dn, and G5 GPU instance families for training and inference.
Inference requests from CPUs generally have a lower average latency than requests from GPUs because there is a tax on CPU-to-GPU communication when you use GPU hardware. However, GPUs generally have higher throughput for larger batches.

**k-NN Hyperparameters**

<table>
<thead>
<tr>
<th><strong>Parameter Name</strong></th>
<th><strong>Description</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><code>feature_dim</code></td>
<td>The number of features in the input data.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer.</td>
</tr>
<tr>
<td><code>k</code></td>
<td>The number of nearest neighbors.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td><code>predictor_type</code></td>
<td>The type of inference to use on the data labels.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: <code>classifier</code> for classification or <code>regressor</code> for regression.</td>
</tr>
<tr>
<td><code>sample_size</code></td>
<td>The number of data points to be sampled from the training data set.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td><code>dimension_reduction_target</code></td>
<td>Target dimension to reduce to.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong> when you specify the <code>dimension_reduction_type</code> parameter.</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer greater than 0 and less than <code>feature_dim</code>.</td>
</tr>
<tr>
<td><code>dimension_reduction_type</code></td>
<td>The type of dimension reduction method.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: <code>sign</code> for random projection or <code>fjlt</code> for the fast Johnson-Lindenstrauss transform.</td>
</tr>
<tr>
<td></td>
<td>Default value: No dimension reduction</td>
</tr>
<tr>
<td><code>faiss_index_ivf_nlist</code></td>
<td>The number of centroids to construct in the index when <code>index_type</code> is <code>faiss.IVFFlat</code> or <code>faiss.IVFPQ</code>.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>auto</code>, which resolves to <code>sqrt(sample_size)</code>.</td>
</tr>
<tr>
<td><code>faiss_index_pq_m</code></td>
<td>The number of vector sub-components to construct in the index when <code>index_type</code> is <code>faiss.IVFPQ</code>.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>auto</code>, which resolves to <code>sqrt(sample_size)</code>.</td>
</tr>
</tbody>
</table>
Use Built-in Algorithms

Parameter Name | Description
--- | ---
faiss_index_pq_m | The FaceBook AI Similarity Search (FAISS) library requires that the value of `faiss_index_pq_m` is a divisor of the data dimension. If `faiss_index_pq_m` is not a divisor of the data dimension, we increase the data dimension to smallest integer divisible by `faiss_index_pq_m`. If no dimension reduction is applied, the algorithm adds a padding of zeros. If dimension reduction is applied, the algorithm increase the value of the `dimension_reduction_target` hyper-parameter.

**Optional**

Valid values: One of the following positive integers: 1, 2, 3, 4, 8, 12, 16, 20, 24, 28, 32, 40, 48, 56, 64, 96

index_metric | The metric to measure the distance between points when finding nearest neighbors. When training with `index_type` set to `faiss.IVFPQ`, the `INNER_PRODUCT` distance and `COSINE` similarity are not supported.

**Optional**

Valid values: `L2` for Euclidean-distance, `INNER_PRODUCT` for inner-product distance, `COSINE` for cosine similarity.

Default value: `L2`

index_type | The type of index.

**Optional**

Valid values: `faiss.Flat`, `faiss.IVFFlat`, `faiss.IVFPQ`.

Default values: `faiss.Flat`

mini_batch_size | The number of observations per mini-batch for the data iterator.

**Optional**

Valid values: positive integer

Default value: 5000

Tune a k-NN Model

The Amazon SageMaker k-nearest neighbors algorithm is a supervised algorithm. The algorithm consumes a test data set and emits a metric about the accuracy for a classification task or about the mean squared error for a regression task. These accuracy metrics compare the model predictions for their respective task to the ground truth provided by the empirical test data. To find the best model that reports the highest accuracy or lowest error on the test dataset, run a hyperparameter tuning job for k-NN.

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric appropriate for the prediction task of the algorithm. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric. The hyperparameters are used only to help estimate model parameters and are not used by the trained model to make predictions.
For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

Metrics Computed by the k-NN Algorithm

The k-nearest neighbors algorithm computes one of two metrics in the following table during training depending on the type of task specified by the predictor_type hyper-parameter.

- **classifier** specifies a classification task and computes test:accuracy
- **regressor** specifies a regression task and computes test:mse.

Choose the predictor_type value appropriate for the type of task undertaken to calculate the relevant objective metric when tuning a model.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test:accuracy</td>
<td>When predictor_type is set to classifier, k-NN compares the predicted label, based on the average of the k-nearest neighbors' labels, to the ground truth label provided in the test channel data. The accuracy reported ranges from 0.0 (0%) to 1.0 (100%).</td>
<td>Maximize</td>
</tr>
<tr>
<td>test:mse</td>
<td>When predictor_type is set to regressor, k-NN compares the predicted label, based on the average of the k-nearest neighbors' labels, to the ground truth label provided in the test channel data. The mean squared error is computed by comparing the two labels.</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

Tunable k-NN Hyperparameters

Tune the Amazon SageMaker k-nearest neighbor model with the following hyperparameters.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>k</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 1024</td>
</tr>
<tr>
<td>sample_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 256, MaxValue: 20000000</td>
</tr>
</tbody>
</table>

Data Formats for k-NN Training Input

All Amazon SageMaker built-in algorithms adhere to the common input training formats described in Common Data Formats - Training. This topic contains a list of the available input formats for the SageMaker k-nearest-neighbor algorithm.

**CSV Data Format**

content-type: text/csv; label_size=1

4,1.2,1.3,9.6,20.3

The first label_size columns are interpreted as the label vector for that row.
RECORDIO Data Format

content-type: application/x-recordio-protobuf

```
[  
  Record = {    
    features = {    
      'values': {    
        values: [1.2, 1.3, 9.6, 20.3]  # float32    
      },    
      label = {    
        'values': {    
          values: [4]  # float32    
        }    
      }    
    }  
  }  
]
```

**k-NN Request and Response Formats**

All Amazon SageMaker built-in algorithms adhere to the common input inference format described in [Common Data Formats - Inference](#). This topic contains a list of the available output formats for the SageMaker k-nearest-neighbor algorithm.

**INPUT: CSV Request Format**

content-type: text/csv

```
1.2,1.3,9.6,20.3
```

This accepts a `label_size` or encoding parameter. It assumes a `label_size` of 0 and a utf-8 encoding.

**INPUT: JSON Request Format**

content-type: application/json

```
{  
  "instances": [  
    {"data": {"features": {"values": [-3, -1, -4, 2]}},  
     {"features": [3.0, 0.1, 0.04, 0.002]}]
  }
```

**INPUT: JSONLINES Request Format**

content-type: application/jsonlines

```
{"features": [1.5, 16.0, 14.0, 23.0]}  
{"data": {"features": {"values": [1.5, 16.0, 14.0, 23.0]}}}
```

**INPUT: RECORDIO Request Format**

content-type: application/x-recordio-protobuf

```
[  
  Record = {    
    features = {    
```

2002
'values': {'values': [-3, -1, -4, 2] # float32}, label = {}, Record = {
  'features': {
    'values': {'values': [3.0, 0.1, 0.04, 0.002] # float32},
    label = {}
  },
},

OUTPUT: JSON Response Format
accept: application/json

{
  "predictions": [
    {"predicted_label": 0.0},
    {"predicted_label": 2.0}
  ]
}

OUTPUT: JSONLINES Response Format
accept: application/jsonlines

{"predicted_label": 0.0}
{"predicted_label": 2.0}

OUTPUT: VERBOSE JSON Response Format
In verbose mode, the API provides the search results with the distances vector sorted from smallest to largest, with corresponding elements in the labels vector. In this example, k is set to 3.
accept: application/json; verbose=true

{
  "predictions": [
    {
      "predicted_label": 0.0,
      "distances": [3.11792408, 3.89746071, 6.32548437],
      "labels": [0.0, 1.0, 0.0]
    },
    {
      "predicted_label": 2.0,
      "distances": [1.08470316, 3.04917915, 5.25393973],
      "labels": [2.0, 2.0, 0.0]
    }
  ]
}

OUTPUT: RECORDIO-PROTOBUF Response Format
content-type: application/x-recordio-protobuf

[ ]
OUTPUT: VERBOSERECORDIO-PROTOBUF Response Format

In verbose mode, the API provides the search results with the distances vector sorted from smallest to largest, with corresponding elements in the labels vector. In this example, k is set to 3.

accept: application/x-recordio-protobuf; verbose=true

```
[  
  Record = {
    features = {},
    label = {
      'predicted_label': {
        values: [0.0]  # float32
      },
      'distances': {
        values: [3.11792408, 3.89746071, 6.32548437]  # float32
      },
      'labels': {
        values: [0.0, 1.0, 0.0]  # float32
      }
    }
  },
  Record = {
    features = {},
    label = {
      'predicted_label': {
        values: [0.0]  # float32
      },
      'distances': {
        values: [1.08470316, 3.04917915, 5.25393973]  # float32
      },
      'labels': {
        values: [2.0, 2.0, 0.0]  # float32
      }
    }
  }
]
```

SAMPLE OUTPUT for the k-NN Algorithm

For regressor tasks:

```
[06/08/2018 20:15:33 INFO 140026520049408] #test_score (algo-1) : ('mse', 0.01333333333333334)
```
For classifier tasks:

```
[06/08/2018 20:15:46 INFO 140285487171328] #test_score (algo-1) : ('accuracy', 0.9866666666666667)
```

**LightGBM**

**LightGBM** is a popular and efficient open-source implementation of the Gradient Boosting Decision Tree (GBDT) algorithm. GBDT is a supervised learning algorithm that attempts to accurately predict a target variable by combining an ensemble of estimates from a set of simpler and weaker models. LightGBM uses additional techniques to significantly improve the efficiency and scalability of conventional GBDT.

**How to use SageMaker LightGBM**

You can use LightGBM as an Amazon SageMaker built-in algorithm. The following section describes how to use LightGBM with the SageMaker Python SDK. For information on how to use LightGBM from the Amazon SageMaker Studio UI, see [SageMaker JumpStart](p. 45).

- **Use LightGBM as a built-in algorithm**

  Use the LightGBM built-in algorithm to build a LightGBM training container as shown in the following code example. You can automatically spot the LightGBM built-in algorithm image URI using the SageMaker `image_uris.retrieve` API (or the `get_image_uri` API if using [Amazon SageMaker Python SDK](version 2).

  After specifying the LightGBM image URI, you can use the LightGBM container to construct an estimator using the SageMaker Estimator API and initiate a training job. The LightGBM built-in algorithm runs in script mode, but the training script is provided for you and there is no need to replace it. If you have extensive experience using script mode to create a SageMaker training job, then you can incorporate your own LightGBM training scripts.

```
from sagemaker import image_uris, model_uris, script_uris

train_model_id, train_model_version, train_scope = "lightgbm-classification-model", "+", "training"
training_instance_type = "ml.m5.xlarge"

# Retrieve the docker image
train_image_uri = image_uris.retrieve(
    region=None,
    framework=None,
    model_id=train_model_id,
    model_version=train_model_version,
    image_scope=train_scope,
    instance_type=training_instance_type
)

# Retrieve the training script
train_source_uri = script_uris.retrieve(
    model_id=train_model_id, model_version=train_model_version, script_scope=train_scope
)

train_model_uri = model_uris.retrieve(
    model_id=train_model_id, model_version=train_model_version, model_scope=train_scope
)

# Sample training data is available in this bucket
training_data_bucket = f"jumpstart-cache-prod-{aws_region}"
training_data_prefix = "training-datasets/tabular_multiclass/"
training_dataset_s3_path = f"s3://{training_data_bucket}/{training_data_prefix}"
```
output_bucket = sess.default_bucket()
output_prefix = "jumpstart-example-tabular-training"
s3_output_location = f"s3://{output_bucket}/{output_prefix}/output"

from sagemaker import hyperparameters

# Retrieve the default hyper-parameters for training the model
hyperparameters = hyperparameters.retrieve_default(model_id=train_model_id, model_version=train_model_version)

# [Optional] Override default hyperparameters with custom values
hyperparameters["num_boost_round"] = "500"

print(hyperparameters)

from sagemaker.estimator import Estimator
from sagemaker.utils import name_from_base

training_job_name = name_from_base(f"built-in-algo-{train_model_id}-training")

# Create SageMaker Estimator instance
tabular_estimator = Estimator(
    role=aws_role,
    image_uri=train_image_uri,
    source_dir=train_source_uri,
    model_uri=train_model_uri,
    entry_point="transfer_learning.py",
    instance_count=1,
    instance_type=training_instance_type,
    max_run=360000,
    hyperparameters=hyperparameters,
    output_path=s3_output_location
)

# Launch a SageMaker Training job by passing the S3 path of the training data
tabular_estimator.fit(
    {"training": training_dataset_s3_path}, logs=True, job_name=training_job_name
)

For more information about how to set up the LightGBM as a built-in algorithm, see the following notebook examples.

- Tabular classification with Amazon SageMaker LightGBM and CatBoost algorithm
- Tabular regression with Amazon SageMaker LightGBM and CatBoost algorithm

Input and Output interface for the LightGBM algorithm

Gradient boosting operates on tabular data, with the rows representing observations, one column representing the target variable or label, and the remaining columns representing features.

The SageMaker implementation of LightGBM supports CSV for training and inference:

- For Training ContentType, valid inputs must be text/csv.
- For Inference ContentType, valid inputs must be text/csv.

Note

For CSV training, the algorithm assumes that the target variable is in the first column and that the CSV does not have a header record.
For CSV inference, the algorithm assumes that CSV input does not have the label column.

Be mindful of how to format your training data for input to the LightGBM model. You must provide the path to an Amazon S3 bucket containing subdirectories for your training and optional validation data. You can also include a list of categorical features.

- **Training data input format**: Your training data should be in a subdirectory named `train/` that contains a `data.csv` file. The target variables should be in the first column of `data.csv`. The predictor variables (features) should be in the remaining columns.

- **Validation data input format**: You can optionally include another directory called `validation/` that also has a `data.csv` file. The validation data is used to compute a validation score at the end of each boosting iteration. Early stopping is applied when the validation score stops improving. If the validation data is not provided, then 20% of your training data is randomly sampled to serve as the validation data.

- **Categorical features input format**: If your predictors include categorical features, you can provide a JSON file named `categorical_index.json` in the same location as your data directories. This file should contain a Python dictionary where the key is the string "cat_index_list" and the value is a list of unique integers. Each integer in the value list should indicate the column index of the corresponding categorical features in your training data CSV file. Each value should be a positive integer (greater than zero because zero represents the target value), less than the `Int32.MaxValue` (2147483647), and less than the total number of columns. There should only be one categorical index JSON file.

For CSV training input mode, the total memory available to the algorithm (instance count multiplied by the memory available in the `InstanceType`) must be able to hold the training dataset.

SageMaker LightGBM uses the Python Joblib module to serialize or deserialize the model, which can be used for saving or loading the model.

**To use a model trained with SageMaker LightGBM with the JobLib module**

- Use the following Python code:

```python
import joblib
import tarfile
t = tarfile.open('model.tar.gz', 'r:gz')
t.extractall()
model = joblib.load(model_file_path)

# prediction with test data
# dtest should be a pandas DataFrame with column names feature_0, feature_1, ..., feature_d
pred = model.predict(dtest)
```

**Amazon EC2 instance recommendation for the LightGBM algorithm**

SageMaker LightGBM currently only trains using CPUs. LightGBM is a memory-bound (as opposed to compute-bound) algorithm. So, a general-purpose compute instance (for example, M5) is a better choice than a compute-optimized instance (for example, C5). Further, we recommend that you have enough total memory in selected instances to hold the training data.

**LightGBM sample notebooks**

The following table outlines a variety of sample notebooks that address different use cases of Amazon SageMaker LightGBM algorithm.
Notebook Title | Description
---|---
Tabular classification with Amazon SageMaker LightGBM and CatBoost algorithm | This notebook demonstrates the use of the Amazon SageMaker LightGBM algorithm to train and host a tabular classification model.
Tabular regression with Amazon SageMaker LightGBM and CatBoost algorithm | This notebook demonstrates the use of the Amazon SageMaker LightGBM algorithm to train and host a tabular regression model.

For instructions on how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, choose the SageMaker Examples tab to see a list of all of the SageMaker samples. To open a notebook, choose its Use tab and choose Create copy.

**How LightGBM works**

LightGBM implements a conventional Gradient Boosting Decision Tree (GBDT) algorithm with the addition of two novel techniques: Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB). These techniques are designed to significantly improve the efficiency and scalability of GBDT.

The LightGBM algorithm performs well in machine learning competitions because of its robust handling of a variety of data types, relationships, distributions, and the diversity of hyperparameters that you can fine-tune. You can use LightGBM for regression, classification (binary and multiclass), and ranking problems.

For more information on gradient boosting, see How XGBoost Works (p. 2043). For in-depth details about the additional GOSS and EFB techniques used in the LightGBM method, see LightGBM: A Highly Efficient Gradient Boosting Decision Tree.

**LightGBM hyperparameters**

The following table contains the subset of hyperparameters that are required or most commonly used for the Amazon SageMaker LightGBM algorithm. Users set these parameters to facilitate the estimation of model parameters from data. The SageMaker LightGBM algorithm is an implementation of the open-source LightGBM package.

**Note**
The default hyperparameters are based on example datasets in the LightGBM sample notebooks (p. 2007).

By default, the SageMaker LightGBM algorithm automatically chooses an evaluation metric and objective function based on the type of classification problem. The LightGBM algorithm detects the type of classification problem based on the number of labels in your data. For regression problems, the evaluation metric is root mean squared error and the objective function is L2 loss. For binary classification problems, the evaluation metric and objective function are both binary cross entropy. For multiclass classification problems, the evaluation metric is multiclass cross entropy and the objective function is softmax. You can use the metric hyperparameter to change the default evaluation metric. Refer to the following table for more information on LightGBM hyperparameters, including descriptions, valid values, and default values.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_boost_round</td>
<td>The maximum number of boosting iterations. <strong>Note:</strong> Internally, LightGBM constructs num_class * num_boost_round trees for multi-class classification problems.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>early_stopping_rounds</td>
<td>The training will stop if one metric of one validation data point does not improve in the last early_stopping_rounds round. If early_stopping_rounds is less than or equal to zero, this hyperparameter is ignored.</td>
</tr>
</tbody>
</table>
| metric                | The evaluation metric for validation data. If metric is set to the default "auto" value, then the algorithm automatically chooses an evaluation metric based on the type of classification problem:  
  - \( \text{rmse} \) for regression  
  - \( \text{binary\_logloss} \) for binary classification  
  - \( \text{multi\_logloss} \) for multi-class classification  
  Valid values: string, any of the following: ("auto", "rmse", "l1", "l2", "huber", "fair", "binary\_logloss", "binary\_error", "auc", "average\_precision", "multi\_logloss", "multi\_error", "auc\_mu", or "cross\_entropy"). |
<p>| learning_rate         | The rate at which the model weights are updated after working through each batch of training examples.                                          |
| num_leaves            | The maximum number of leaves in one tree.                                                                                                    |
| feature_fraction      | A subset of features to be selected on each iteration (tree). Must be less than 1.0.                                                        |
| bagging_fraction      | A subset of features similar to feature_fraction, but bagging_fraction randomly selects part of the data without resampling.                |</p>
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>bagging_freq</td>
<td>The frequency to perform bagging. At every bagging_freq iteration, LightGBM randomly selects a percentage of the data to use for the next bagging_freq iteration. This percentage is determined by the bagging_fraction hyperparameter. If bagging_freq is zero, then bagging is deactivated. Valid values: integer, range: Non-negative integer. Default value: 1.</td>
</tr>
<tr>
<td>max_depth</td>
<td>The maximum depth for a tree model. This is used to deal with overfitting when the amount of data is small. If max_depth is less than or equal to zero, this means there is no limit for maximum depth. Valid values: integer. Default value: 6.</td>
</tr>
<tr>
<td>min_data_in_leaf</td>
<td>The minimum amount of data in one leaf. Can be used to deal with overfitting. Valid values: integer, range: Non-negative integer. Default value: 3.</td>
</tr>
<tr>
<td>max_delta_step</td>
<td>Used to limit the max output of tree leaves. If max_delta_step is less than or equal to 0, then there is no constraint. The final max output of leaves is learning_rate * max_delta_step. Valid values: float. Default value: 0.0.</td>
</tr>
<tr>
<td>lambda_l1</td>
<td>L1 regularization. Valid values: float, range: Non-negative float. Default value: 0.0.</td>
</tr>
<tr>
<td>lambda_l2</td>
<td>L2 regularization. Valid values: float, range: Non-negative float. Default value: 0.0.</td>
</tr>
<tr>
<td>boosting</td>
<td>Boosting type Valid values: string, any of the following: (&quot;gbdt&quot;, &quot;rf&quot;, &quot;dart&quot;, or &quot;goss&quot;). Default value: &quot;gbdt&quot;.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>min_gain_to_split</td>
<td>The minimum gain to perform a split. Can be used to speed up training. Valid values: integer, float: Non-negative float. Default value: 0.0.</td>
</tr>
<tr>
<td>scale_pos_weight</td>
<td>The weight of the labels with positive class. Used only for binary classification tasks. <code>scale_pos_weight</code> cannot be used if <code>is_unbalance</code> is set to &quot;True&quot;. Valid values: float, range: Positive float. Default value: 1.0.</td>
</tr>
<tr>
<td>tree_learner</td>
<td>Tree learner type. Valid values: string, any of the following: (&quot;serial&quot;, &quot;feature&quot;, &quot;data&quot;, or &quot;voting&quot;). Default value: &quot;serial&quot;.</td>
</tr>
<tr>
<td>feature_fraction_by_node</td>
<td>Selects a subset of random features on each tree node. For example, if <code>feature_fraction_by_node</code> is 0.8, then 80% of features are selected. Can be used to deal with overfitting. Valid values: integer, range: (0.0, 1.0]. Default value: 1.0.</td>
</tr>
<tr>
<td>is_unbalance</td>
<td>Set to &quot;True&quot; if training data is unbalanced. Used only for binary classification tasks. <code>is_unbalance</code> cannot be used with <code>scale_pos_weight</code>. Valid values: string, either: (&quot;True&quot; or &quot;False&quot;). Default value: &quot;False&quot;.</td>
</tr>
<tr>
<td>max_bin</td>
<td>The maximum number of bins used to bucket feature values. A small number of bins may reduce training accuracy, but may increase general performance. Can be used to deal with overfitting. Valid values: integer, range: (1, ∞). Default value: 255.</td>
</tr>
<tr>
<td>tweedie_variance_power</td>
<td>Controls the variance of the Tweedie distribution. Set this closer to 2.0 to shift toward a gamma distribution. Set this closer to 1.0 to shift toward a Poisson distribution. Used only for regression tasks. Valid values: float, range: [1.0, 2.0]. Default value: 1.5.</td>
</tr>
</tbody>
</table>
## Parameter Name: `num_threads`

Number of parallel threads used to run LightGBM. Value 0 means default number of threads in OpenMP.

Valid values: integer, range: Non-negative integer.

Default value: 0.

## Parameter Name: `verbosity`

The verbosity of print messages. If the verbosity is less than 0, then print messages only show fatal errors. If verbosity is set to 0, then print messages include errors and warnings. If verbosity is 1, then print messages show more information. A verbosity greater than 1 shows the most information in print messages and can be used for debugging.

Valid values: integer.

Default value: 1.

---

### Tune a LightGBM model

**Automatic model tuning**, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your training and validation datasets. Model tuning focuses on the following hyperparameters:

- A learning objective function to optimize during model training
- An evaluation metric that is used to evaluate model performance during validation
- A set of hyperparameters and a range of values for each to use when tuning the model automatically

Automatic model tuning searches your specified hyperparameters to find the combination of values that results in a model that optimizes the chosen evaluation metric.

**Note**

Automatic model tuning for LightGBM is only available from the Amazon SageMaker SDKs, not from the SageMaker console.

For more information about model tuning, see [Perform Automatic Model Tuning with SageMaker](p. 2436).

### Evaluation metrics computed by the LightGBM algorithm

The SageMaker LightGBM algorithm computes the following metrics to use for model validation. The evaluation metric is automatically assigned based on the type of classification task, which is determined by the number of unique integers in the label column.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
<th>Regex Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>rmse</td>
<td>root mean square error</td>
<td>minimize</td>
<td>&quot;rmse: ([0-9]+)&quot;</td>
</tr>
</tbody>
</table>

---

2012
## Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
<th>Regex Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>l1</td>
<td>mean absolute error</td>
<td>minimize</td>
<td>&quot;l1: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>l2</td>
<td>mean squared error</td>
<td>minimize</td>
<td>&quot;l2: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>huber</td>
<td>huber loss</td>
<td>minimize</td>
<td>&quot;huber: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>fair</td>
<td>fair loss</td>
<td>minimize</td>
<td>&quot;fair: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>binary_logloss</td>
<td>binary cross entropy</td>
<td>maximize</td>
<td>&quot;binary_logloss: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>binary_error</td>
<td>binary error</td>
<td>minimize</td>
<td>&quot;binary_error: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>auc</td>
<td>AUC</td>
<td>maximize</td>
<td>&quot;auc: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>average_precision</td>
<td>average precision score</td>
<td>maximize</td>
<td>&quot;average_precision: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>multi_logloss</td>
<td>multiclass cross entropy</td>
<td>maximize</td>
<td>&quot;multi_logloss: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>multi_error</td>
<td>multiclass error score</td>
<td>minimize</td>
<td>&quot;multi_error: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>auc_mu</td>
<td>AUC-mu</td>
<td>maximize</td>
<td>&quot;auc_mu: ([0-9.]+)&quot;</td>
</tr>
<tr>
<td>cross_entropy</td>
<td>cross entropy</td>
<td>minimize</td>
<td>&quot;cross_entropy: ([0-9.]+)&quot;</td>
</tr>
</tbody>
</table>

### Tunable LightGBM hyperparameters

Tune the LightGBM model with the following hyperparameters. The hyperparameters that have the greatest effect on optimizing the LightGBM evaluation metrics are: `learning_rate`, `num_leaves`, `feature_fraction`, `bagging_fraction`, `bagging_freq`, `max_depth` and `min_data_in_leaf`. For a list of all the LightGBM hyperparameters, see LightGBM hyperparameters (p. 2008).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.001, MaxValue: 0.01</td>
</tr>
<tr>
<td>num_leaves</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 10, MaxValue: 100</td>
</tr>
<tr>
<td>feature_fraction</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.1, MaxValue: 1.0</td>
</tr>
</tbody>
</table>
### Linear Learner Algorithm

*Linear models* are supervised learning algorithms used for solving either classification or regression problems. For input, you give the model labeled examples \((x, y)\). \(x\) is a high-dimensional vector and \(y\) is a numeric label. For binary classification problems, the label must be either 0 or 1. For multiclass classification problems, the labels must be from 0 to \(num\_classes - 1\). For regression problems, \(y\) is a real number. The algorithm learns a linear function, or, for classification problems, a linear threshold function, and maps a vector \(x\) to an approximation of the label \(y\).

The Amazon SageMaker linear learner algorithm provides a solution for both classification and regression problems. With the SageMaker algorithm, you can simultaneously explore different training objectives and choose the best solution from a validation set. You can also explore a large number of models and choose the best. The best model optimizes either of the following:

- Continuous objectives, such as mean square error, cross entropy loss, absolute error.
- Discrete objectives suited for classification, such as F1 measure, precision, recall, or accuracy.

Compared with methods that provide a solution for only continuous objectives, the SageMaker linear learner algorithm provides a significant increase in speed over naive hyperparameter optimization techniques. It is also more convenient.

The linear learner algorithm requires a data matrix, with rows representing the observations, and columns representing the dimensions of the features. It also requires an additional column that contains the labels that match the data points. At a minimum, Amazon SageMaker linear learner requires you to specify input and output data locations, and objective type (classification or regression) as arguments. The feature dimension is also required. For more information, see CreateTrainingJob. You can specify additional parameters in the HyperParameters string map of the request body. These parameters control the optimization procedure, or specifics of the objective function that you train on. For example, the number of epochs, regularization, and loss type.

If you're using Managed Spot Training, the linear learner algorithm supports using checkpoints to take a snapshot of the state of the model.

**Topics**

- Input/Output interface for the linear learner algorithm (p. 2015)
- EC2 instance recommendation for the linear learner algorithm (p. 2015)
- Linear learner sample notebooks (p. 2015)
- How linear learner works (p. 2016)
- Linear learner hyperparameters (p. 2017)
- Tune a linear learner model (p. 2025)
- Linear learner response formats (p. 2029)
Input/Output interface for the linear learner algorithm

The Amazon SageMaker linear learner algorithm supports three data channels: train, validation (optional), and test (optional). If you provide validation data, the S3DataDistributionType should be FullyReplicated. The algorithm logs validation loss at every epoch, and uses a sample of the validation data to calibrate and select the best model. If you don’t provide validation data, the algorithm uses a sample of the training data to calibrate and select the model. If you provide test data, the algorithm logs include the test score for the final model.

For training, the linear learner algorithm supports both recordIO-wrapped protobuf and CSV formats. For the application/x-recordio-protobuf input type, only Float32 tensors are supported. For the text/csv input type, the first column is assumed to be the label, which is the target variable for prediction. You can use either File mode or Pipe mode to train linear learner models on data that is formatted as recordIO-wrapped-protobuf or as CSV.

For inference, the linear learner algorithm supports the application/json, application/x-recordio-protobuf, and text/csv formats. When you make predictions on new data, the format of the response depends on the type of model. For regression (predictor_type='regressor'), the score is the prediction produced by the model. For classification (predictor_type='binary_classifier' or predictor_type='multiclass_classifier'), the model returns a score and also a predicted_label. The predicted_label is the class predicted by the model and the score measures the strength of that prediction.

- For binary classification, predicted_label is 0 or 1, and score is a single floating point number that indicates how strongly the algorithm believes that the label should be 1.
- For multiclass classification, the predicted_class will be an integer from 0 to num_classes-1, and score will be a list of one floating point number per class.

To interpret the score in classification problems, you have to consider the loss function used. If the loss hyperparameter value is logistic for binary classification or softmax_loss for multiclass classification, then the score can be interpreted as the probability of the corresponding class. These are the loss values used by the linear learner when the loss value is auto default value. But if the loss is set to hinge_loss, then the score cannot be interpreted as a probability. This is because hinge loss corresponds to a Support Vector Classifier, which does not produce probability estimates.

For more information on input and output file formats, see Linear learner response formats (p. 2029). For more information on inference formats, and the Linear learner sample notebooks (p. 2015).

EC2 instance recommendation for the linear learner algorithm

The linear learner algorithm supports both CPU and GPU instances for training and inference. For GPU, the linear learner algorithm supports P2, P3, G4dn, and G5 GPU families.

During testing, we have not found substantial evidence that multi-GPU instances are faster than single-GPU instances. Results can vary, depending on your specific use case.

Linear learner sample notebooks

The following table outlines a variety of sample notebooks that address different use cases of Amazon SageMaker linear learner algorithm.

<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>An Introduction with the MNIST dataset</td>
<td>Using the MNIST dataset, we train a binary classifier to predict a single digit.</td>
</tr>
<tr>
<td>Notebook Title</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Predict Breast Cancer</td>
<td>Using UCI's Breast Cancer dataset, we train a model to predict Breast Cancer.</td>
</tr>
<tr>
<td>How to Build a Multiclass Classifier?</td>
<td>Using UCI's Covertype dataset, we demonstrate how to train a multiclass classifier.</td>
</tr>
<tr>
<td>How to Build a Machine Learning (ML) Pipeline for Inference?</td>
<td>Using a Scikit-learn container, we demonstrate how to build an end-to-end ML pipeline.</td>
</tr>
</tbody>
</table>

For instructions on how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, choose the SageMaker Examples tab to see a list of all of the SageMaker samples. The topic modeling example notebooks using the linear learning algorithm are located in the Introduction to Amazon algorithms section. To open a notebook, choose its Use tab and choose Create copy.

How linear learner works

There are three steps involved in the implementation of the linear learner algorithm: preprocess, train, and validate.

**Step 1: Preprocess**

Normalization, or feature scaling, is an important preprocessing step for certain loss functions that ensures the model being trained on a dataset does not become dominated by the weight of a single feature. The Amazon SageMaker Linear Learner algorithm has a normalization option to assist with this preprocessing step. If normalization is turned on, the algorithm first goes over a small sample of the data to learn the mean value and standard deviation for each feature and for the label. Each of the features in the full dataset is then shifted to have mean of zero and scaled to have a unit standard deviation.

**Note**

For best results, ensure your data is shuffled before training. Training with unshuffled data may cause training to fail.

You can configure whether the linear learner algorithm normalizes the feature data and the labels using the `normalize_data` and `normalize_label` hyperparameters, respectively. Normalization is enabled by default for both features and labels for regression. Only the features can be normalized for binary classification and this is the default behavior.

**Step 2: Train**

With the linear learner algorithm, you train with a distributed implementation of stochastic gradient descent (SGD). You can control the optimization process by choosing the optimization algorithm. For example, you can choose to use Adam, AdaGrad, stochastic gradient descent, or other optimization algorithms. You also specify their hyperparameters, such as momentum, learning rate, and the learning rate schedule. If you aren't sure which algorithm or hyperparameter value to use, choose a default that works for the majority of datasets.

During training, you simultaneously optimize multiple models, each with slightly different objectives. For example, you vary L1 or L2 regularization and try out different optimizer settings.

**Step 3: Validate and set the threshold**

When training multiple models in parallel, the models are evaluated against a validation set to select the most optimal model once training is complete. For regression, the most optimal model is the one that achieves the best loss on the validation set. For classification, a sample of the validation set is used to calibrate the classification threshold. The most optimal model selected is the one that achieves the...
best binary classification selection criteria on the validation set. Examples of such criteria include the F1 measure, accuracy, and cross-entropy loss.

**Note**
If the algorithm is not provided a validation set, then evaluating and selecting the most optimal model is not possible. To take advantage of parallel training and model selection ensure you provide a validation set to the algorithm.

**Linear learner hyperparameters**

The following table contains the hyperparameters for the linear learner algorithm. These are parameters that are set by users to facilitate the estimation of model parameters from data. The required hyperparameters that must be set are listed first, in alphabetical order. The optional hyperparameters that can be set are listed next, also in alphabetical order. When a hyperparameter is set to auto, Amazon SageMaker will automatically calculate and set the value of that hyperparameter.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_classes</td>
<td>The number of classes for the response variable. The algorithm assumes that classes are labeled 0, ..., num_classes - 1. Required when predictor_type is multiclass_classifier. Otherwise, the algorithm ignores it. Valid values: Integers from 3 to 1,000,000</td>
</tr>
<tr>
<td>predictor_type</td>
<td>Specifies the type of target variable as a binary classification, multiclass classification, or regression. Required Valid values: binary_classifier, multiclass_classifier, or regressor</td>
</tr>
<tr>
<td>accuracy_top_k</td>
<td>When computing the top-k accuracy metric for multiclass classification, the value of k. If the model assigns one of the top-k scores to the true label, an example is scored as correct. Optional Valid values: Positive integers Default value: 3</td>
</tr>
<tr>
<td>balance_multiclass_weights</td>
<td>Specifies whether to use class weights, which give each class equal importance in the loss function. Used only when the predictor_type is multiclass_classifier. Optional Valid values: true, false Default value: false</td>
</tr>
<tr>
<td>beta_1</td>
<td>The exponential decay rate for first-moment estimates. Applies only when the optimizer value is adam. Optional Valid values: auto or floating-point value between 0 and 1.0</td>
</tr>
</tbody>
</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>beta_2</strong></td>
<td>The exponential decay rate for second-moment estimates. Applies only when the optimizer value is adam.</td>
</tr>
<tr>
<td><strong>bias_lr_mult</strong></td>
<td>Allows a different learning rate for the bias term. The actual learning rate for the bias is learning_rate * bias_lr_mult.</td>
</tr>
<tr>
<td><strong>bias_wd_mult</strong></td>
<td>Allows different regularization for the bias term. The actual L2 regularization weight for the bias is wd * bias_wd_mult. By default, there is no regularization on the bias term.</td>
</tr>
<tr>
<td><strong>binary_classifier_model_selection_criteria</strong></td>
<td>When predictor_type is set to binary_classifier, the model evaluation criteria for the validation dataset (or for the training dataset if you don't provide a validation dataset). Criteria include:</td>
</tr>
<tr>
<td></td>
<td>• accuracy—The model with the highest accuracy.</td>
</tr>
<tr>
<td></td>
<td>• f_beta—The model with the highest F1 score. The default is F1.</td>
</tr>
<tr>
<td></td>
<td>• precision_at_target_recall—The model with the highest precision at a given recall target.</td>
</tr>
<tr>
<td></td>
<td>• recall_at_target_precision—The model with the highest recall at a given precision target.</td>
</tr>
<tr>
<td></td>
<td>• loss_function—The model with the lowest value of the loss function used in training.</td>
</tr>
</tbody>
</table>

Optional

Valid values: accuracy, f_beta, precision_at_target_recall, recall_at_target_precision, or loss_function

Default value: accuracy
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>early_stopping_patience</td>
<td>The number of epochs to wait before ending training. If you have provided a value for <code>binary_classifier_model_selection_criteria</code>, the metric is that value. Otherwise, the metric is the same as the value specified for the <code>loss</code> hyperparameter. The metric is evaluated on the validation data. If you haven’t provided validation data, the metric is always the same as the value specified for the <code>loss</code> hyperparameter and is evaluated on the training data. To disable early stopping, set <code>early_stopping_patience</code> to a value greater than the value specified for <code>epochs</code>. Optional Valid values: Positive integer Default value: 3</td>
</tr>
<tr>
<td>early_stopping_tolerance</td>
<td>The relative tolerance to measure an improvement in loss. If the ratio of the improvement in loss divided by the previous best loss is smaller than this value, early stopping considers the improvement to be zero. Optional Valid values: Positive floating-point integer Default value: 0.001</td>
</tr>
<tr>
<td>epochs</td>
<td>The maximum number of passes over the training data. Optional Valid values: Positive integer Default value: 15</td>
</tr>
<tr>
<td>f_beta</td>
<td>The value of beta to use when calculating F score metrics for binary or multiclass classification. Also used if the value specified for <code>binary_classifier_model_selection_criteria</code> is <code>f_beta</code>. Optional Valid values: Positive floating-point integers Default value: 1.0</td>
</tr>
<tr>
<td>feature_dim</td>
<td>The number of features in the input data. Optional Valid values: auto or positive integer Default values: auto</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td>huber_delta</td>
<td>The parameter for Huber loss. During training and metric evaluation, compute L2 loss for errors smaller than delta and L1 loss for errors larger than delta.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive floating-point integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 1.0</td>
</tr>
<tr>
<td>init_bias</td>
<td>Initial weight for the bias term.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Floating-point integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>init_method</td>
<td>Sets the initial distribution function used for model weights. Functions include:</td>
</tr>
<tr>
<td></td>
<td>• uniform—Uniformly distributed between (-scale, +scale)</td>
</tr>
<tr>
<td></td>
<td>• normal—Normal distribution, with mean 0 and sigma</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: uniform or normal</td>
</tr>
<tr>
<td></td>
<td>Default value: uniform</td>
</tr>
<tr>
<td>init_scale</td>
<td>Scales an initial uniform distribution for model weights. Applies only when the init_method hyperparameter is set to uniform.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive floating-point integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.07</td>
</tr>
<tr>
<td>init_sigma</td>
<td>The initial standard deviation for the normal distribution. Applies only when the init_method hyperparameter is set to normal.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive floating-point integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.01</td>
</tr>
<tr>
<td>l1</td>
<td>The L1 regularization parameter. If you don’t want to use L1 regularization, set the value to 0.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto or non-negative float</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The step size used by the optimizer for parameter updates. Optional. Valid values: auto or positive floating-point integer. Default value: auto, whose value depends on the optimizer chosen.</td>
</tr>
<tr>
<td>loss</td>
<td>Specifies the loss function. The available loss functions and their default values depend on the value of predictor_type:</td>
</tr>
<tr>
<td></td>
<td>• If the predictor_type is set to regressor, the available options are auto, squared_loss, absolute_loss, eps_insensitive_squared_loss, eps_insensitive_absolute_loss, quantile_loss, and huber_loss. The default value for auto is squared_loss.</td>
</tr>
<tr>
<td></td>
<td>• If the predictor_type is set to binary_classifier, the available options are auto, logistic, and hinge_loss. The default value for auto is logistic.</td>
</tr>
<tr>
<td></td>
<td>• If the predictor_type is set to multiclass_classifier, the available options are auto and softmax_loss. The default value for auto is softmax_loss.</td>
</tr>
<tr>
<td></td>
<td>Valid values: auto, logistic, squared_loss, absolute_loss, hinge_loss, eps_insensitive_squared_loss, eps_insensitive_absolute_loss, quantile_loss, or huber_loss</td>
</tr>
<tr>
<td></td>
<td>Optional. Default value: auto</td>
</tr>
<tr>
<td>loss_insensitivity</td>
<td>The parameter for the epsilon-insensitive loss type. During training and metric evaluation, any error smaller than this value is considered to be zero. Optional. Valid values: Positive floating-point integer.</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.01</td>
</tr>
<tr>
<td>lr_scheduler_factor</td>
<td>For every lr_scheduler_step hyperparameter, the learning rate decreases by this quantity. Applies only when the use_lr_scheduler hyperparameter is set to true. Optional. Valid values: auto or positive floating-point integer between 0 and 1.</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>lr_scheduler_minimum_lr</td>
<td>The learning rate never decreases to a value lower than the value set for lr_scheduler_minimum_lr. Applies only when the use_lr_scheduler hyperparameter is set to true.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto or positive floating-point integer</td>
</tr>
<tr>
<td></td>
<td>Default values: auto</td>
</tr>
<tr>
<td>lr_scheduler_step</td>
<td>The number of steps between decreases of the learning rate. Applies only when the use_lr_scheduler hyperparameter is set to true.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto or positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>margin</td>
<td>The margin for the hinge_loss function.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive floating-point integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 1.0</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The number of observations per mini-batch for the data iterator.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 1000</td>
</tr>
<tr>
<td>momentum</td>
<td>The momentum of the sgd optimizer.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto or a floating-point integer between 0 and 1.0</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>normalize_data</td>
<td>Normalizes the feature data before training. Data normalization shifts the data for each feature to have a mean of zero and scales it to have unit standard deviation.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto, true, or false</td>
</tr>
<tr>
<td></td>
<td>Default value: true</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>normalize_label</td>
<td>Normalizes the label. Label normalization shifts the label to have a mean of zero and scales it to have unit standard deviation.</td>
</tr>
<tr>
<td></td>
<td>The auto default value normalizes the label for regression problems but does not for classification problems. If you set the normalize_label hyperparameter to true for classification problems, the algorithm ignores it.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto, true, or false</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>num_calibration_samples</td>
<td>The number of observations from the validation dataset to use for model calibration (when finding the best threshold).</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto or positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>num_models</td>
<td>The number of models to train in parallel. For the default, auto, the algorithm decides the number of parallel models to train. One model is trained according to the given training parameter (regularization, optimizer, loss), and the rest by close parameters.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto or positive integer</td>
</tr>
<tr>
<td></td>
<td>Default values: auto</td>
</tr>
<tr>
<td>num_point_for_scaler</td>
<td>The number of data points to use for calculating normalization or unbiasing of terms.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 10,000</td>
</tr>
<tr>
<td>optimizer</td>
<td>The optimization algorithm to use.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values:</td>
</tr>
<tr>
<td></td>
<td>• auto—The default value.</td>
</tr>
<tr>
<td></td>
<td>• sgd—Stochastic gradient descent.</td>
</tr>
<tr>
<td></td>
<td>• adam—Adaptive momentum estimation.</td>
</tr>
<tr>
<td></td>
<td>• rmsprop—A gradient-based optimization technique that uses a moving average of squared gradients to normalize the gradient.</td>
</tr>
<tr>
<td></td>
<td>Default value: auto. The default setting for auto is adam.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>positive_example_weight_mult</td>
<td>The weight assigned to positive examples when training a binary classifier. The weight of negative examples is fixed at 1. If you want the algorithm to choose a weight so that errors in classifying negative vs. positive examples have equal impact on training loss, specify balanced. If you want the algorithm to choose the weight that optimizes performance, specify auto.</td>
</tr>
<tr>
<td>quantile</td>
<td>The quantile for quantile loss. For quantile q, the model attempts to produce predictions so that the value of true_label is greater than the prediction with probability q.</td>
</tr>
<tr>
<td>target_precision</td>
<td>The target precision. If binary_classifier_model_selection_criteria is recall_at_target_precision, then precision is held at this value while recall is maximized.</td>
</tr>
<tr>
<td>target_recall</td>
<td>The target recall. If binary_classifier_model_selection_criteria is precision_at_target_recall, then recall is held at this value while precision is maximized.</td>
</tr>
<tr>
<td>unbias_data</td>
<td>Unbiases the features before training so that the mean is 0. By default data is unbiased as the use_bias hyperparameter is set to true.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>unbias_label</td>
<td>Unbiases labels before training so that the mean is 0. Applies to regression only if the use_bias hyperparameter is set to true.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto, true, or false</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>use_bias</td>
<td>Specifies whether the model should include a bias term, which is the intercept term in the linear equation.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: true or false</td>
</tr>
<tr>
<td></td>
<td>Default value: true</td>
</tr>
<tr>
<td>use_lr_scheduler</td>
<td>Whether to use a scheduler for the learning rate. If you want to use a scheduler, specify true.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: true or false</td>
</tr>
<tr>
<td></td>
<td>Default value: true</td>
</tr>
<tr>
<td>wd</td>
<td>The weight decay parameter, also known as the L2 regularization parameter. If you don't want to use L2 regularization, set the value to 0.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto or non-negative floating-point integer</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
</tbody>
</table>

**Tune a linear learner model**

Automatic model tuning, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

The linear learner algorithm also has an internal mechanism for tuning hyperparameters separate from the automatic model tuning feature described here. By default, the linear learner algorithm tunes hyperparameters by training multiple models in parallel. When you use automatic model tuning, the linear learner internal tuning mechanism is turned off automatically. This sets the number of parallel models, num_models, to 1. The algorithm ignores any value that you set for num_models.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

**Metrics computed by the linear learner algorithm**

The linear learner algorithm reports the metrics in the following table, which are computed during training. Choose one of them as the objective metric. To avoid overfitting, we recommend tuning the model against a validation metric instead of a training metric.
<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test: absolute_loss</td>
<td>The absolute loss of the final model on the test dataset. This objective metric is only valid for regression.</td>
<td>Minimize</td>
</tr>
<tr>
<td>test: binary_classification_accuracy</td>
<td>The accuracy of the final model on the test dataset. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test: binary_f_beta</td>
<td>The F-beta score of the final model on the test dataset. By default, it is the F1 score, which is the harmonic mean of precision and recall. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test: dcg</td>
<td>The discounted cumulative gain of the final model on the test dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test: macro_f_beta</td>
<td>The F-beta score of the final model on the test dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test: macro_precision</td>
<td>The precision score of the final model on the test dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test: macro_recall</td>
<td>The recall score of the final model on the test dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test: mse</td>
<td>The mean square error of the final model on the test dataset. This objective metric is only valid for regression.</td>
<td>Minimize</td>
</tr>
<tr>
<td>test: multiclass_accuracy</td>
<td>The accuracy of the final model on the test dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test: multiclass_top_k_accuracy</td>
<td>The accuracy among the top k labels predicted on the test dataset. If you choose this metric as the objective, we recommend setting the value of k using the accuracy_top_k hyperparameter. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test: objective_loss</td>
<td>The mean value of the objective loss function on the test dataset after the model is trained. By default, the loss is logistic loss for binary classification and squared loss for regression. To set the loss to other types, use the loss hyperparameter.</td>
<td>Minimize</td>
</tr>
<tr>
<td>test: precision</td>
<td>The precision of the final model on the test dataset. If you choose this metric as the objective, we recommend setting a target recall by setting the binary_classifier_model_selection hyperparameter to</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>precision_at_target_recall</td>
<td>and setting the value for the target_recall hyperparameter. This objective metric is only valid for binary classification.</td>
<td></td>
</tr>
<tr>
<td>test:recall</td>
<td>The recall of the final model on the test dataset. If you choose this metric as the objective, we recommend setting a target precision by setting the binary_classifier_model_selection hyperparameter to recall_at_target_precision and setting the value for the target_precision hyperparameter. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>test:roc_auc_score</td>
<td>The area under receiving operating characteristic curve (ROC curve) of the final model on the test dataset. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:absolute_loss</td>
<td>The absolute loss of the final model on the validation dataset. This objective metric is only valid for regression.</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:binary_classification</td>
<td>The accuracy of the final model on the validation dataset. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:binary_f_beta</td>
<td>The F-beta score of the final model on the validation dataset. By default, the F-beta score is the F1 score, which is the harmonic mean of the validation:precision and validation:recall metrics. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:dcg</td>
<td>The discounted cumulative gain of the final model on the validation dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:macro_f_beta</td>
<td>F-beta score of the final model on the validation dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:macro_precision</td>
<td>The precision score of the final model on the validation dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:macro_recall</td>
<td>The recall score of the final model on the validation dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:mse</td>
<td>The mean square error of the final model on the validation dataset. This objective metric is only valid for regression.</td>
<td>Minimize</td>
</tr>
</tbody>
</table>
### Metric Name

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>validation:multiclass_accuracy</td>
<td>The accuracy of the final model on the validation dataset. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:multiclass_top_k_accuracy</td>
<td>The accuracy among the top k labels predicted on the validation dataset. If you choose this metric as the objective, we recommend setting the value of k using the accuracy_top_k hyperparameter. This objective metric is only valid for multiclass classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:objective_loss</td>
<td>The mean value of the objective loss function on the validation dataset every epoch. By default, the loss is logistic loss for binary classification and squared loss for regression. To set loss to other types, use the loss hyperparameter.</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:precision</td>
<td>The precision of the final model on the validation dataset. If you choose this metric as the objective, we recommend setting a target recall by setting the binary_classifier_model_selection hyperparameter to precision_at_target_recall and setting the value for the target_recall hyperparameter. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:recall</td>
<td>The recall of the final model on the validation dataset. If you choose this metric as the objective, we recommend setting a target precision by setting the binary_classifier_model_selection hyperparameter to recall_at_target_precision and setting the value for the target_precision hyperparameter. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:rmse</td>
<td>The root mean square error of the final model on the validation dataset. This objective metric is only valid for regression.</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:roc_auc_score</td>
<td>The area under receiving operating characteristic curve (ROC curve) of the final model on the validation dataset. This objective metric is only valid for binary classification.</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

### Tuning linear learner hyperparameters

You can tune a linear learner model with the following hyperparameters.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>wd</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-7, MaxValue: 1</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Parameter Type</td>
<td>Recommended Ranges</td>
</tr>
<tr>
<td>----------------------</td>
<td>-----------------------------</td>
<td>--------------------------------</td>
</tr>
<tr>
<td>l1</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-7, MaxValue: 1</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-5, MaxValue: 1</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 100, MaxValue: 5000</td>
</tr>
<tr>
<td>use_bias</td>
<td>CategoricalParameterRanges</td>
<td>[True, False]</td>
</tr>
<tr>
<td>positive_example_weight</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-5, MaxValue: 1e5</td>
</tr>
</tbody>
</table>

**Linear learner response formats**

**JSON response formats**

All Amazon SageMaker built-in algorithms adhere to the common input inference format described in [Common Data Formats - Inference](#). The following are the available output formats for the SageMaker linear learner algorithm.

**Binary Classification**

```json
let response = {
  "predictions": [
    {
      "score": 0.4,
      "predicted_label": 0
    }
  ]
}
```

**Multiclass Classification**

```json
let response = {
  "predictions": [
    {
      "score": [0.1, 0.2, 0.4, 0.3],
      "predicted_label": 2
    }
  ]
}
```

**Regression**

```json
let response = {
  "predictions": [
    {
      "score": 0.4
    }
  ]
}
```

**JSONLINES response formats**

**Binary Classification**

```
```
Multiclass Classification

["score": [0.1, 0.2, 0.4, 0.3], "predicted_label": 2]

Regression

["score": 0.4]

RECORDIO response formats

Binary Classification

[    Record = {        features = {},        label = {            'score': {                keys: [],                values: [0.4]  # float32            },            'predicted_label': {                keys: [],                values: [0.0]  # float32            }        }    }]

Multiclass Classification

[    Record = {        "features": [],        "label": {            "score": {                "values": [0.1, 0.2, 0.3, 0.4]            },            "predicted_label": {                "values": [3]            }        },        "uid": "abc123",        "metadata": "{created_at: '2017-06-03'}"    }]

Regression

[    Record = {        features = {},        label = {            'score': {                keys: [],                values: [0.4]  # float32            }        }    }]
TabTransformer

TabTransformer is a novel deep tabular data modeling architecture for supervised learning. The TabTransformer architecture is built on self-attention-based Transformers. The Transformer layers transform the embeddings of categorical features into robust contextual embeddings to achieve higher prediction accuracy. Furthermore, the contextual embeddings learned from TabTransformer are highly robust against both missing and noisy data features, and provide better interpretability.

How to use SageMaker TabTransformer

You can use TabTransformer as an Amazon SageMaker built-in algorithm. The following section describes how to use TabTransformer with the SageMaker Python SDK. For information on how to use TabTransformer from the Amazon SageMaker Studio UI, see SageMaker JumpStart (p. 45).

• Use TabTransformer as a built-in algorithm

Use the TabTransformer built-in algorithm to build a TabTransformer training container as shown in the following code example. You can automatically spot the TabTransformer built-in algorithm image URI using the SageMaker `image_uris.retrieve` API (or the `get_image_uri` API if using Amazon SageMaker Python SDK version 2).

After specifying the TabTransformer image URI, you can use the TabTransformer container to construct an estimator using the SageMaker Estimator API and initiate a training job. The TabTransformer built-in algorithm runs in script mode, but the training script is provided for you and there is no need to replace it. If you have extensive experience using script mode to create a SageMaker training job, then you can incorporate your own TabTransformer training scripts.

```python
from sagemaker import image_uris, model_uris, script_uris

train_model_id, train_model_version, train_scope = "pytorch-tabtransformerclassification-model", "*", "training"
training_instance_type = "ml.p3.2xlarge"

# Retrieve the docker image
train_image_uri = image_uris.retrieve(
    region=None,
    framework=None,
    model_id=train_model_id,
    model_version=train_model_version,
    image_scope=train_scope,
    instance_type=training_instance_type
)

# Retrieve the training script
train_source_uri = script_uris.retrieve(
    model_id=train_model_id, model_version=train_model_version, script_scope=train_scope
)

train_model_uri = model_uris.retrieve(
    model_id=train_model_id, model_version=train_model_version, model_scope=train_scope
)

# Sample training data is available in this bucket
training_data_bucket = f"jumpstart-cache-prod-{aws_region}"
training_data_prefix = "training-datasets/tabular_multiclass/"
training_dataset_s3_path = f"s3://{training_data_bucket}/{training_data_prefix}"
output_bucket = sess.default_bucket()
```
output_prefix = "jumpstart-example-tabular-training"

s3_output_location = f"s3://{output_bucket}/{output_prefix}/output"

from sagemaker import hyperparameters

# Retrieve the default hyper-parameters for training the model
hyperparameters = hyperparameters.retrieve_default(
    model_id=train_model_id, model_version=train_model_version
)

# [Optional] Override default hyperparameters with custom values
hyperparameters["n_epochs"] = "50"
print(hyperparameters)

from sagemaker.estimator import Estimator
from sagemaker.utils import name_from_base

training_job_name = name_from_base(f"built-in-algo-{train_model_id}-training")

# Create SageMaker Estimator instance

tabular_estimator = Estimator(
    role=aws_role,
    image_uri=train_image_uri,
    source_dir=train_source_uri,
    model_uri=train_model_uri,
    entry_point="transfer_learning.py",
    instance_count=1,
    instance_type=training_instance_type,
    max_run=360000,
    hyperparameters=hyperparameters,
    output_path=s3_output_location
)

# Launch a SageMaker Training job by passing the S3 path of the training data

tabular_estimator.fit(
    {"training": training_dataset_s3_path}, logs=True, job_name=training_job_name
)

For more information about how to set up the TabTransformer as a built-in algorithm, see the following notebook examples.

- Tabular classification with Amazon SageMaker TabTransformer algorithm
- Tabular regression with Amazon SageMaker TabTransformer algorithm

### Input and Output interface for the TabTransformer algorithm

TabTransformer operates on tabular data, with the rows representing observations, one column representing the target variable or label, and the remaining columns representing features.

The SageMaker implementation of TabTransformer supports CSV for training and inference:

- For **Training ContentType**, valid inputs must be text/csv.
- For **Inference ContentType**, valid inputs must be text/csv.

**Note**

For CSV training, the algorithm assumes that the target variable is in the first column and that the CSV does not have a header record.

For CSV inference, the algorithm assumes that CSV input does not have the label column.
Be mindful of how to format your training data for input to the TabTransformer model. You must provide the path to an Amazon S3 bucket containing subdirectories for your training and optional validation data. You can also include a list of categorical features.

- **Training data input format**: Your training data should be in a subdirectory named `train/` that contains a `data.csv` file. The target variables should be in the first column of `data.csv`. The predictor variables (features) should be in the remaining columns.

- **Validation data input format**: You can optionally include another directory called `validation/` that also has a `data.csv` file. The validation data is used to compute a validation score at the end of each boosting iteration. Early stopping is applied when the validation score stops improving. If the validation data is not provided, then 20% of your training data is randomly sampled to serve as the validation data.

- **Categorical features input format**: If your predictors include categorical features, you can provide a JSON file named `categorical_index.json` in the same location as your data directories. This file should contain a Python dictionary where the key is the string "cat_index_list" and the value is a list of unique integers. Each integer in the value list should indicate the column index of the corresponding categorical features in your training data CSV file. Each value should be a positive integer (greater than zero because zero represents the target value), less than the `Int32.MaxValue` (2147483647), and less than the total number of columns. There should only be one categorical index JSON file.

For CSV training input mode, the total memory available to the algorithm (instance count multiplied by the memory available in the `InstanceType`) must be able to hold the training dataset.

**Amazon EC2 instance recommendation for the TabTransformer algorithm**

SageMaker TabTransformer supports single-instance CPU and single-instance GPU training. Despite higher per-instance costs, GPUs train more quickly, making them more cost effective. To take advantage of GPU training, specify the instance type as one of the GPU instances (for example, P3). SageMaker TabTransformer currently does not support multi-GPU training.

**TabTransformer sample notebooks**

The following table outlines a variety of sample notebooks that address different use cases of Amazon SageMaker TabTransformer algorithm.

<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tabular classification with Amazon SageMaker TabTransformer algorithm</td>
<td>This notebook demonstrates the use of the Amazon SageMaker TabTransformer algorithm to train and host a tabular classification model.</td>
</tr>
<tr>
<td>Tabular regression with Amazon SageMaker TabTransformer algorithm</td>
<td>This notebook demonstrates the use of the Amazon SageMaker TabTransformer algorithm to train and host a tabular regression model.</td>
</tr>
</tbody>
</table>

For instructions on how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, choose the SageMaker Examples tab to see a list of all of the SageMaker samples. To open a notebook, choose its Use tab and choose Create copy.

**How TabTransformer works**

TabTransformer is a novel deep tabular data modeling architecture for supervised learning. The TabTransformer is built upon self-attention based Transformers. The Transformer layers transform the
embeddings of categorical features into robust contextual embeddings to achieve higher prediction accuracy. Furthermore, the contextual embeddings learned from TabTransformer are highly robust against both missing and noisy data features, and provide better interpretability.

TabTransformer performs well in machine learning competitions because of its robust handling of a variety of data types, relationships, distributions, and the diversity of hyperparameters that you can fine-tune. You can use TabTransformer for regression, classification (binary and multiclass), and ranking problems.

The following diagram illustrates the TabTransformer architecture.
Figure 1: The architecture of TabTransformer.

For more information, see TabTransformer: Tabular Data Modeling Using Contextual Embeddings.
**TabTransformer hyperparameters**

The following table contains the subset of hyperparameters that are required or most commonly used for the Amazon SageMaker TabTransformer algorithm. Users set these parameters to facilitate the estimation of model parameters from data. The SageMaker TabTransformer algorithm is an implementation of the open-source TabTransformer package.

**Note**
The default hyperparameters are based on example datasets in the TabTransformer sample notebooks (p. 2033).

The SageMaker TabTransformer algorithm automatically chooses an evaluation metric and objective function based on the type of classification problem. The TabTransformer algorithm detects the type of classification problem based on the number of labels in your data. For regression problems, the evaluation metric is r square and the objective function is mean square error. For binary classification problems, the evaluation metric and objective function are both binary cross entropy. For multiclass classification problems, the evaluation metric and objective function are both multiclass cross entropy.

**Note**
The TabTransformer evaluation metric and objective functions are not currently available as hyperparameters. Instead, the SageMaker TabTransformer built-in algorithm automatically detects the type of classification task (regression, binary, or multiclass) based on the number of unique integers in the label column and assigns an evaluation metric and objective function.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>n_epochs</td>
<td>Number of epochs to train the deep neural network.</td>
</tr>
<tr>
<td></td>
<td>Valid values: integer, range: Positive integer.</td>
</tr>
<tr>
<td></td>
<td>Default value: 5.</td>
</tr>
<tr>
<td>patience</td>
<td>The training will stop if one metric of one validation data point does not improve in the last patience round.</td>
</tr>
<tr>
<td></td>
<td>Valid values: integer, range: (2, 60).</td>
</tr>
<tr>
<td></td>
<td>Default value: 10.</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The rate at which the model weights are updated after working through each batch of training examples.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: Positive floating point number.</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.001.</td>
</tr>
<tr>
<td>batch_size</td>
<td>The number of examples propagated through the network.</td>
</tr>
<tr>
<td></td>
<td>Valid values: integer, range: (1, 2048).</td>
</tr>
<tr>
<td></td>
<td>Default value: 256.</td>
</tr>
<tr>
<td>input_dim</td>
<td>The dimension of embeddings to encode the categorical and/or continuous columns.</td>
</tr>
<tr>
<td></td>
<td>Valid values: string, any of the following: &quot;16&quot;, &quot;32&quot;, &quot;64&quot;, &quot;128&quot;, &quot;256&quot;, or &quot;512&quot;.</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;32&quot;.</td>
</tr>
<tr>
<td>n_blocks</td>
<td>The number of Transformer encoder blocks.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>attn_dropout</td>
<td>Dropout rate applied to the Multi-Head Attention layers. Valid values: float, range: (0, 1). Default value: 0.2.</td>
</tr>
<tr>
<td>mlp_dropout</td>
<td>Dropout rate applied to the FeedForward network within the encoder layers and the final MLP layers on top of Transformer encoders. Valid values: float, range: (0, 1). Default value: 0.1.</td>
</tr>
<tr>
<td>frac_shared_embed</td>
<td>The fraction of embeddings shared by all the different categories for one particular column. Valid values: float, range: (0, 1). Default value: 0.25.</td>
</tr>
</tbody>
</table>

**Tune a TabTransformer model**

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your training and validation datasets. Model tuning focuses on the following hyperparameters:

- A learning objective function to optimize during model training
- An evaluation metric that is used to evaluate model performance during validation
- A set of hyperparameters and a range of values for each to use when tuning the model automatically

Note

The learning objective function and evaluation metric are both automatically assigned based on the type of classification task, which is determined by the number of unique integers in the label column. For more information, see TabTransformer hyperparameters (p. 2036).

Evaluation metrics computed by the TabTransformer algorithm

The SageMaker TabTransformer algorithm computes the following metrics to use for model validation. The evaluation metric is automatically assigned based on the type of classification task, which is determined by the number of unique integers in the label column.
**Tunable TabTransformer hyperparameters**

Tune the TabTransformer model with the following hyperparameters. The hyperparameters that have the greatest effect on optimizing the TabTransformer evaluation metrics are: `learning_rate`, `input_dim`, `n_blocks`, `attn_dropout`, `mlp_dropout`, and `frac_shared_embed`. For a list of all the TabTransformer hyperparameters, see [TabTransformer hyperparameters](p. 2036).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.001, MaxValue: 0.01</td>
</tr>
<tr>
<td>input_dim</td>
<td>CategoricalParameterRanges</td>
<td>[16, 32, 64, 128, 256, 512]</td>
</tr>
<tr>
<td>n_blocks</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 12</td>
</tr>
<tr>
<td>attn_dropout</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.8</td>
</tr>
<tr>
<td>mlp_dropout</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.8</td>
</tr>
<tr>
<td>frac_shared_embed</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.5</td>
</tr>
</tbody>
</table>

**XGBoost Algorithm**

The XGBoost (eXtreme Gradient Boosting) is a popular and efficient open-source implementation of the gradient boosted trees algorithm. Gradient boosting is a supervised learning algorithm that attempts to accurately predict a target variable by combining an ensemble of estimates from a set of simpler and weaker models. The XGBoost algorithm performs well in machine learning competitions because of its robust handling of a variety of data types, relationships, distributions, and the variety of hyperparameters that you can fine-tune. You can use XGBoost for regression, classification (binary and multiclass), and ranking problems.

You can use the new release of the XGBoost algorithm either as a Amazon SageMaker built-in algorithm or as a framework to run training scripts in your local environments. This implementation has a smaller memory footprint, better logging, improved hyperparameter validation, and an expanded set of metrics than the original versions. It provides an XGBoost estimator that executes a training script in a managed XGBoost environment. The current release of SageMaker XGBoost is based on the original XGBoost versions 1.0, 1.2, 1.3, and 1.5.
**Supported versions**

- Framework (open source) mode: 1.0-1, 1.2-1, 1.2-2, 1.3-1, 1.5-1
- Algorithm mode: 1.0-1, 1.2-1, 1.2-2, 1.3-1, 1.5-1

**Important**

When you retrieve the SageMaker XGBoost image URI, do not use :latest or :1 for the image URI tag. You must specify one of the **Supported versions** (p. 2039) to choose the SageMaker-managed XGBoost container with the native XGBoost package version that you want to use. To find the package version migrated into the SageMaker XGBoost containers, see **Docker Registry Paths and Example Code**, choose your AWS Region, and navigate to the XGBoost (algorithm) section.

**Warning**

The XGBoost 0.90 versions are deprecated. Supports for security updates or bug fixes for XGBoost 0.90 is discontinued. It is highly recommended to upgrade the XGBoost version to one of the newer versions.

**Note**

XGBoost v1.1 is not supported on SageMaker because XGBoost 1.1 has a broken capability to run prediction when the test input has fewer features than the training data in LIBSVM inputs. This capability has been restored in XGBoost v1.2. Consider using SageMaker XGBoost 1.2-2 or later.

**How to Use SageMaker XGBoost**

With SageMaker, you can use XGBoost as a built-in algorithm or framework. By using XGBoost as a framework, you have more flexibility and access to more advanced scenarios, such as k-fold cross-validation, because you can customize your own training scripts. The following sections describe how to use XGBoost with the SageMaker Python SDK. For information on how to use XGBoost from the Amazon SageMaker Studio UI, see **SageMaker JumpStart** (p. 45).

**Use XGBoost as a framework**

Use XGBoost as a framework to run your customized training scripts that can incorporate additional data processing into your training jobs. In the following code example, you can find how SageMaker Python SDK provides the XGBoost API as a framework in the same way it provides other framework APIs, such as TensorFlow, MXNet, and PyTorch.

```python
import boto3
import sagemaker
from sagemaker.xgboost.estimator import XGBoost
from sagemaker.session import Session
from sagemaker.inputs import TrainingInput

# initialize hyperparameters
hyperparameters = {
    "max_depth":"5",
    "eta":"0.2",
    "gamma":"4",
    "min_child_weight":"6",
    "subsample":"0.7",
    "verbosity":"1",
    "objective":"reg:squarederror",
    "num_round":"50"
}

# set an output path where the trained model will be saved
bucket = sagemaker.Session().default_bucket()
prefix = 'DEMO-xgboost-as-a-framework'
output_path = 's3://{}/{}/output'.format(bucket, prefix, 'abalone-xgboost-framework')
```
# construct a SageMaker XGBoost estimator

estimator = XGBoost(entry_point = "your_xgboost_abalone_script.py",
                    framework_version='1.5-1',
                    hyperparameters=hyperparameters,
                    role=sagemaker.get_execution_role(),
                    instance_count=1,
                    instance_type='ml.m5.2xlarge',
                    output_path=output_path)

# define the data type and paths to the training and validation datasets
content_type = "libsvm"
train_input = TrainingInput("s3://{}/*/*.format(bucket, prefix, 'train'),
                             content_type=content_type)
validation_input = TrainingInput("s3://{}/*/*.format(bucket, prefix, 'validation'),
                                content_type=content_type)

# execute the XGBoost training job
estimator.fit({'train': train_input, 'validation': validation_input})

For an end-to-end example of using SageMaker XGBoost as a framework, see Regression with Amazon SageMaker XGBoost

* Use XGBoost as a built-in algorithm

Use the XGBoost built-in algorithm to build an XGBoost training container as shown in the following code example. You can automatically spot the XGBoost built-in algorithm image URI using the SageMaker image_uris.retrieve API (or the get_image_uri API if using Amazon SageMaker Python SDK version 1). If you want to ensure if the image_uris.retrieve API finds the correct URI, see Common parameters for built-in algorithms and look up xgboost from the full list of built-in algorithm image URIs and available regions.

After specifying the XGBoost image URI, you can use the XGBoost container to construct an estimator using the SageMaker Estimator API and initiate a training job. This XGBoost built-in algorithm mode does not incorporate your own XGBoost training script and runs directly on the input datasets.

**Important**

When you retrieve the SageMaker XGBoost image URI, do not use :latest or :1 for the image URI tag. You must specify one of the Supported versions (p. 2039) to choose the SageMaker-managed XGBoost container with the native XGBoost package version that you want to use. To find the package version migrated into the SageMaker XGBoost containers, see Docker Registry Paths and Example Code, choose your AWS Region, and navigate to the XGBoost (algorithm) section.
output_path = 's3://{}/{}/{}/output'.format(bucket, prefix, 'abalone-xgb-built-in-algo')

# this line automatically looks for the XGBoost image URI and builds an XGBoost container.
# specify the repo_version depending on your preference.
xgboost_container = sagemaker.image_uris.retrieve("xgboost", region, "1.5-1")

# construct a SageMaker estimator that calls the xgboost-container
estimator = sagemaker.estimator.Estimator(image_uri=xgboost_container,
                                           hyperparameters=hyperparameters,
                                           role=sagemaker.get_execution_role(),
                                           instance_count=1,
                                           instance_type='ml.m5.2xlarge',
                                           volume_size=5, # 5 GB
                                           output_path=output_path)

# define the data type and paths to the training and validation datasets
content_type = "libsvm"
train_input = TrainingInput("s3://{}/{}/{}/".format(bucket, prefix, 'train'),
                           content_type=content_type)
validation_input = TrainingInput("s3://{}/{}/{}/".format(bucket, prefix, 'validation'),
                                content_type=content_type)

# execute the XGBoost training job
estimator.fit({'train': train_input, 'validation': validation_input})

For more information about how to set up the XGBoost as a built-in algorithm, see the following notebook examples.

- Managed Spot Training for XGBoost
- Regression with Amazon SageMaker XGBoost (Parquet input)

Input/Output Interface for the XGBoost Algorithm

Gradient boosting operates on tabular data, with the rows representing observations, one column representing the target variable or label, and the remaining columns representing features.

The SageMaker implementation of XGBoost supports CSV and libsvm formats for training and inference:

- For Training ContentType, valid inputs are text/libsvm (default) or text/csv.
- For Inference ContentType, valid inputs are text/libsvm (default) or text/csv.

**Note**
For CSV training, the algorithm assumes that the target variable is in the first column and that the CSV does not have a header record.

For CSV inference, the algorithm assumes that CSV input does not have the label column.

For libsvm training, the algorithm assumes that the label is in the first column. Subsequent columns contain the zero-based index value pairs for features. So each row has the format: <label> <index0>:<value0> <index1>:<value1> ... Inference requests for libsvm might not have labels in the libsvm format.

This differs from other SageMaker algorithms, which use the protobuf training input format to maintain greater consistency with standard XGBoost data formats.

For CSV training input mode, the total memory available to the algorithm (Instance Count * the memory available in the InstanceType) must be able to hold the training dataset. For libsvm training input mode, it's not required, but we recommend it.
For v1.3-1 and later, SageMaker XGBoost saves the model in the XGBoost internal binary format, using `Booster.save_model`. Previous versions use the Python pickle module to serialize/deserialize the model.

**Note**
Be mindful of versions when using an SageMaker XGBoost model in open source XGBoost. Versions 1.3-1 and later use the XGBoost internal binary format while previous versions use the Python pickle module.

**To use a model trained with SageMaker XGBoost v1.3-1 or later in open source XGBoost**

- Use the following Python code:

```python
import xgboost as xgb
xgb_model = xgb.Booster()
xgb_model.load_model(model_file_path)
xgb_model.predict(dtest)
```

**To use a model trained with previous versions of SageMaker XGBoost in open source XGBoost**

- Use the following Python code:

```python
import pickle as pkl
import tarfile
t = tarfile.open('model.tar.gz', 'r:gz')
t.extractall()
model = pkl.load(open(model_file_path, 'rb'))
# prediction with test data
pred = model.predict(dtest)
```

**To differentiate the importance of labelled data points use Instance Weight Supports**

- SageMaker XGBoost allows customers to differentiate the importance of labelled data points by assigning each instance a weight value. For text/libsvm input, customers can assign weight values to data instances by attaching them after the labels. For example, `label:weight idx_0:val_0 idx_1:val_1...`. For text/csv input, customers need to turn on the `csv_weights` flag in the parameters and attach weight values in the column after labels. For example: `label,weight,val_0,val_1,...`.

**EC2 Instance Recommendation for the XGBoost Algorithm**

SageMaker XGBoost 1.0-1 or earlier only trains using CPUs. It is a memory-bound (as opposed to compute-bound) algorithm. So, a general-purpose compute instance (for example, M5) is a better choice than a compute-optimized instance (for example, C4). Further, we recommend that you have enough total memory in selected instances to hold the training data. Although it supports the use of disk space to handle data that does not fit into main memory (the out-of-core feature available with the libsvm input mode), writing cache files onto disk slows the algorithm processing time.

SageMaker XGBoost version 1.2 or later supports single-instance GPU training. Despite higher per-instance costs, GPUs train more quickly, making them more cost effective. SageMaker XGBoost version 1.2 or later supports P2 and P3 instances.

SageMaker XGBoost version 1.2-2 or later supports P2, P3, G4dn, and G5 GPU instance families.
To take advantage of GPU training, specify the instance type as one of the GPU instances (for example, P3) and set the `tree_method` hyperparameter to `gpu_hist` in your existing XGBoost script. SageMaker XGBoost currently does not support multi-GPU training.

SageMaker XGBoost supports CPU and GPU instances for inference. For information about the instance types for inference, see [Amazon SageMaker ML Instance Types](#).

**XGBoost Sample Notebooks**

The following table outlines a variety of sample notebooks that address different use cases of Amazon SageMaker XGBoost algorithm.

<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>How to Create a Custom XGBoost container?</td>
<td>This notebook shows you how to build a custom XGBoost Container with Amazon SageMaker Batch Transform.</td>
</tr>
<tr>
<td>Regression with XGBoost using Parquet</td>
<td>This notebook shows you how to use the Abalone dataset in Parquet to train a XGBoost model.</td>
</tr>
<tr>
<td>How to Train and Host a Multiclass Classification Model?</td>
<td>This notebook shows how to use the MNIST dataset to train and host a multiclass classification model.</td>
</tr>
<tr>
<td>How to train a Model for Customer Churn Prediction?</td>
<td>This notebook shows you how to train a model to Predict Mobile Customer Departure in an effort to identify unhappy customers.</td>
</tr>
<tr>
<td>An Introduction to Amazon SageMaker Managed Spot infrastructure for XGBoost Training</td>
<td>This notebook shows you how to use Spot Instances for training with a XGBoost Container.</td>
</tr>
<tr>
<td>How to use Amazon SageMaker Debugger to debug XGBoost Training Jobs?</td>
<td>This notebook shows how to use Amazon SageMaker Debugger to monitor training jobs to detect inconsistencies.</td>
</tr>
<tr>
<td>How to use Amazon SageMaker Debugger to debug XGBoost Training Jobs in Real-Time?</td>
<td>This notebook shows how to use the MNIST dataset and Amazon SageMaker Debugger to perform real-time analysis of XGBoost training jobs while training jobs are running.</td>
</tr>
</tbody>
</table>

For instructions on how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see [Use Amazon SageMaker Notebook Instances](#). After you have created a notebook instance and opened it, choose the SageMaker Examples tab to see a list of all of the SageMaker samples. The topic modeling example notebooks using the linear learning algorithm are located in the Introduction to Amazon algorithms section. To open a notebook, choose its Use tab and choose Create copy.

**How XGBoost Works**

XGBoost is a popular and efficient open-source implementation of the gradient boosted trees algorithm. Gradient boosting is a supervised learning algorithm, which attempts to accurately predict a target variable by combining the estimates of a set of simpler, weaker models.

When using gradient boosting for regression, the weak learners are regression trees, and each regression tree maps an input data point to one of its leaves that contains a continuous score. XGBoost minimizes a regularized (L1 and L2) objective function that combines a convex loss function (based on the difference between the predicted and target outputs) and a penalty term for model complexity (in other words, the
regression tree functions). The training proceeds iteratively, adding new trees that predict the residuals or errors of prior trees that are then combined with previous trees to make the final prediction. It's called gradient boosting because it uses a gradient descent algorithm to minimize the loss when adding new models.

Below is a brief illustration on how gradient tree boosting works.

\[
F_m(X) = F_{m-1}(X) + \alpha_m h_m(X, r_{m-1}),
\]

where \(\alpha_i\) and \(r_i\) are the regularization parameters and residuals computed with the \(i^{th}\) tree respectfully, and \(h_i\) is a function that is trained to predict residuals, \(r_i\) using \(X\) for the \(i^{th}\) tree. To compute \(\alpha_i\) we use the residuals computed, \(r_i\) and compute the following: 

\[
\arg \min_{\alpha} \sum_{i=1}^{m} L(Y_i, F_{i-1}(X_i) + \alpha h_i(X_i, r_{i-1})).
\]

\(L(Y, F(X))\) is a differentiable loss function.

For more detail on XGBoost, see:

- XGBoost: A Scalable Tree Boosting System
- Gradient Tree Boosting
- Introduction to Boosted Trees

**XGBoost Hyperparameters**

The following table contains the subset of hyperparameters that are required or most commonly used for the Amazon SageMaker XGBoost algorithm. These are parameters that are set by users to facilitate the estimation of model parameters from data. The required hyperparameters that must be set are listed first, in alphabetical order. The optional hyperparameters that can be set are listed next, also in alphabetical order. The SageMaker XGBoost algorithm is an implementation of the open-source DMLC XGBoost package. Currently SageMaker supports version 1.2.2. For details about full set of hyperparameter that can be configured for this version of XGBoost, see XGBoost Parameters.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_class</td>
<td>The number of classes.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------</td>
<td>-------------</td>
</tr>
<tr>
<td><strong>num_round</strong></td>
<td>The number of rounds to run the training.</td>
</tr>
<tr>
<td><strong>alpha</strong></td>
<td>L1 regularization term on weights. Increasing this value makes models more conservative.</td>
</tr>
<tr>
<td><strong>base_score</strong></td>
<td>The initial prediction score of all instances, global bias.</td>
</tr>
<tr>
<td><strong>booster</strong></td>
<td>Which booster to use. The gbtree and dart values use a tree-based model, while gblinear uses a linear function.</td>
</tr>
<tr>
<td><strong>colsample_bylevel</strong></td>
<td>Subsample ratio of columns for each split, in each level.</td>
</tr>
<tr>
<td><strong>colsample_bynode</strong></td>
<td>Subsample ratio of columns from each node.</td>
</tr>
<tr>
<td><strong>colsample_bytree</strong></td>
<td>Subsample ratio of columns when constructing each tree.</td>
</tr>
</tbody>
</table>

**Required** if objective is set to `multi:softmax` or `multi:softprob`. Valid values: integer

Valid values: integer

Valid values: float

Default value: 0

Valid values: float

Default value: 0.5

Valid values: String. One of gbtree, gblinear, or dart.

Default value: gbtree

Valid values: Float. Range: [0,1].

Default value: 1

Valid values: Float. Range: (0,1].

Default value: 1

Valid values: Float. Range: [0,1].

Default value: 1
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>csv_weights</td>
<td>When this flag is enabled, XGBoost differentiates the importance of instances for csv input by taking the second column (the column after labels) in training data as the instance weights.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 or 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>deterministic_histogram</td>
<td>When this flag is enabled, XGBoost builds histogram on GPU deterministically. Used only if tree_method is set to gpu_hist.</td>
</tr>
<tr>
<td></td>
<td>For a full list of valid inputs, please refer to <a href="#">XGBoost Parameters</a>.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. Range: true or false</td>
</tr>
<tr>
<td></td>
<td>Default value: true</td>
</tr>
<tr>
<td>early_stopping_rounds</td>
<td>The model trains until the validation score stops improving. Validation error needs to decrease at least every early_stopping_rounds to continue training. SageMaker hosting uses the best model for inference.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td></td>
<td>Default value: -</td>
</tr>
<tr>
<td>eta</td>
<td>Step size shrinkage used in updates to prevent overfitting. After each boosting step, you can directly get the weights of new features. The eta parameter actually shrinks the feature weights to make the boosting process more conservative.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0,1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.3</td>
</tr>
<tr>
<td>eval_metric</td>
<td>Evaluation metrics for validation data. A default metric is assigned according to the objective:</td>
</tr>
<tr>
<td></td>
<td>• rmse: for regression</td>
</tr>
<tr>
<td></td>
<td>• error: for classification</td>
</tr>
<tr>
<td></td>
<td>• map: for ranking</td>
</tr>
<tr>
<td></td>
<td>For a list of valid inputs, see <a href="#">XGBoost Learning Task Parameters</a>.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: string</td>
</tr>
<tr>
<td></td>
<td>Default value: Default according to objective.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>gamma</td>
<td>Minimum loss reduction required to make a further partition on a leaf node of the tree. The larger, the more conservative the algorithm is.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0,∞).</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>grow_policy</td>
<td>Controls the way that new nodes are added to the tree. Currently supported only if <code>tree_method</code> is set to <code>hist</code>.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. Either <code>depthwise</code> or <code>lossguide</code>.</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>depthwise</code></td>
</tr>
<tr>
<td>interaction_constraints</td>
<td>Specify groups of variables that are allowed to interact.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Nested list of integers. Each integer represents a feature, and each nested list contains features that are allowed to interact e.g., [[1,2], [3,4,5]].</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>lambda</td>
<td>L2 regularization term on weights. Increasing this value makes models more conservative.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>lambda_bias</td>
<td>L2 regularization term on bias.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>max_bin</td>
<td>Maximum number of discrete bins to bucket continuous features. Used only if <code>tree_method</code> is set to <code>hist</code>.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 256</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>max_delta_step</td>
<td>Maximum delta step allowed for each tree's weight estimation. When a positive integer is used, it helps make the update more conservative. The preferred option is to use it in logistic regression. Set it to 1-10 to help control the update. Optional Valid values: Integer. Range: ([0,\infty)). Default value: 0</td>
</tr>
<tr>
<td>max_depth</td>
<td>Maximum depth of a tree. Increasing this value makes the model more complex and likely to be overfit. 0 indicates no limit. A limit is required when grow_policy=depth-wise. Optional Valid values: Integer. Range: ([0,\infty)). Default value: 6</td>
</tr>
<tr>
<td>max_leaves</td>
<td>Maximum number of nodes to be added. Relevant only if grow_policy is set to lossguide. Optional Valid values: integer Default value: 0</td>
</tr>
<tr>
<td>min_child_weight</td>
<td>Minimum sum of instance weight (hessian) needed in a child. If the tree partition step results in a leaf node with the sum of instance weight less than min_child_weight, the building process gives up further partitioning. In linear regression models, this simply corresponds to a minimum number of instances needed in each node. The larger the algorithm, the more conservative it is. Optional Valid values: Float. Range: ([0,\infty)). Default value: 1</td>
</tr>
<tr>
<td>monotone_constraints</td>
<td>Specifies monotonicity constraints on any feature. Optional Valid values: Tuple of Integers. Valid integers: -1 (decreasing constraint), 0 (no constraint), 1 (increasing constraint). E.g., ((0, 1)): No constraint on first predictor, and an increasing constraint on the second. ((-1, 1)): Decreasing constraint on first predictor, and an increasing constraint on the second. Default value: ((0, 0))</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td>normalize_type</td>
<td>Type of normalization algorithm.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Either tree or forest.</td>
</tr>
<tr>
<td></td>
<td>Default value: tree</td>
</tr>
<tr>
<td>nthread</td>
<td>Number of parallel threads used to run xgboost.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td></td>
<td>Default value: Maximum number of threads</td>
</tr>
<tr>
<td>objective</td>
<td>Specifies the learning task and the corresponding learning objective. Examples: reg:logistic, multi:softmax, reg:squarederror. For a full list of valid inputs, refer to XGBoost Learning Task Parameters.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: string</td>
</tr>
<tr>
<td></td>
<td>Default value: reg:squarederror</td>
</tr>
<tr>
<td>one_drop</td>
<td>When this flag is enabled, at least one tree is always dropped during the dropout.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 or 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>process_type</td>
<td>The type of boosting process to run.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. Either default or update.</td>
</tr>
<tr>
<td></td>
<td>Default value: default</td>
</tr>
<tr>
<td>rate_drop</td>
<td>The dropout rate that specifies the fraction of previous trees to drop during the dropout.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>refresh_leaf</td>
<td>This is a parameter of the 'refresh' updater plug-in. When set to true (1), tree leaves and tree node stats are updated. When set to false (0), only tree node stats are updated.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0/1</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>sample_type</td>
<td>Type of sampling algorithm.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Either uniform or weighted.</td>
</tr>
<tr>
<td></td>
<td>Default value: uniform</td>
</tr>
<tr>
<td>scale_pos_weight</td>
<td>Controls the balance of positive and negative weights. It's useful for unbalanced classes. A typical value to consider: <code>sum(negative cases) / sum(positive cases)</code></td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>seed</td>
<td>Random number seed.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>single_precision_histogram</td>
<td>When this flag is enabled, XGBoost uses single precision to build histograms instead of double precision. Used only if <code>tree_method</code> is set to <code>hist</code> or <code>gpu_hist</code>.</td>
</tr>
<tr>
<td></td>
<td>For a full list of valid inputs, please refer to XGBoost Parameters.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. Range: true or false</td>
</tr>
<tr>
<td></td>
<td>Default value: false</td>
</tr>
<tr>
<td>sketch_eps</td>
<td>Used only for approximate greedy algorithm. This translates into $O(1 / \text{sketch_eps})$ number of bins. Compared to directly select number of bins, this comes with theoretical guarantee with sketch accuracy.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float, Range: [0, 1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.03</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>skip_drop</td>
<td>Probability of skipping the dropout procedure during a boosting iteration.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0</td>
</tr>
<tr>
<td>subsample</td>
<td>Subsample ratio of the training instance. Setting it to 0.5 means that XGBoost randomly collects half of the data instances to grow trees. This prevents overfitting.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0,1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>tree_method</td>
<td>The tree construction algorithm used in XGBoost.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: One of auto, exact, approx, hist, or gpu_hist.</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>tweedie_variance_power</td>
<td>Parameter that controls the variance of the Tweedie distribution.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: (1, 2).</td>
</tr>
<tr>
<td></td>
<td>Default value: 1.5</td>
</tr>
<tr>
<td>updater</td>
<td>A comma-separated string that defines the sequence of tree updaters to run. This provides a modular way to construct and to modify the trees.</td>
</tr>
<tr>
<td></td>
<td>For a full list of valid inputs, please refer to XGBoost Parameters.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: comma-separated string.</td>
</tr>
<tr>
<td></td>
<td>Default value: grow_colmaker, prune</td>
</tr>
<tr>
<td>verbosity</td>
<td>Verbosity of printing messages.</td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 (silent), 1 (warning), 2 (info), 3 (debug).</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
</tbody>
</table>
Tune an XGBoost Model

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your training and validation datasets. You choose three types of hyperparameters:

- a learning objective function to optimize during model training
- an `eval_metric` to use to evaluate model performance during validation
- a set of hyperparameters and a range of values for each to use when tuning the model automatically

You choose the evaluation metric from set of evaluation metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the evaluation metric.

**Note**
Automatic model tuning for XGBoost 0.90 is only available from the Amazon SageMaker SDKs, not from the SageMaker console.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

**Evaluation Metrics Computed by the XGBoost Algorithm**

The XGBoost algorithm computes the following metrics to use for model validation. When tuning the model, choose one of these metrics to evaluate the model. For full list of valid `eval_metric` values, refer to XGBoost Learning Task Parameters

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>validation:accuracy</code></td>
<td>Classification rate, calculated as #right/#all cases.</td>
<td>Maximize</td>
</tr>
<tr>
<td><code>validation:auc</code></td>
<td>Area under the curve.</td>
<td>Maximize</td>
</tr>
<tr>
<td><code>validation:error</code></td>
<td>Binary classification error rate, calculated as #(wrong cases)/#all cases.</td>
<td>Minimize</td>
</tr>
<tr>
<td><code>validation:f1</code></td>
<td>Indicator of classification accuracy, calculated as the harmonic mean of precision and recall.</td>
<td>Maximize</td>
</tr>
<tr>
<td><code>validation:logloss</code></td>
<td>Negative log-likelihood.</td>
<td>Minimize</td>
</tr>
<tr>
<td><code>validation:mae</code></td>
<td>Mean absolute error.</td>
<td>Minimize</td>
</tr>
<tr>
<td><code>validation:map</code></td>
<td>Mean average precision.</td>
<td>Maximize</td>
</tr>
<tr>
<td><code>validation:merror</code></td>
<td>Multiclass classification error rate, calculated as #(wrong cases)/#all cases.</td>
<td>Minimize</td>
</tr>
<tr>
<td><code>validation:mlogloss</code></td>
<td>Negative log-likelihood for multiclass classification.</td>
<td>Minimize</td>
</tr>
<tr>
<td><code>validation:mse</code></td>
<td>Mean squared error.</td>
<td>Minimize</td>
</tr>
<tr>
<td><code>validation:ndcg</code></td>
<td>Normalized Discounted Cumulative Gain.</td>
<td>Maximize</td>
</tr>
<tr>
<td><code>validation:rmse</code></td>
<td>Root mean square error.</td>
<td>Minimize</td>
</tr>
</tbody>
</table>
Tunable XGBoost Hyperparameters

Tune the XGBoost model with the following hyperparameters. The hyperparameters that have the greatest effect on optimizing the XGBoost evaluation metrics are: alpha, min_child_weight, subsample, eta, and num_round.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>alpha</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 1000</td>
</tr>
<tr>
<td>colsample_bylevel</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.1, MaxValue: 1</td>
</tr>
<tr>
<td>colsample_bynode</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.1, MaxValue: 1</td>
</tr>
<tr>
<td>colsample_bytree</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.5, MaxValue: 1</td>
</tr>
<tr>
<td>eta</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.1, MaxValue: 0.5</td>
</tr>
<tr>
<td>gamma</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 5</td>
</tr>
<tr>
<td>lambda</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 1000</td>
</tr>
<tr>
<td>max_delta_step</td>
<td>IntegerParameterRanges</td>
<td>[0, 10]</td>
</tr>
<tr>
<td>max_depth</td>
<td>IntegerParameterRanges</td>
<td>[0, 10]</td>
</tr>
<tr>
<td>min_child_weight</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 120</td>
</tr>
<tr>
<td>num_round</td>
<td>IntegerParameterRanges</td>
<td>[1, 4000]</td>
</tr>
<tr>
<td>subsample</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.5, MaxValue: 1</td>
</tr>
</tbody>
</table>

Deprecated Versions of XGBoost and their Upgrades

This topic contains documentation for previous versions of Amazon SageMaker XGBoost that are still available but deprecated. It also provides instructions on how to upgrade deprecated versions of XGBoost, when possible, to more current versions.

Topics
- Upgrade XGBoost Version 0.90 to Version 1.5 (p. 2053)
- XGBoost Version 0.72 (p. 2055)

Upgrade XGBoost Version 0.90 to Version 1.5

If you are using the SageMaker Python SDK, to upgrade existing XGBoost 0.90 jobs to version 1.5, you must have version 2.x of the SDK installed and change the XGBoost version and framework_version parameters to 1.5-1. If you are using Boto3, you need to update the Docker image, and a few hyperparameters and learning objectives.
Topics

- Upgrade SageMaker Python SDK Version 1.x to Version 2.x (p. 2054)
- Change the image tag to 1.5-1 (p. 2054)
- Change Docker Image for Boto3 (p. 2054)
- Update Hyperparameters and Learning Objectives (p. 2055)

Upgrade SageMaker Python SDK Version 1.x to Version 2.x

If you are still using Version 1.x of the SageMaker Python SDK, you must upgrade version 2.x of the SageMaker Python SDK. For information on the latest version of the SageMaker Python SDK, see Use Version 2.x of the SageMaker Python SDK. To install the latest version, run:

```
python -m pip install --upgrade sagemaker
```

Change the image tag to 1.5-1

If you are using the SageMaker Python SDK and using the XGBoost build-in algorithm, change the version parameter in `image_uris.retrieve`.

```python
from sagemaker import image_uris
image_uris.retrieve(framework="xgboost", region="us-west-2", version="1.5-1")

estimator = sagemaker.estimator.Estimator(image_uri=xgboost_container,
                                          hyperparameters=hyperparameters,
                                          role=sagemaker.get_execution_role(),
                                          instance_count=1,
                                          instance_type='ml.m5.2xlarge',
                                          volume_size=5, # 5 GB
                                          output_path=output_path)
```

If you are using the SageMaker Python SDK and using XGBoost as a framework to run your customized training scripts, change the `framework_version` parameter in the XGBoost API.

```python
estimator = XGBoost(entry_point = "your_xgboost_abalone_script.py",
                     framework_version='1.5-1',
                     hyperparameters=hyperparameters,
                     role=sagemaker.get_execution_role(),
                     instance_count=1,
                     instance_type='ml.m5.2xlarge',
                     output_path=output_path)
```

`sagemaker.session.s3_input` in SageMaker Python SDK version 1.x has been renamed to `sagemaker.inputs.TrainingInput`. You must use `sagemaker.inputs.TrainingInput` as in the following example.

```python
content_type = "libsvm"
train_input = TrainingInput("s3:///{}/{}/*".format(bucket, prefix, 'train'),
                          content_type=content_type)
validation_input = TrainingInput("s3:///{}/{}/*".format(bucket, prefix, 'validation'),
                               content_type=content_type)
```

For the full list of SageMaker Python SDK version 2.x changes, see Use Version 2.x of the SageMaker Python SDK.

Change Docker Image for Boto3

If you are using Boto3 to train or deploy your model, change the docker image tag (1, 0.72, 0.90-1 or 0.90-2) to 1.5-1.
Use Built-in Algorithms

```json
{
    "AlgorithmSpecification": {
        "TrainingImage": "746614075791.dkr.ecr.us-west-1.amazonaws.com/sagemaker-xgboost:1.5-1"
    }
}
```

If you using the SageMaker Python SDK to retrieve registry path, change the version parameter in `image_uris.retrieve`.

```python
from sagemaker import image_uris
image_uris.retrieve(framework="xgboost", region="us-west-2", version="1.5-1")
```

Update Hyperparameters and Learning Objectives

The silent parameter has been deprecated and is no longer available in XGBoost 1.5 and later versions. Use verbosity instead. If you were using the `reg:linear` learning objective, it has been deprecated as well in favor of `reg:squarederror`. Use `reg:squarederror` instead.

```python
hyperparameters = {
    "verbosity": "2",
    "objective": "reg:squarederror",
    "num_round": "50",
    ...
}
estimator = sagemaker.estimator.Estimator(image_uri=xgboost_container,
                                          hyperparameters=hyperparameters,
                                          ...
)
```

XGBoost Version 0.72

**Important**

The XGBoost 0.72 is deprecated by Amazon SageMaker. You can still use this old version of XGBoost (as a built-in algorithm) by pulling its image URI as shown in the following code sample. For XGBoost, the image URI ending with :1 is for the old version.

SageMaker Python SDK v1

```python
import boto3
from sagemaker.amazon.amazon_estimator import get_image_uri
xgb_image_uri = get_image_uri(boto3.Session().region_name, "xgboost",
                             repo_version="1")
```

SageMaker Python SDK v2

```python
import boto3
from sagemaker import image_uris
xgb_image_uri = image_uris.retrieve("xgboost", boto3.Session().region_name, "1")
```

If you want to use newer versions, you have to explicitly specify the image URI tags (see Supported versions (p. 2039)).

This previous release of the Amazon SageMaker XGBoost algorithm is based on the 0.72 release. XGBoost (eXtreme Gradient Boosting) is a popular and efficient open-source implementation of
the gradient boosted trees algorithm. Gradient boosting is a supervised learning algorithm that attempts to accurately predict a target variable by combining the estimates of a set of simpler, weaker models. XGBoost has done remarkably well in machine learning competitions because it robustly handles a variety of data types, relationships, and distributions, and because of the large number of hyperparameters that can be tweaked and tuned for improved fits. This flexibility makes XGBoost a solid choice for problems in regression, classification (binary and multiclass), and ranking.

Customers should consider using the new release of XGBoost Algorithm (p. 2038). They can use it as a SageMaker built-in algorithm or as a framework to run scripts in their local environments as they would typically, for example, do with a Tensorflow deep learning framework. The new implementation has a smaller memory footprint, better logging, improved hyperparameter validation, and an expanded set of metrics. The earlier implementation of XGBoost remains available to customers if they need to postpone migrating to the new version. But this previous implementation will remain tied to the 0.72 release of XGBoost.

Input/Output Interface for the XGBoost Release 0.72

Gradient boosting operates on tabular data, with the rows representing observations, one column representing the target variable or label, and the remaining columns representing features.

The SageMaker implementation of XGBoost supports CSV and libsvm formats for training and inference:

- For Training ContentType, valid inputs are text/libsvm (default) or text/csv.
- For Inference ContentType, valid inputs are text/libsvm or (the default) text/csv.

Note

For CSV training, the algorithm assumes that the target variable is in the first column and that the CSV does not have a header record. For CSV inference, the algorithm assumes that CSV input does not have the label column.

For libsvm training, the algorithm assumes that the label is in the first column. Subsequent columns contain the zero-based index value pairs for features. So each row has the format: <label> <index0>:<value0> <index1>:<value1> ... Inference requests for libsvm may or may not have labels in the libsvm format.

This differs from other SageMaker algorithms, which use the protobuf training input format to maintain greater consistency with standard XGBoost data formats.

For CSV training input mode, the total memory available to the algorithm (Instance Count * the memory available in the InstanceType) must be able to hold the training dataset. For libsvm training input mode, it's not required, but we recommend it.

SageMaker XGBoost uses the Python pickle module to serialize/deserialize the model, which can be used for saving/loading the model.

To use a model trained with SageMaker XGBoost in open source XGBoost

- Use the following Python code:

```python
import pickle as pkl
import tarfile
import xgboost

t = tarfile.open('model.tar.gz', 'r:gz')
t.extractall()

model = pkl.load(open(model_file_path, 'rb'))

# prediction with test data
```
To differentiate the importance of labelled data points use Instance Weight Supports

- SageMaker XGBoost allows customers to differentiate the importance of labelled data points by assigning each instance a weight value. For text/libsvm input, customers can assign weight values to data instances by attaching them after the labels. For example, label:weight id_0:val_0 id_1:val_1.... For text/csv input, customers need to turn on the csv_weights flag in the parameters and attach weight values in the column after labels. For example: label,weight,val_0,val_1,...).

EC2 Instance Recommendation for the XGBoost Release 0.72

SageMaker XGBoost currently only trains using CPUs. It is a memory-bound (as opposed to compute-bound) algorithm. So, a general-purpose compute instance (for example, M4) is a better choice than a compute-optimized instance (for example, C4). Further, we recommend that you have enough total memory in selected instances to hold the training data. Although it supports the use of disk space to handle data that does not fit into main memory (the out-of-core feature available with the libsvm input mode), writing cache files onto disk slows the algorithm processing time.

XGBoost Release 0.72 Sample Notebooks

For a sample notebook that shows how to use the latest version of SageMaker XGBoost as a built-in algorithm to train and host a regression model, see Regression with Amazon SageMaker XGBoost algorithm. To use the 0.72 version of XGBoost, you need to change the version in the sample code to 0.72. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. The topic modeling example notebooks using the XGBoost algorithms are located in the Introduction to Amazon algorithms section. To open a notebook, click on its Use tab and select Create copy.

XGBoost Release 0.72 Hyperparameters

The following table contains the hyperparameters for the XGBoost algorithm. These are parameters that are set by users to facilitate the estimation of model parameters from data. The required hyperparameters that must be set are listed first, in alphabetical order. The optional hyperparameters that can be set are listed next, also in alphabetical order. The SageMaker XGBoost algorithm is an implementation of the open-source XGBoost package. Currently SageMaker supports version 0.72. For more detail about hyperparameter configuration for this version of XGBoost, see XGBoost Parameters.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_class</td>
<td>The number of classes.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong> if objective is set to <em>multi:softmax</em> or <em>multi:softprob</em>.</td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td>num_round</td>
<td>The number of rounds to run the training.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td>alpha</td>
<td>L1 regularization term on weights. Increasing this value makes models more conservative.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>-------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>base_score</td>
<td>The initial prediction score of all instances, global bias.</td>
</tr>
<tr>
<td>booster</td>
<td>Which booster to use. The gbtree and dart values use a tree-based model, while gblinear uses a linear function.</td>
</tr>
<tr>
<td>colsample_bylevel</td>
<td>Subsample ratio of columns for each split, in each level.</td>
</tr>
<tr>
<td>colsample_bytree</td>
<td>Subsample ratio of columns when constructing each tree.</td>
</tr>
<tr>
<td>csv_weights</td>
<td>When this flag is enabled, XGBoost differentiates the importance of instances for csv input by taking the second column (the column after labels) in training data as the instance weights.</td>
</tr>
<tr>
<td>early_stopping_rounds</td>
<td>The model trains until the validation score stops improving. Validation error needs to decrease at least every early_stopping_rounds to continue training. SageMaker hosting uses the best model for inference.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>----------------</td>
</tr>
<tr>
<td><strong>eta</strong></td>
<td>Step size shrinkage used in updates to prevent overfitting. After each boosting step, you can directly get the weights of new features. The eta parameter actually shrinks the feature weights to make the boosting process more conservative.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0,1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.3</td>
</tr>
<tr>
<td><strong>eval_metric</strong></td>
<td>Evaluation metrics for validation data. A default metric is assigned according to the objective:</td>
</tr>
<tr>
<td></td>
<td>• rmse: for regression</td>
</tr>
<tr>
<td></td>
<td>• error: for classification</td>
</tr>
<tr>
<td></td>
<td>• map: for ranking</td>
</tr>
<tr>
<td></td>
<td>For a list of valid inputs, see XGBoost Parameters.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: string</td>
</tr>
<tr>
<td></td>
<td>Default value: Default according to objective.</td>
</tr>
<tr>
<td><strong>gamma</strong></td>
<td>Minimum loss reduction required to make a further partition on a leaf node of the tree. The larger, the more conservative the algorithm is.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0,∞).</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td><strong>grow_policy</strong></td>
<td>Controls the way that new nodes are added to the tree. Currently supported only if tree_method is set to hist.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. Either depthwise or lossguide.</td>
</tr>
<tr>
<td></td>
<td>Default value: depthwise</td>
</tr>
<tr>
<td><strong>lambda</strong></td>
<td>L2 regularization term on weights. Increasing this value makes models more conservative.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------</td>
<td>--------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>lambda_bias</td>
<td>L2 regularization term on bias.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>max_bin</td>
<td>Maximum number of discrete bins to bucket continuous features. Used only if <code>tree_method</code> is set to <code>hist</code>.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 256</td>
</tr>
<tr>
<td>max_delta_step</td>
<td>Maximum delta step allowed for each tree's weight estimation. When a positive integer is used, it helps make the update more conservative. The preferred option is to use it in logistic regression. Set it to 1-10 to help control the update.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer. Range: [0,∞).</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>max_depth</td>
<td>Maximum depth of a tree. Increasing this value makes the model more complex and likely to be overfit. 0 indicates no limit. A limit is required when <code>grow_policy</code>=depth-wise.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer. Range: [0,∞)</td>
</tr>
<tr>
<td></td>
<td>Default value: 6</td>
</tr>
<tr>
<td>max_leaves</td>
<td>Maximum number of nodes to be added. Relevant only if <code>grow_policy</code> is set to <code>lossguide</code>.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| min_child_weight | Minimum sum of instance weight (hessian) needed in a child. If the tree partition step results in a leaf node with the sum of instance weight less than min_child_weight, the building process gives up further partitioning. In linear regression models, this simply corresponds to a minimum number of instances needed in each node. The larger the algorithm, the more conservative it is.  
Optional  
Valid values: Float. Range: \([0,\infty)\).  
Default value: 1  |
| normalize_type   | Type of normalization algorithm.  
Optional  
Valid values: Either tree or forest.  
Default value: tree  |
| nthread          | Number of parallel threads used to run xgboost.  
Optional  
Valid values: integer  
Default value: Maximum number of threads.  |
| objective        | Specifies the learning task and the corresponding learning objective. Examples: reg:logistic, reg:softmax, multi:squarederror. For a full list of valid inputs, refer to XGBoost Parameters.  
Optional  
Valid values: string  
Default value: reg:squarederror  |
| one_drop         | When this flag is enabled, at least one tree is always dropped during the dropout.  
Optional  
Valid values: 0 or 1  
Default value: 0  |
| process_type     | The type of boosting process to run.  
Optional  
Valid values: String. Either default or update.  
Default value: default  |
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| rate_drop        | The dropout rate that specifies the fraction of previous trees to drop during the dropout.  
|                  | **Optional**  
|                  | Valid values: Float. Range: [0.0, 1.0].  
|                  | Default value: 0.0  |
| refresh_leaf     | This is a parameter of the 'refresh' updater plug-in. When set to true (1), tree leaves and tree node stats are updated. When set to false(0), only tree node stats are updated.  
|                  | **Optional**  
|                  | Valid values: 0/1  
|                  | Default value: 1  |
| sample_type      | Type of sampling algorithm.  
|                  | **Optional**  
|                  | Valid values: Either uniform or weighted.  
|                  | Default value: uniform  |
| scale_pos_weight | Controls the balance of positive and negative weights. It's useful for unbalanced classes. A typical value to consider: sum(negative cases) / sum(positive cases).  
|                  | **Optional**  
|                  | Valid values: float  
|                  | Default value: 1  |
| seed             | Random number seed.  
|                  | **Optional**  
|                  | Valid values: integer  
|                  | Default value: 0  |
| silent           | 0 means print running messages, 1 means silent mode.  
|                  | **Optional**  
|                  | Valid values: 0 or 1  
<p>|                  | Default value: 0  |</p>
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>sketch_eps</td>
<td>Used only for approximate greedy algorithm. This translates into $O(1 / \text{sketch_eps})$ number of bins. Compared to directly select number of bins, this comes with theoretical guarantee with sketch accuracy.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float, Range: [0, 1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.03</td>
</tr>
<tr>
<td>skip_drop</td>
<td>Probability of skipping the dropout procedure during a boosting iteration.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0</td>
</tr>
<tr>
<td>subsample</td>
<td>Subsample ratio of the training instance. Setting it to 0.5 means that XGBoost randomly collects half of the data instances to grow trees. This prevents overfitting.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: [0, 1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>tree_method</td>
<td>The tree construction algorithm used in XGBoost.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: One of auto, exact, approx, or hist.</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>tweedie_variance_power</td>
<td>Parameter that controls the variance of the Tweedie distribution.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range: (1, 2).</td>
</tr>
<tr>
<td></td>
<td>Default value: 1.5</td>
</tr>
<tr>
<td>updater</td>
<td>A comma-separated string that defines the sequence of tree updaters to run. This provides a modular way to construct and to modify the trees.</td>
</tr>
<tr>
<td></td>
<td>For a full list of valid inputs, please refer to XGBoost Parameters.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: comma-separated string.</td>
</tr>
<tr>
<td></td>
<td>Default value: grow_colmaker, prune</td>
</tr>
</tbody>
</table>
Tune an XGBoost Release 0.72 Model

Automatic model tuning, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your training and validation datasets. You choose three types of hyperparameters:

- a learning objective function to optimize during model training
- an eval_metric to use to evaluate model performance during validation
- a set of hyperparameters and a range of values for each to use when tuning the model automatically

You choose the evaluation metric from set of evaluation metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the evaluation metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

Metrics Computed by the XGBoost Release 0.72 Algorithm

The XGBoost algorithm based on version 0.72 computes the following nine metrics to use for model validation. When tuning the model, choose one of these metrics to evaluate the model. For full list of valid eval_metric values, refer to XGBoost Learning Task Parameters

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>validation:auc</td>
<td>Area under the curve.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:error</td>
<td>Binary classification error rate, calculated as #wrong cases/#all cases.</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:logloss</td>
<td>Negative log-likelihood.</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:mae</td>
<td>Mean absolute error.</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:map</td>
<td>Mean average precision.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:merror</td>
<td>Multiclass classification error rate, calculated as #wrong cases/#all cases.</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:mlogloss</td>
<td>Negative log-likelihood for multiclass classification.</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:ndcg</td>
<td>Normalized Discounted Cumulative Gain.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:rmse</td>
<td>Root mean square error.</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

Tunable XGBoost Release 0.72 Hyperparameters

Tune the XGBoost model with the following hyperparameters. The hyperparameters that have the greatest effect on optimizing the XGBoost evaluation metrics are: alpha, min_child_weight, subsample, eta, and num_round.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>alpha</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 1000</td>
</tr>
</tbody>
</table>
## Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>colsample_bylevel</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.1, MaxValue: 1</td>
</tr>
<tr>
<td>colsample_bytree</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.5, MaxValue: 1</td>
</tr>
<tr>
<td>eta</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.1, MaxValue: 0.5</td>
</tr>
<tr>
<td>gamma</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 5</td>
</tr>
<tr>
<td>lambda</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 1000</td>
</tr>
<tr>
<td>max_delta_step</td>
<td>IntegerParameterRanges</td>
<td>[0, 10]</td>
</tr>
<tr>
<td>max_depth</td>
<td>IntegerParameterRanges</td>
<td>[0, 10]</td>
</tr>
<tr>
<td>min_child_weight</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0, MaxValue: 120</td>
</tr>
<tr>
<td>num_round</td>
<td>IntegerParameterRanges</td>
<td>[1, 4000]</td>
</tr>
<tr>
<td>subsample</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.5, MaxValue: 1</td>
</tr>
</tbody>
</table>

### Built-in SageMaker Algorithms for Text Data

SageMaker provides algorithms that are tailored to the analysis of textual documents used in natural language processing, document classification or summarization, topic modeling or classification, and language transcription or translation.

- **BlazingText algorithm (p. 2066)**—a highly optimized implementation of the Word2Vec and text classification algorithms that scale to large datasets easily. It is useful for many downstream natural language processing (NLP) tasks.
- **Latent Dirichlet Allocation (LDA) Algorithm (p. 2076)**—an algorithm suitable for determining topics in a set of documents. It is an unsupervised algorithm, which means that it doesn’t use example data with answers during training.
- **Neural Topic Model (NTM) Algorithm (p. 2081)**—another unsupervised technique for determining topics in a set of documents, using a neural network approach.
- **Object2Vec Algorithm (p. 2087)**—a general-purpose neural embedding algorithm that can be used for recommendation systems, document classification, and sentence embeddings.
- **Sequence-to-Sequence Algorithm (p. 2103)**—a supervised algorithm commonly used for neural machine translation.
- **Text Classification - TensorFlow (p. 2116)**—a supervised algorithm that supports transfer learning with available pretrained models for text classification.
<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>BlazingText</td>
<td>train</td>
<td>File or Pipe</td>
<td>Text file (one sentence per line with space-separated tokens)</td>
<td>GPU (single instance only) or CPU</td>
<td>No</td>
</tr>
<tr>
<td>LDA</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>Neural Topic Model</td>
<td>train and (optionally) validation, test, or both</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>GPU or CPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Object2Vec</td>
<td>train and (optionally) validation, test, or both</td>
<td>File</td>
<td>JSON Lines</td>
<td>GPU or CPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>Seq2Seq Modeling</td>
<td>train, validation, and vocab</td>
<td>File</td>
<td>recordIO-protobuf</td>
<td>GPU (single instance only)</td>
<td>No</td>
</tr>
<tr>
<td>Text Classification - TensorFlow</td>
<td>training and validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU or GPU</td>
<td>Yes (only across multiple GPUs on a single instance)</td>
</tr>
</tbody>
</table>

**BlazingText algorithm**

The Amazon SageMaker BlazingText algorithm provides highly optimized implementations of the Word2vec and text classification algorithms. The Word2vec algorithm is useful for many downstream natural language processing (NLP) tasks, such as sentiment analysis, named entity recognition, machine translation, etc. Text classification is an important task for applications that perform web searches, information retrieval, ranking, and document classification.

The Word2vec algorithm maps words to high-quality distributed vectors. The resulting vector representation of a word is called a word embedding. Words that are semantically similar correspond to vectors that are close together. That way, word embeddings capture the semantic relationships between words.

Many natural language processing (NLP) applications learn word embeddings by training on large collections of documents. These pretrained vector representations provide information about semantics and word distributions that typically improves the generalizability of other models that are later trained on a more limited amount of data. Most implementations of the Word2vec algorithm are not optimized for multi-core CPU architectures. This makes it difficult to scale to large datasets.

With the BlazingText algorithm, you can scale to large datasets easily. Similar to Word2vec, it provides the Skip-gram and continuous bag-of-words (CBOW) training architectures. BlazingText's
implementation of the supervised multi-class, multi-label text classification algorithm extends the fastText text classifier to use GPU acceleration with custom CUDA kernels. You can train a model on more than a billion words in a couple of minutes using a multi-core CPU or a GPU. And, you achieve performance on par with the state-of-the-art deep learning text classification algorithms.

The BlazingText algorithm is not parallelizable. For more information on parameters related to training, see Docker Registry Paths for SageMaker Built-in Algorithms.

The SageMaker BlazingText algorithms provides the following features:

- Accelerated training of the fastText text classifier on multi-core CPUs or a GPU and Word2Vec on GPUs using highly optimized CUDA kernels. For more information, see BlazingText: Scaling and Accelerating Word2Vec using Multiple GPUs.
- Enriched Word Vectors with Subword Information by learning vector representations for character n-grams. This approach enables BlazingText to generate meaningful vectors for out-of-vocabulary (OOV) words by representing their vectors as the sum of the character n-gram (subword) vectors.
- A batch_skipgram mode for the Word2Vec algorithm that allows faster training and distributed computation across multiple CPU nodes. The batch_skipgram mode does mini-batching using the Negative Sample Sharing strategy to convert level-1 BLAS operations into level-3 BLAS operations. This efficiently leverages the multiply-add instructions of modern architectures. For more information, see Parallelizing Word2Vec in Shared and Distributed Memory.

To summarize, the following modes are supported by BlazingText on different types instances:

<table>
<thead>
<tr>
<th>Modes</th>
<th>Word2Vec (Unsupervised Learning)</th>
<th>Text Classification (Supervised Learning)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single CPU instance</td>
<td>cbow</td>
<td>supervised</td>
</tr>
<tr>
<td></td>
<td>Skip-gram</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Batch Skip-gram</td>
<td></td>
</tr>
<tr>
<td>Single GPU instance (with 1 or more GPUs)</td>
<td>cbow</td>
<td>supervised with one GPU</td>
</tr>
<tr>
<td></td>
<td>Skip-gram</td>
<td></td>
</tr>
<tr>
<td>Multiple CPU instances</td>
<td>Batch Skip-gram</td>
<td>None</td>
</tr>
</tbody>
</table>

For more information about the mathematics behind BlazingText, see BlazingText: Scaling and Accelerating Word2Vec using Multiple GPUs.

Topics

- Input/Output Interface for the BlazingText Algorithm (p. 2067)
- EC2 Instance Recommendation for the BlazingText Algorithm (p. 2070)
- BlazingText Sample Notebooks (p. 2070)
- BlazingText Hyperparameters (p. 2071)
- Tune a BlazingText Model (p. 2074)

Input/Output Interface for the BlazingText Algorithm

The BlazingText algorithm expects a single preprocessed text file with space-separated tokens. Each line in the file should contain a single sentence. If you need to train on multiple text files, concatenate them into one file and upload the file in the respective channel.
Training and Validation Data Format

Training and Validation Data Format for the Word2Vec Algorithm

For Word2Vec training, upload the file under the train channel. No other channels are supported. The file should contain a training sentence per line.

Training and Validation Data Format for the Text Classification Algorithm

For supervised mode, you can train with file mode or with the augmented manifest text format.

Train with File Mode

For supervised mode, the training/validation file should contain a training sentence per line along with the labels. Labels are words that are prefixed by the string __label__. Here is an example of a training/validation file:

```
__label__4  linux ready for prime time , intel says , despite all the linux hype , the open-source movement has yet to make a huge splash in the desktop market . that may be about to change , thanks to chipmaking giant intel corp .
__label__2  bowled by the slower one again , kolkata , november 14 the past caught up with sourav ganguly as the indian skippers return to international cricket was short lived .
```

Note
The order of labels within the sentence doesn't matter.

Upload the training file under the train channel, and optionally upload the validation file under the validation channel.

Train with Augmented Manifest Text Format

The supervised mode also supports the augmented manifest format, which enables you to do training in pipe mode without needing to create RecordIO files. While using the format, an S3 manifest file needs to be generated that contains the list of sentences and their corresponding labels. The manifest file format should be in JSON Lines format in which each line represents one sample. The sentences are specified using the source tag and the label can be specified using the label tag. Both source and label tags should be provided under the AttributeNames parameter value as specified in the request.

```
{"source":"linux ready for prime time , intel says , despite all the linux hype", "label":1}
{"source":"bowled by the slower one again , kolkata , november 14 the past caught up with sourav ganguly", "label":2}
```

Multi-label training is also supported by specifying a JSON array of labels.

```
{"source":"linux ready for prime time , intel says , despite all the linux hype", "label": [1, 3]}
{"source":"bowled by the slower one again , kolkata , november 14 the past caught up with sourav ganguly", "label": [2, 4, 5]}
```

For more information on augmented manifest files, see Provide Dataset Metadata to Training Jobs with an Augmented Manifest File (p. 2700).

Model Artifacts and Inference

Model Artifacts for the Word2Vec Algorithm

For Word2Vec training, the model artifacts consist of vectors.txt, which contains words-to-vectors mapping, and vectors.bin, a binary used by BlazingText for hosting, inference, or both. vectors.txt stores
the vectors in a format that is compatible with other tools like Gensim and Spacy. For example, a Gensim user can run the following commands to load the vectors.txt file:

```python
from gensim.models import KeyedVectors
word_vectors = KeyedVectors.load_word2vec_format('vectors.txt', binary=False)
word_vectors.most_similar(positive=['woman', 'king'], negative=['man'])
word_vectors.doesn't_match('breakfast cereal dinner lunch'.split())
```

If the evaluation parameter is set to `True`, an additional file, `eval.json`, is created. This file contains the similarity evaluation results (using Spearman's rank correlation coefficients) on WS-353 dataset. The number of words from the WS-353 dataset that aren't there in the training corpus are reported.

For inference requests, the model accepts a JSON file containing a list of strings and returns a list of vectors. If the word is not found in vocabulary, inference returns a vector of zeros. If subwords is set to `True` during training, the model is able to generate vectors for out-of-vocabulary (OOV) words.

**Sample JSON Request**

Mime-type: application/json

```json
{
  "instances": ["word1", "word2", "word3"]
}
```

**Model Artifacts for the Text Classification Algorithm**

Training with supervised outputs creates a `model.bin` file that can be consumed by BlazingText hosting. For inference, the BlazingText model accepts a JSON file containing a list of sentences and returns a list of corresponding predicted labels and probability scores. Each sentence is expected to be a string with space-separated tokens, words, or both.

**Sample JSON Request**

Mime-type: application/json

```json
{
  "instances": ["the movie was excellent", "i did not like the plot ."]
}
```

By default, the server returns only one prediction, the one with the highest probability. For retrieving the top \( k \) predictions, you can set \( k \) in the configuration, as follows:

```json
{
  "instances": ["the movie was excellent", "i did not like the plot ."],
  "configuration": {"k": 2}
}
```

For BlazingText, the `content-type` and `accept` parameters must be equal. For batch transform, they both need to be `application/jsonlines`. If they differ, the `Accept` field is ignored. The format for input follows:

```json
content-type: application/jsonlines

{"source": "source_0"}
{"source": "source_1"}

if you need to pass the value of \( k \) for top-\( k \), then you can do it in the following way:

```json
{"source": "source_0", "k": 2}
```
For both supervised (text classification) and unsupervised (Word2Vec) modes, the binaries (*.bin) produced by BlazingText can be cross-consumed by fastText and vice versa. You can use binaries produced by BlazingText by fastText. Likewise, you can host the model binaries created with fastText using BlazingText.

Here is an example of how to use a model generated with BlazingText with fastText:

```bash
#Download the model artifact from S3
aws s3 cp s3://<YOUR_S3_BUCKET>/<PREFIX>/model.tar.gz model.tar.gz

#Unzip the model archive
tar -xzf model.tar.gz

#Use the model archive with fastText
fasttext predict ./model.bin test.txt
```

However, the binaries are only supported when training on CPU and single GPU; training on multi-GPU will not produce binaries.

For more details on dataset formats and model hosting, see the example notebooks Text Classification with the BlazingText Algorithm, FastText Models, and Generating Subword Embeddings with the Word2Vec Algorithm.

EC2 Instance Recommendation for the BlazingText Algorithm

For cbow and skipgram modes, BlazingText supports single CPU and single GPU instances. Both of these modes support learning of subwords embeddings. To achieve the highest speed without compromising accuracy, we recommend that you use an ml.p3.2xlarge instance.

For batch_skipgram mode, BlazingText supports single or multiple CPU instances. When training on multiple instances, set the value of the S3DataDistributionType field of the S3DataSource object that you pass to CreateTrainingJob to FullyReplicated. BlazingText takes care of distributing data across machines.

For the supervised text classification mode, a C5 instance is recommended if the training dataset is less than 2 GB. For larger datasets, use an instance with a single GPU. BlazingText supports P2, P3, G4dn, and G5 instances for training and inference.

BlazingText Sample Notebooks

For a sample notebook that uses the SageMaker BlazingText algorithm to train and deploy supervised binary and multiclass classification models, see Blazing Text classification on the DBPedia dataset. For instructions for creating and accessing Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After creating and opening a
notebook instance, choose the **SageMaker Examples** tab to see a list of all the SageMaker examples. The topic modeling example notebooks that use the Blazing Text are located in the **Introduction to Amazon algorithms** section. To open a notebook, choose its **Use** tab, then choose **Create copy**.

### BlazingText Hyperparameters

When you start a training job with a `CreateTrainingJob` request, you specify a training algorithm. You can also specify algorithm-specific hyperparameters as string-to-string maps. The hyperparameters for the BlazingText algorithm depend on which mode you use: Word2Vec (unsupervised) and Text Classification (supervised).

### Word2Vec Hyperparameters

The following table lists the hyperparameters for the BlazingText Word2Vec training algorithm provided by Amazon SageMaker.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>mode</td>
<td>The Word2vec architecture used for training. Required</td>
</tr>
<tr>
<td></td>
<td>Valid values: <code>batch_skipgram</code>, <code>skipgram</code>, or <code>cbow</code></td>
</tr>
<tr>
<td>batch_size</td>
<td>The size of each batch when <code>mode</code> is set to <code>batch_skipgram</code>. Set to a number between 10 and 20. Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 11</td>
</tr>
<tr>
<td>buckets</td>
<td>The number of hash buckets to use for subwords. Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 2000000</td>
</tr>
<tr>
<td>epochs</td>
<td>The number of complete passes through the training data. Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 5</td>
</tr>
<tr>
<td>evaluation</td>
<td>Whether the trained model is evaluated using the WordSimilarity-353 Test. Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: (Boolean) <code>True</code> or <code>False</code></td>
</tr>
<tr>
<td></td>
<td>Default value: <code>True</code></td>
</tr>
<tr>
<td>learning_rate</td>
<td>The step size used for parameter updates. Optional</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td><strong>Valid values:</strong> Positive float</td>
</tr>
<tr>
<td></td>
<td><strong>Default value:</strong> 0.05</td>
</tr>
<tr>
<td>min_char</td>
<td>The minimum number of characters to use for subwords/character n-grams.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Valid values:</strong> positive integer</td>
</tr>
<tr>
<td></td>
<td><strong>Default value:</strong> 3</td>
</tr>
<tr>
<td>min_count</td>
<td>Words that appear less than min_count times are discarded.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Valid values:</strong> Non-negative integer</td>
</tr>
<tr>
<td></td>
<td><strong>Default value:</strong> 5</td>
</tr>
<tr>
<td>max_char</td>
<td>The maximum number of characters to use for subwords/character n-grams.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Valid values:</strong> positive integer</td>
</tr>
<tr>
<td></td>
<td><strong>Default value:</strong> 6</td>
</tr>
<tr>
<td>negative_samples</td>
<td>The number of negative samples for the negative sample sharing strategy.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Valid values:</strong> Positive integer</td>
</tr>
<tr>
<td></td>
<td><strong>Default value:</strong> 5</td>
</tr>
<tr>
<td>sampling_threshold</td>
<td>The threshold for the occurrence of words. Words that appear with</td>
</tr>
<tr>
<td></td>
<td>higher frequency in the training data are randomly down-sampled.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Valid values:</strong> Positive fraction. The recommended range is (0, 1e-3]</td>
</tr>
<tr>
<td></td>
<td><strong>Default value:</strong> 0.0001</td>
</tr>
<tr>
<td>subwords</td>
<td>Whether to learn subword embeddings on not.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td><strong>Valid values:</strong> (Boolean) True or False</td>
</tr>
<tr>
<td></td>
<td><strong>Default value:</strong> False</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>vector_dim</td>
<td>The dimension of the word vectors that the algorithm learns.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 100</td>
</tr>
<tr>
<td>window_size</td>
<td>The size of the context window. The context window is the number of words</td>
</tr>
<tr>
<td></td>
<td>surrounding the target word used for training.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 5</td>
</tr>
</tbody>
</table>

**Text Classification Hyperparameters**

The following table lists the hyperparameters for the Text Classification training algorithm provided by Amazon SageMaker.

*Note* Although some of the parameters are common between the Text Classification and Word2Vec modes, they might have different meanings depending on the context.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>mode</td>
<td>The training mode.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: supervised</td>
</tr>
<tr>
<td>buckets</td>
<td>The number of hash buckets to use for word n-grams.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 2000000</td>
</tr>
<tr>
<td>early_stopping</td>
<td>Whether to stop training if validation accuracy doesn't improve after a</td>
</tr>
<tr>
<td></td>
<td>patience number of epochs.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: (Boolean) True or False</td>
</tr>
<tr>
<td></td>
<td>Default value: False</td>
</tr>
<tr>
<td>epochs</td>
<td>The maximum number of complete passes through the training data.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
</tbody>
</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| **learning_rate** | The step size used for parameter updates.  
  **Optional**  
  Valid values: Positive float  
  Default value: 0.05 |
| **min_count** | Words that appear less than min_count times are discarded.  
  **Optional**  
  Valid values: Non-negative integer  
  Default value: 5 |
| **min_epochs** | The minimum number of epochs to train before early stopping logic is invoked.  
  **Optional**  
  Valid values: Positive integer  
  Default value: 5 |
| **patience** | The number of epochs to wait before applying early stopping when no progress is made on the validation set. Used only when early_stopping is True.  
  **Optional**  
  Valid values: Positive integer  
  Default value: 4 |
| **vector_dim** | The dimension of the embedding layer.  
  **Optional**  
  Valid values: Positive integer  
  Default value: 100 |
| **word_ngrams** | The number of word n-gram features to use.  
  **Optional**  
  Valid values: Positive integer  
  Default value: 2 |

### Tune a BlazingText Model

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric
from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

**Metrics Computed by the BlazingText Algorithm**

The BlazingText Word2Vec algorithm (skipgram, cbow, and batch_skipgram modes) reports on a single metric during training: `train:mean_rho`. This metric is computed on WS-353 word similarity datasets. When tuning the hyperparameter values for the Word2Vec algorithm, use this metric as the objective.

The BlazingText Text Classification algorithm (supervised mode), also reports on a single metric during training: the `validation:accuracy`. When tuning the hyperparameter values for the text classification algorithm, use these metrics as the objective.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>train:mean_rho</td>
<td>The mean rho (Spearman's rank correlation coefficient) on WS-353 word similarity datasets</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:accuracy</td>
<td>The classification accuracy on the user-specified validation dataset</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

**Tunable BlazingText Hyperparameters**

**Tunable Hyperparameters for the Word2Vec Algorithm**

Tune an Amazon SageMaker BlazingText Word2Vec model with the following hyperparameters. The hyperparameters that have the greatest impact on Word2Vec objective metrics are: `mode`, `learning_rate`, `window_size`, `vector_dim`, and `negative_samples`.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges or Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch_size</td>
<td>IntegerParameterRange</td>
<td>[8-32]</td>
</tr>
<tr>
<td>epochs</td>
<td>IntegerParameterRange</td>
<td>[5-15]</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.005, MaxValue: 0.01</td>
</tr>
<tr>
<td>min_count</td>
<td>IntegerParameterRange</td>
<td>[0-100]</td>
</tr>
<tr>
<td>mode</td>
<td>CategoricalParameterRange</td>
<td>['batch_skipgram', 'skipgram', 'cbow']</td>
</tr>
<tr>
<td>negative_samples</td>
<td>IntegerParameterRange</td>
<td>[5-25]</td>
</tr>
<tr>
<td>sampling_threshold</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0001, MaxValue: 0.001</td>
</tr>
<tr>
<td>vector_dim</td>
<td>IntegerParameterRange</td>
<td>[32-300]</td>
</tr>
<tr>
<td>window_size</td>
<td>IntegerParameterRange</td>
<td>[1-10]</td>
</tr>
</tbody>
</table>
Tunable Hyperparameters for the Text Classification Algorithm

Tune an Amazon SageMaker BlazingText text classification model with the following hyperparameters.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges or Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>buckets</td>
<td>IntegerParameterRange</td>
<td>[1000000-10000000]</td>
</tr>
<tr>
<td>epochs</td>
<td>IntegerParameterRange</td>
<td>[5-15]</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.005, MaxValue: 0.01</td>
</tr>
<tr>
<td>min_count</td>
<td>IntegerParameterRange</td>
<td>[0-100]</td>
</tr>
<tr>
<td>vector_dim</td>
<td>IntegerParameterRange</td>
<td>[32-300]</td>
</tr>
<tr>
<td>word_ngrams</td>
<td>IntegerParameterRange</td>
<td>[1-3]</td>
</tr>
</tbody>
</table>

Latent Dirichlet Allocation (LDA) Algorithm

The Amazon SageMaker Latent Dirichlet Allocation (LDA) algorithm is an unsupervised learning algorithm that attempts to describe a set of observations as a mixture of distinct categories. LDA is most commonly used to discover a user-specified number of topics shared by documents within a text corpus. Here each observation is a document, the features are the presence (or occurrence count) of each word, and the categories are the topics. Since the method is unsupervised, the topics are not specified up front, and are not guaranteed to align with how a human may naturally categorize documents. The topics are learned as a probability distribution over the words that occur in each document. Each document, in turn, is described as a mixture of topics.

The exact content of two documents with similar topic mixtures will not be the same. But overall, you would expect these documents to more frequently use a shared subset of words, than when compared with a document from a different topic mixture. This allows LDA to discover these word groups and use them to form topics. As an extremely simple example, given a set of documents where the only words that occur within them are: eat, sleep, play, meow, and bark, LDA might produce topics like the following:

<table>
<thead>
<tr>
<th>Topic</th>
<th>eat</th>
<th>sleep</th>
<th>play</th>
<th>meow</th>
<th>bark</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topic 1</td>
<td>0.1</td>
<td>0.3</td>
<td>0.2</td>
<td>0.4</td>
<td>0.0</td>
</tr>
<tr>
<td>Topic 2</td>
<td>0.2</td>
<td>0.1</td>
<td>0.4</td>
<td>0.0</td>
<td>0.3</td>
</tr>
</tbody>
</table>

You can infer that documents that are more likely to fall into Topic 1 are about cats (who are more likely to meow and sleep), and documents that fall into Topic 2 are about dogs (who prefer to play and bark). These topics can be found even though the words dog and cat never appear in any of the texts.

Topics
- Choosing between Latent Dirichlet Allocation (LDA) and Neural Topic Model (NTM) (p. 2077)
- Input/Output Interface for the LDA Algorithm (p. 2077)
- EC2 Instance Recommendation for the LDA Algorithm (p. 2077)
- LDA Sample Notebooks (p. 2078)
- How LDA Works (p. 2078)
Choosing between Latent Dirichlet Allocation (LDA) and Neural Topic Model (NTM)

Topic models are commonly used to produce topics from corpuses that (1) coherently encapsulate semantic meaning and (2) describe documents well. As such, topic models aim to minimize perplexity and maximize topic coherence.

Perplexity is an intrinsic language modeling evaluation metric that measures the inverse of the geometric mean per-word likelihood in your test data. A lower perplexity score indicates better generalization performance. Research has shown that the likelihood computed per word often does not align to human judgement, and can be entirely non-correlated, thus topic coherence has been introduced. Each inferred topic from your model consists of words, and topic coherence is computed to the top N words for that particular topic from your model. It is often defined as the average or median of the pairwise word-similarity scores of the words in that topic e.g., Pointwise Mutual Information (PMI). A promising model generates coherent topics or topics with high topic coherence scores.

While the objective is to train a topic model that minimizes perplexity and maximizes topic coherence, there is often a tradeoff with both LDA and NTM. Recent research by Amazon, Dinget et al., 2018 has shown that NTM is promising for achieving high topic coherence but LDA trained with collapsed Gibbs sampling achieves better perplexity. There is a tradeoff between perplexity and topic coherence. From a practicality standpoint regarding hardware and compute power, SageMaker NTM hardware is more flexible than LDA and can scale better because NTM can run on CPU and GPU and can be parallelized across multiple GPU instances, whereas LDA only supports single-instance CPU training.

Topics

- Input/Output Interface for the LDA Algorithm (p. 2077)
- EC2 Instance Recommendation for the LDA Algorithm (p. 2077)
- LDA Sample Notebooks (p. 2078)
- How LDA Works (p. 2078)
- LDA Hyperparameters (p. 2079)
- Tune an LDA Model (p. 2081)

Input/Output Interface for the LDA Algorithm

LDA expects data to be provided on the train channel, and optionally supports a test channel, which is scored by the final model. LDA supports both recordIO-wrapped-protobuf (dense and sparse) and CSV file formats. For CSV, the data must be dense and have dimension equal to number of records * vocabulary size. LDA can be trained in File or Pipe mode when using recordIO-wrapped protobuf, but only in File mode for the CSV format.

For inference, text/csv, application/json, and application/x-recordio-protobuf content types are supported. Sparse data can also be passed for application/json and application/x-recordio-protobuf. LDA inference returns application/json or application/x-recordio-protobuf predictions, which include the topic_mixture vector for each observation.

Please see the LDA Sample Notebooks (p. 2078) for more detail on training and inference formats.

EC2 Instance Recommendation for the LDA Algorithm

LDA currently only supports single-instance CPU training. CPU instances are recommended for hosting/inference.
LDA Sample Notebooks

For a sample notebook that shows how to train the SageMaker Latent Dirichlet Allocation algorithm on a dataset and then how to deploy the trained model to perform inferences about the topic mixtures in input documents, see the An Introduction to SageMaker LDA. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. The topic modeling example notebooks using the NTM algorithms are located in the Introduction to Amazon algorithms section. To open a notebook, click on its Use tab and select Create copy.

How LDA Works

Amazon SageMaker LDA is an unsupervised learning algorithm that attempts to describe a set of observations as a mixture of different categories. These categories are themselves a probability distribution over the features. LDA is a generative probability model, which means it attempts to provide a model for the distribution of outputs and inputs based on latent variables. This is opposed to discriminative models, which attempt to learn how inputs map to outputs.

You can use LDA for a variety of tasks, from clustering customers based on product purchases to automatic harmonic analysis in music. However, it is most commonly associated with topic modeling in text corpuses. Observations are referred to as documents. The feature set is referred to as vocabulary. A feature is referred to as a word. And the resulting categories are referred to as topics.

Note
Lemmatisation significantly increases algorithm performance and accuracy. Consider pre-processing any input text data.

An LDA model is defined by two parameters:

- \( \alpha \) — A prior estimate on topic probability (in other words, the average frequency that each topic within a given document occurs).
- \( \beta \) — A collection of k topics where each topic is given a probability distribution over the vocabulary used in a document corpus, also called a "topic-word distribution."

LDA is a "bag-of-words" model, which means that the order of words does not matter. LDA is a generative model where each document is generated word-by-word by choosing a topic mixture \( \theta \sim \text{Dirichlet}(\alpha) \).

For each word in the document:

- Choose a topic \( z \sim \text{Multinomial}(\theta) \)
- Choose the corresponding topic-word distribution \( \beta_z \).
- Draw a word \( w \sim \text{Multinomial}(\beta_z) \).

When training the model, the goal is to find parameters \( \alpha \) and \( \beta \), which maximize the probability that the text corpus is generated by the model.

The most popular methods for estimating the LDA model use Gibbs sampling or Expectation Maximization (EM) techniques. The Amazon SageMaker LDA uses tensor spectral decomposition. This provides several advantages:

- **Theoretical guarantees on results.** The standard EM-method is guaranteed to converge only to local optima, which are often of poor quality.
- **Embarrassingly parallelizable.** The work can be trivially divided over input documents in both training and inference. The EM-method and Gibbs Sampling approaches can be parallelized, but not as easily.
• **Fast.** Although the EM-method has low iteration cost it is prone to slow convergence rates. Gibbs Sampling is also subject to slow convergence rates and also requires a large number of samples.

At a high-level, the tensor decomposition algorithm follows this process:

1. The goal is to calculate the spectral decomposition of a $V \times V \times V$ tensor, which summarizes the moments of the documents in our corpus. $V$ is vocabulary size (in other words, the number of distinct words in all of the documents). The spectral components of this tensor are the LDA parameters $\alpha$ and $\beta$, which maximize the overall likelihood of the document corpus. However, because vocabulary size tends to be large, this $V \times V \times V$ tensor is prohibitively large to store in memory.

2. Instead, it uses a $V \times V$ moment matrix, which is the two-dimensional analog of the tensor from step 1, to find a whitening matrix of dimension $V \times k$. This matrix can be used to convert the $V \times V$ moment matrix into a $k \times k$ identity matrix. $k$ is the number of topics in the model.

3. This same whitening matrix can then be used to find a smaller $k \times k \times k$ tensor. When spectrally decomposed, this tensor has components that have a simple relationship with the components of the $V \times V \times V$ tensor.

4. **Alternating Least Squares** is used to decompose the smaller $k \times k \times k$ tensor. This provides a substantial improvement in memory consumption and speed. The parameters $\alpha$ and $\beta$ can be found by “unwhitening” these outputs in the spectral decomposition.

After the LDA model’s parameters have been found, you can find the topic mixtures for each document. You use stochastic gradient descent to maximize the likelihood function of observing a given topic mixture corresponding to these data.

Topic quality can be improved by increasing the number of topics to look for in training and then filtering out poor quality ones. This is in fact done automatically in SageMaker LDA: 25% more topics are computed and only the ones with largest associated Dirichlet priors are returned. To perform further topic filtering and analysis, you can increase the topic count and modify the resulting LDA model as follows:

```python
> import mxnet as mx
> alpha, beta = mx.ndarray.load('model.tar.gz')
> # modify alpha and beta
> mx.nd.save('new_model.tar.gz', [new_alpha, new_beta])
> # upload to S3 and create new SageMaker model using the console
```

For more information about algorithms for LDA and the SageMaker implementation, see the following:


**LDA Hyperparameters**

In the `CreateTrainingJob` request, you specify the training algorithm. You can also specify algorithm-specific hyperparameters as string-to-string maps. The following table lists the hyperparameters for the LDA training algorithm provided by Amazon SageMaker. For more information, see *How LDA Works* (p. 2078).
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_topics</td>
<td>The number of topics for LDA to find within the data. Required Valid values: positive integer</td>
</tr>
<tr>
<td>feature_dim</td>
<td>The size of the vocabulary of the input document corpus. Required Valid values: positive integer</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The total number of documents in the input document corpus. Required Valid values: positive integer</td>
</tr>
<tr>
<td>alpha0</td>
<td>Initial guess for the concentration parameter: the sum of the elements of the Dirichlet prior. Small values are more likely to generate sparse topic mixtures and large values (greater than 1.0) produce more uniform mixtures. Optional Valid values: Positive float Default value: 1.0</td>
</tr>
<tr>
<td>max_restarts</td>
<td>The number of restarts to perform during the Alternating Least Squares (ALS) spectral decomposition phase of the algorithm. Can be used to find better quality local minima at the expense of additional computation, but typically should not be adjusted. Optional Valid values: Positive integer Default value: 10</td>
</tr>
<tr>
<td>max_iterations</td>
<td>The maximum number of iterations to perform during the ALS phase of the algorithm. Can be used to find better quality minima at the expense of additional computation, but typically should not be adjusted. Optional Valid values: Positive integer Default value: 1000</td>
</tr>
<tr>
<td>tol</td>
<td>Target error tolerance for the ALS phase of the algorithm. Can be used to find better quality minima at the expense of additional computation, but typically should not be adjusted. Optional Valid values: Positive float</td>
</tr>
</tbody>
</table>
Use Built-in Algorithms

Parameter Name | Description | Default value: 1e-8
---|---|---

Tune an LDA Model

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

LDA is an unsupervised topic modeling algorithm that attempts to describe a set of observations (documents) as a mixture of different categories (topics). The “per-word log-likelihood” (PWLL) metric measures the likelihood that a learned set of topics (an LDA model) accurately describes a test document dataset. Larger values of PWLL indicate that the test data is more likely to be described by the LDA model.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

**Metrics Computed by the LDA Algorithm**

The LDA algorithm reports on a single metric during training: `test:pwll`. When tuning a model, choose this metric as the objective metric.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>test:pwll</code></td>
<td>Per-word log-likelihood on the test dataset. The likelihood that the test dataset is accurately described by the learned LDA model.</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

**Tunable LDA Hyperparameters**

You can tune the following hyperparameters for the LDA algorithm. Both hyperparameters, `alpha0` and `num_topics`, can affect the LDA objective metric (`test:pwll`). If you don't already know the optimal values for these hyperparameters, which maximize per-word log-likelihood and produce an accurate LDA model, automatic model tuning can help find them.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>alpha0</code></td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.1, MaxValue: 10</td>
</tr>
<tr>
<td><code>num_topics</code></td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 150</td>
</tr>
</tbody>
</table>

**Neural Topic Model (NTM) Algorithm**

Amazon SageMaker NTM is an unsupervised learning algorithm that is used to organize a corpus of documents into topics that contain word groupings based on their statistical distribution. Documents that contain frequent occurrences of words such as "bike", "car", "train", "mileage", and "speed" are likely to share a topic on "transportation" for example. Topic modeling can be used to classify or summarize documents based on the topics detected or to retrieve information or recommend content based on...
topic similarities. The topics from documents that NTM learns are characterized as a latent representation because the topics are inferred from the observed word distributions in the corpus. The semantics of topics are usually inferred by examining the top ranking words they contain. Because the method is unsupervised, only the number of topics, not the topics themselves, are prespecified. In addition, the topics are not guaranteed to align with how a human might naturally categorize documents.

Topic modeling provides a way to visualize the contents of a large document corpus in terms of the learned topics. Documents relevant to each topic might be indexed or searched for based on their soft topic labels. The latent representations of documents might also be used to find similar documents in the topic space. You can also use the latent representations of documents that the topic model learns for input to another supervised algorithm such as a document classifier. Because the latent representations of documents are expected to capture the semantics of the underlying documents, algorithms based in part on these representations are expected to perform better than those based on lexical features alone.

Although you can use both the Amazon SageMaker NTM and LDA algorithms for topic modeling, they are distinct algorithms and can be expected to produce different results on the same input data.

For more information on the mathematics behind NTM, see Neural Variational Inference for Text Processing.

Topics

- Input/Output Interface for the NTM Algorithm (p. 2082)
- EC2 Instance Recommendation for the NTM Algorithm (p. 2083)
- NTM Sample Notebooks (p. 2083)
- NTM Hyperparameters (p. 2083)
- Tune an NTM Model (p. 2085)
- NTM Response Formats (p. 2086)

Input/Output Interface for the NTM Algorithm

Amazon SageMaker Neural Topic Model supports four data channels: train, validation, test, and auxiliary. The validation, test, and auxiliary data channels are optional. If you specify any of these optional channels, set the value of the S3DataDistributionType parameter for them to FullyReplicated. If you provide validation data, the loss on this data is logged at every epoch, and the model stops training as soon as it detects that the validation loss is not improving. If you don't provide validation data, the algorithm stops early based on the training data, but this can be less efficient. If you provide test data, the algorithm reports the test loss from the final model.

The train, validation, and test data channels for NTM support both recordIO-wrapped-protobuf (dense and sparse) and CSV file formats. For CSV format, each row must be represented densely with zero counts for words not present in the corresponding document, and have dimension equal to: (number of records) * (vocabulary size). You can use either File mode or Pipe mode to train models on data that is formatted as recordIO-wrapped-protobuf or as CSV. The auxiliary channel is used to supply a text file that contains vocabulary. By supplying the vocabulary file, users are able to see the top words for each of the topics printed in the log instead of their integer IDs. Having the vocabulary file also allows NTM to compute the Word Embedding Topic Coherence (WETC) scores, a new metric displayed in the log that captures similarity among the top words in each topic effectively. The ContentType for the auxiliary channel is text/plain, with each line containing a single word, in the order corresponding to the integer IDs provided in the data. The vocabulary file must be named vocab.txt and currently only UTF-8 encoding is supported.

For inference, text/csv, application/json, application/jsonlines, and application/x-recordio-protobuf content types are supported. Sparse data can also be passed for application/json and application/x-recordio-protobuf. NTM inference returns application/json or application/x-recordio-protobuf predictions, which include the topic_weights vector for each observation.
See the blog post and the companion notebook for more details on using the auxiliary channel and the WETC scores. For more information on how to compute the WETC score, see Coherence-Aware Neural Topic Modeling. We used the pairwise WETC described in this paper for the Amazon SageMaker Neural Topic Model.

For more information on input and output file formats, see NTM Response Formats (p. 2086) for inference and the NTM Sample Notebooks (p. 2083).

**EC2 Instance Recommendation for the NTM Algorithm**

NTM training supports both GPU and CPU instance types. We recommend GPU instances, but for certain workloads, CPU instances may result in lower training costs. CPU instances should be sufficient for inference. NTM training supports P2, P3, G4dn, and G5 GPU instance families for training and inference.

**NTM Sample Notebooks**

For a sample notebook that uses the SageMaker NTM algorithm to uncover topics in documents from a synthetic data source where the topic distributions are known, see the Introduction to Basic Functionality of NTM. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. The topic modeling example notebooks using the NTM algorithms are located in the Introduction to Amazon algorithms section. To open a notebook, click on its Use tab and select Create copy.

**NTM Hyperparameters**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>feature_dim</td>
<td>The vocabulary size of the dataset. Required&lt;br&gt;Valid values: Positive integer (min: 1, max: 1,000,000)</td>
</tr>
<tr>
<td>num_topics</td>
<td>The number of required topics. Required&lt;br&gt;Valid values: Positive integer (min: 2, max: 1000)</td>
</tr>
<tr>
<td>batch_norm</td>
<td>Whether to use batch normalization during training. Optional&lt;br&gt;Valid values: true or false&lt;br&gt;Default value: false</td>
</tr>
<tr>
<td>clip_gradient</td>
<td>The maximum magnitude for each gradient component. Optional&lt;br&gt;Valid values: Float (min: 1e-3)&lt;br&gt;Default value: Infinity</td>
</tr>
<tr>
<td>encoder_layers</td>
<td>The number of layers in the encoder and the output size of each layer. When set to auto, the algorithm uses two layers of sizes 3 x num_topics and 2 x num_topics respectively.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>encoder_layers_activation</td>
<td>The activation function to use in the encoder layers.</td>
</tr>
<tr>
<td>epochs</td>
<td>The maximum number of passes over the training data.</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The learning rate for the optimizer.</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The number of examples in each mini batch.</td>
</tr>
<tr>
<td>num_patience_epochs</td>
<td>The number of successive epochs over which early stopping criterion is evaluated. Early stopping is triggered when the change in the loss function drops below the specified tolerance within the last num_patience_epochs number of epochs. To disable early stopping, set num_patience_epochs to a value larger than epochs.</td>
</tr>
</tbody>
</table>

| Optional | Valid values: Comma-separated list of positive integers or auto  |
| Optional | Valid values: |
| Optional | Valid values: |
| Optional | Valid values: |
| Optional | Valid values: |
| Optional | Valid values: |
| Optional | Valid values: |

Default value: auto

- sigmoid: Sigmoid function
- tanh: Hyperbolic tangent
- relu: Rectified linear unit

Default value: sigmoid

Default value: 50

Default value: 0.001

Default value: 256

Default value: 3
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>optimizer</td>
<td>The optimizer to use for training.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values:</td>
</tr>
<tr>
<td></td>
<td>• sgd: Stochastic gradient descent</td>
</tr>
<tr>
<td></td>
<td>• adam: Adaptive momentum estimation</td>
</tr>
<tr>
<td></td>
<td>• adagrad: Adaptive gradient algorithm</td>
</tr>
<tr>
<td></td>
<td>• adadelta: An adaptive learning rate algorithm</td>
</tr>
<tr>
<td></td>
<td>• rmsprop: Root mean square propagation</td>
</tr>
<tr>
<td></td>
<td>Default value: adadelta</td>
</tr>
<tr>
<td>rescale_gradient</td>
<td>The rescale factor for gradient.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: float (min: 1e-3, max: 1.0)</td>
</tr>
<tr>
<td></td>
<td>Default value: 1.0</td>
</tr>
<tr>
<td>sub_sample</td>
<td>The fraction of the training data to sample for training per epoch.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Float (min: 0.0, max: 1.0)</td>
</tr>
<tr>
<td></td>
<td>Default value: 1.0</td>
</tr>
<tr>
<td>tolerance</td>
<td>The maximum relative change in the loss function. Early stopping is</td>
</tr>
<tr>
<td></td>
<td>triggered when change in the loss function drops below this value</td>
</tr>
<tr>
<td></td>
<td>within the last num_patience_epochs number of epochs.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Float (min: 1e-6, max: 0.1)</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.001</td>
</tr>
<tr>
<td>weight_decay</td>
<td>The weight decay coefficient. Adds L2 regularization.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Float (min: 0.0, max: 1.0)</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0</td>
</tr>
</tbody>
</table>

**Tune an NTM Model**

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.
Amazon SageMaker NTM is an unsupervised learning algorithm that learns latent representations of large collections of discrete data, such as a corpus of documents. Latent representations use inferred variables that are not directly measured to model the observations in a dataset. Automatic model tuning on NTM helps you find the model that minimizes loss over the training or validation data. \textit{Training loss} measures how well the model fits the training data. \textit{Validation loss} measures how well the model can generalize to data that it is not trained on. Low training loss indicates that a model is a good fit to the training data. Low validation loss indicates that a model has not overfit the training data and so should be able to model documents successfully on which it has not been trained. Usually, it's preferable to have both losses be small. However, minimizing training loss too much might result in overfitting and increase validation loss, which would reduce the generality of the model.

For more information about model tuning, see \href{https://docs.aws.amazon.com/sagemaker/latest/dg/perform-automatic-model-tuning-with-sagemaker.html}{Perform Automatic Model Tuning with SageMaker (p. 2436)}.

\textbf{Metrics Computed by the NTM Algorithm}

The NTM algorithm reports a single metric that is computed during training: \texttt{validation:total_loss}. The total loss is the sum of the reconstruction loss and Kullback-Leibler divergence. When tuning hyperparameter values, choose this metric as the objective.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>\texttt{validation:total_loss}</td>
<td>Total Loss on validation set</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

\textbf{Tunable NTM Hyperparameters}

You can tune the following hyperparameters for the NTM algorithm. Usually setting low \texttt{mini_batch_size} and small \texttt{learning_rate} values results in lower validation losses, although it might take longer to train. Low validation losses don't necessarily produce more coherent topics as interpreted by humans. The effect of other hyperparameters on training and validation loss can vary from dataset to dataset. To see which values are compatible, see \href{https://docs.aws.amazon.com/sagemaker/latest/dg/ntm-hyperparameters.html}{NTM Hyperparameters (p. 2083)}.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>\texttt{encoder_layers_activation}</td>
<td>CategoricalParameterRanges</td>
<td>['sigmoid', 'tanh', 'relu']</td>
</tr>
<tr>
<td>\texttt{learning_rate}</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-4, MaxValue: 0.1</td>
</tr>
<tr>
<td>\texttt{mini_batch_size}</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 16, MaxValue: 2048</td>
</tr>
<tr>
<td>\texttt{optimizer}</td>
<td>CategoricalParameterRanges</td>
<td>['sgd', 'adam', 'adadelta']</td>
</tr>
<tr>
<td>\texttt{rescale_gradient}</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.1, MaxValue: 1.0</td>
</tr>
<tr>
<td>\texttt{weight_decay}</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 1.0</td>
</tr>
</tbody>
</table>

\textbf{NTM Response Formats}

All Amazon SageMaker built-in algorithms adhere to the common input inference format described in \href{https://docs.aws.amazon.com/sagemaker/latest/dg/common-data-formats-inference.html}{Common Data Formats - Inference}. This topic contains a list of the available output formats for the SageMaker NTM algorithm.
**Object2Vec Algorithm**

The Amazon SageMaker Object2Vec algorithm is a general-purpose neural embedding algorithm that is highly customizable. It can learn low-dimensional dense embeddings of high-dimensional objects. The embeddings are learned in a way that preserves the semantics of the relationship between pairs of objects in the original space in the embedding space. You can use the learned embeddings to efficiently compute nearest neighbors of objects and to visualize natural clusters of related objects in low-dimensional space, for example. You can also use the embeddings as features of the corresponding objects in downstream supervised tasks, such as classification or regression.

Object2Vec generalizes the well-known Word2Vec embedding technique for words that is optimized in the SageMaker BlazingText algorithm (p. 2066). For a blog post that discusses how to apply Object2Vec to some practical use cases, see Introduction to Amazon SageMaker Object2Vec.

**Topics**

- I/O Interface for the Object2Vec Algorithm (p. 2088)
- EC2 Instance Recommendation for the Object2Vec Algorithm (p. 2089)
- Object2Vec Sample Notebooks (p. 2089)
- How Object2Vec Works (p. 2089)
- Object2Vec Hyperparameters (p. 2091)
I/O Interface for the Object2Vec Algorithm

You can use Object2Vec on many input data types, including the following examples.

<table>
<thead>
<tr>
<th>Input Data Type</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sentence-sentence pairs</td>
<td>&quot;A soccer game with multiple males playing.&quot; and &quot;Some men are playing a sport.&quot;</td>
</tr>
<tr>
<td>Labels-sequence pairs</td>
<td>The genre tags of the movie &quot;Titanic&quot;, such as &quot;Romance&quot; and &quot;Drama&quot;, and its short description: &quot;James Cameron's Titanic is an epic, action-packed romance set against the ill-fated maiden voyage of the R.M.S. Titanic. She was the most luxurious liner of her era, a ship of dreams, which ultimately carried over 1,500 people to their death in the ice cold waters of the North Atlantic in the early hours of April 15, 1912.&quot;</td>
</tr>
<tr>
<td>Customer-customer pairs</td>
<td>The customer ID of Jane and customer ID of Jackie.</td>
</tr>
<tr>
<td>Product-product pairs</td>
<td>The product ID of football and product ID of basketball.</td>
</tr>
<tr>
<td>Item review user-item pairs</td>
<td>A user's ID and the items she has bought, such as apple, pear, and orange.</td>
</tr>
</tbody>
</table>

To transform the input data into the supported formats, you must preprocess it. Currently, Object2Vec natively supports two types of input:

- A discrete token, which is represented as a list of a single integer-id. For example, [10].
- A sequences of discrete tokens, which is represented as a list of integer-ids. For example, [0,12,10,13].

The object in each pair can be asymmetric. For example, the pairs can be (token, sequence) or (token, token) or (sequence, sequence). For token inputs, the algorithm supports simple embeddings as compatible encoders. For sequences of token vectors, the algorithm supports the following as encoders:

- Average-pooled embeddings
- Hierarchical convolutional neural networks (CNNs),
- Multi-layered bidirectional long short-term memory (BiLSTMs)

The input label for each pair can be one of the following:

- A categorical label that expresses the relationship between the objects in the pair
- A score that expresses the strength of the similarity between the two objects

For categorical labels used in classification, the algorithm supports the cross-entropy loss function. For ratings/score-based labels used in regression, the algorithm supports the mean squared error (MSE) loss function. Specify these loss functions with the `output_{layer}` hyperparameter when you create the model training job.
EC2 Instance Recommendation for the Object2Vec Algorithm

The type of Amazon Elastic Compute Cloud (Amazon EC2) instance that you use depends on whether you are training or running inference.

When training a model using the Object2Vec algorithm on a CPU, start with an ml.m5.2xlarge instance. For training on a GPU, start with an ml.p2.xlarge instance. If the training takes too long on this instance, you can use a larger instance. Currently, the Object2Vec algorithm can train only on a single machine. However, it does offer support for multiple GPUs. Object2Vec supports P2, P3, G4dn, and G5 GPU instance families for training and inference.

For inference with a trained Object2Vec model that has a deep neural network, we recommend using ml.p3.2xlarge GPU instance. Due to GPU memory scarcity, the `INJECTION_PREFERRED_MODE` environment variable can be specified to optimize on whether the section called “GPU optimization: Classification or Regression” (p. 2101) or the section called “GPU optimization: Encoder Embeddings” (p. 2102) inference network is loaded into GPU.

Object2Vec Sample Notebooks

- Using Object2Vec to Encode Sentences into Fixed Length Embeddings
- Using Object2Vec to learn document embeddings

Note

To run the notebooks on a notebook instance, see Example Notebooks (p. 306). To run the notebooks on Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133).

How Object2Vec Works

When using the Amazon SageMaker Object2Vec algorithm, you follow the standard workflow: process the data, train the model, and produce inferences.

Topics

- Step 1: Process Data (p. 2089)
- Step 2: Train a Model (p. 2089)
- Step 3: Produce Inferences (p. 2090)

Step 1: Process Data

During preprocessing, convert the data to the JSON Lines text file format specified in Data Formats for Object2Vec Training (p. 2101). To get the highest accuracy during training, also randomly shuffle the data before feeding it into the model. How you generate random permutations depends on the language. For python, you could use `np.random.shuffle`; for Unix, `shuf`.

Step 2: Train a Model

The SageMaker Object2Vec algorithm has the following main components:

- **Two input channels** – The input channels take a pair of objects of the same or different types as inputs, and pass them to independent and customizable encoders.
- **Two encoders** – The two encoders, enc0 and enc1, convert each object into a fixed-length embedding vector. The encoded embeddings of the objects in the pair are then passed into a comparator.
- **A comparator** – The comparator compares the embeddings in different ways and outputs scores that indicate the strength of the relationship between the paired objects. In the output score for a sentence pair. For example, 1 indicates a strong relationship between a sentence pair, and 0 represents a weak relationship.
During training, the algorithm accepts pairs of objects and their relationship labels or scores as inputs. The objects in each pair can be of different types, as described earlier. If the inputs to both encoders are composed of the same token-level units, you can use a shared token embedding layer by setting the `tied_token_embedding_weight` hyperparameter to `True` when you create the training job. This is possible, for example, when comparing sentences that both have word token-level units. To generate negative samples at a specified rate, set the `negative_sampling_rate` hyperparameter to the desired ratio of negative to positive samples. This hyperparameter expedites learning how to discriminate between the positive samples observed in the training data and the negative samples that are not likely to be observed.

Pairs of objects are passed through independent, customizable encoders that are compatible with the input types of corresponding objects. The encoders convert each object into a fixed-length embedding vector of equal length. The pair of vectors are passed to a comparator operator, which assembles the vectors into a single vector using the value specified in the `comparator_list` hyperparameter. The assembled vector then passes through a multilayer perceptron (MLP) layer, which produces an output that the loss function compares with the labels that you provided. This comparison evaluates the strength of the relationship between the objects in the pair as predicted by the model. The following figure shows this workflow.

![Architecture of the Object2Vec Algorithm from Data Inputs to Scores](image)

**Step 3: Produce Inferences**

After the model is trained, you can use the trained encoder to preprocess input objects or to perform two types of inference:

- To convert singleton input objects into fixed-length embeddings using the corresponding encoder
- To predict the relationship label or score between a pair of input objects

The inference server automatically figures out which of the types is requested based on the input data. To get the embeddings as output, provide only one input. To predict the relationship label or score, provide both inputs in the pair.
Object2Vec Hyperparameters

In the CreateTrainingJob request, you specify the training algorithm. You can also specify algorithm-specific hyperparameters as string-to-string maps. The following table lists the hyperparameters for the Object2Vec training algorithm.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>enc0_max_seq_len</td>
<td>The maximum sequence length for the enc0 encoder.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 1 ≤ integer ≤ 5000</td>
</tr>
<tr>
<td>enc0_vocab_size</td>
<td>The vocabulary size of enc0 tokens.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 2 ≤ integer ≤ 3000000</td>
</tr>
<tr>
<td>bucket_width</td>
<td>The allowed difference between data sequence length when bucketing is enabled.</td>
</tr>
<tr>
<td></td>
<td>To enable bucketing, specify a non-zero value for this parameter.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 ≤ integer ≤ 100</td>
</tr>
<tr>
<td></td>
<td>Default value: 0 (no bucketing)</td>
</tr>
<tr>
<td>comparator_list</td>
<td>A list used to customize the way in which two embeddings are compared. The</td>
</tr>
<tr>
<td></td>
<td>Object2Vec comparator operator layer takes the encodings from both encoders</td>
</tr>
<tr>
<td></td>
<td>as inputs and outputs a single vector. This vector is a concatenation of</td>
</tr>
<tr>
<td></td>
<td>subvectors. The string values passed to the comparator_list and the order</td>
</tr>
<tr>
<td></td>
<td>in which they are passed determine how these subvectors are assembled. For</td>
</tr>
<tr>
<td></td>
<td>example, if comparator_list=“hadamard, concat”, then the comparator</td>
</tr>
<tr>
<td></td>
<td>operator constructs the vector by concatenating the Hadamard product of</td>
</tr>
<tr>
<td></td>
<td>two encodings and the concatenation of two encodings.</td>
</tr>
<tr>
<td></td>
<td>If, on the other hand, comparator_list=&quot;hadamard&quot;, then the comparator</td>
</tr>
<tr>
<td></td>
<td>operator constructs the vector as the hadamard product of only two</td>
</tr>
<tr>
<td></td>
<td>encodings.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: A string that contains any combination of the names of the</td>
</tr>
<tr>
<td></td>
<td>three binary operators: hadamard, concat, or abs_diff. The Object2Vec</td>
</tr>
<tr>
<td></td>
<td>algorithm currently requires that the two vector encodings have the same</td>
</tr>
<tr>
<td></td>
<td>dimension. These operators produce the subvectors as follows:</td>
</tr>
<tr>
<td></td>
<td>• hadamard: Constructs a vector as the Hadamard (element-wise) product of</td>
</tr>
<tr>
<td></td>
<td>two encodings.</td>
</tr>
<tr>
<td></td>
<td>• concat: Constructs a vector as the concatenation of two encodings.</td>
</tr>
<tr>
<td></td>
<td>• abs_diff: Constructs a vector as the absolute difference between two</td>
</tr>
<tr>
<td></td>
<td>encodings.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;hadamard, concat, abs_diff&quot;</td>
</tr>
<tr>
<td>dropout</td>
<td>The dropout probability for network layers. Dropout is a form of regularization used in neural networks that reduces overfitting by trimming codependent neurons. Optional Valid values: 0.0 ≤ float ≤ 1.0 Default value: 0.0</td>
</tr>
<tr>
<td>early_stopping_patience</td>
<td>The number of consecutive epochs without improvement allowed before early stopping is applied. Improvement is defined by with the early_stopping_tolerance hyperparameter. Optional Valid values: 1 ≤ integer ≤ 5 Default value: 3</td>
</tr>
<tr>
<td>early_stopping_tolerance</td>
<td>The reduction in the loss function that an algorithm must achieve between consecutive epochs to avoid early stopping after the number of consecutive epochs specified in the early_stopping_patience hyperparameter concludes. Optional Valid values: 0.000001 ≤ float ≤ 0.1 Default value: 0.01</td>
</tr>
<tr>
<td>enc_dim</td>
<td>The dimension of the output of the embedding layer. Optional Valid values: 4 ≤ integer ≤ 10000 Default value: 4096</td>
</tr>
</tbody>
</table>
| enc0_network                  | The network model for the enc0 encoder. Optional Valid values: hcnn, bilstm, or pooled_embedding  
  • hcnn: A hierarchical convolutional neural network.  
  • bilstm: A bidirectional long short-term memory network (biLSTM), in which the signal propagates backward and forward in time. This is an appropriate recurrent neural network (RNN) architecture for sequential learning tasks.  
  • pooled_embedding: Averages the embeddings of all of the tokens in the input. Default value: hcnn |
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>enc0_cnn_filter_width</code></td>
<td>The filter width of the convolutional neural network (CNN) enc0 encoder.</td>
</tr>
<tr>
<td><strong>Conditional</strong></td>
<td>Valid values: 1 ≤ integer ≤ 9</td>
</tr>
<tr>
<td><strong>Default value:</strong></td>
<td>3</td>
</tr>
<tr>
<td><code>enc0_freeze_pretrained_embedding</code></td>
<td>Whether to freeze enc0 pretrained embedding weights.</td>
</tr>
<tr>
<td><strong>Conditional</strong></td>
<td>Valid values: True or False</td>
</tr>
<tr>
<td><strong>Default value:</strong></td>
<td>True</td>
</tr>
<tr>
<td><code>enc0_layers</code></td>
<td>The number of layers in the enc0 encoder.</td>
</tr>
<tr>
<td><strong>Conditional</strong></td>
<td>Valid values: auto or 1 ≤ integer ≤ 4</td>
</tr>
<tr>
<td>• For <code>hcnn</code>, auto means 4.</td>
<td></td>
</tr>
<tr>
<td>• For <code>bilstm</code>, auto means 1.</td>
<td></td>
</tr>
<tr>
<td>• For <code>pooled_embedding</code>, auto ignores the number of layers.</td>
<td></td>
</tr>
<tr>
<td><strong>Default value:</strong></td>
<td>auto</td>
</tr>
<tr>
<td><code>enc0_pretrained_embedding_file</code></td>
<td>The filename of the pretrained enc0 token embedding file in the auxiliary data channel.</td>
</tr>
<tr>
<td><strong>Conditional</strong></td>
<td>Valid values: String with alphanumeric characters, underscore, or period. [A-Za-z0-9_]</td>
</tr>
<tr>
<td><strong>Default value:</strong></td>
<td>&quot;&quot; (empty string)</td>
</tr>
<tr>
<td><code>enc0_token_embedding_dim</code></td>
<td>The output dimension of the enc0 token embedding layer.</td>
</tr>
<tr>
<td><strong>Conditional</strong></td>
<td>Valid values: 2 ≤ integer ≤ 1000</td>
</tr>
<tr>
<td><strong>Default value:</strong></td>
<td>300</td>
</tr>
<tr>
<td><code>enc0_vocab_file</code></td>
<td>The vocabulary file for mapping pretrained enc0 token embedding vectors to numerical vocabulary IDs.</td>
</tr>
<tr>
<td><strong>Conditional</strong></td>
<td>Valid values: String with alphanumeric characters, underscore, or period. [A-Za-z0-9_]</td>
</tr>
<tr>
<td><strong>Default value:</strong></td>
<td>&quot;&quot; (empty string)</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>enc1_network</td>
<td>The network model for the enc1 encoder. If you want the enc1 encoder to use the same network model as enc0, including the hyperparameter values, set the value to enc0.</td>
</tr>
<tr>
<td></td>
<td><strong>Note</strong></td>
</tr>
<tr>
<td></td>
<td>Even when the enc0 and enc1 encoder networks have symmetric architectures, you can't shared parameter values for these networks.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: enc0, hcnn, bilstm, or pooled_embedding</td>
</tr>
<tr>
<td></td>
<td>• enc0: The network model for the enc0 encoder.</td>
</tr>
<tr>
<td></td>
<td>• hcnn: A hierarchical convolutional neural network.</td>
</tr>
<tr>
<td></td>
<td>• bilstm: A bidirectional LSTM, in which the signal propagates backward and forward in time. This is an appropriate recurrent neural network (RNN) architecture for sequential learning tasks.</td>
</tr>
<tr>
<td></td>
<td>• pooled_embedding: The averages of the embeddings of all of the tokens in the input.</td>
</tr>
<tr>
<td></td>
<td>Default value: enc0</td>
</tr>
<tr>
<td>enc1_cnn_filter_width</td>
<td>The filter width of the CNN enc1 encoder.</td>
</tr>
<tr>
<td></td>
<td><strong>Conditional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 1 ≤ integer ≤ 9</td>
</tr>
<tr>
<td></td>
<td>Default value: 3</td>
</tr>
<tr>
<td>enc1_freeze_pretrained_embedding</td>
<td>Whether to freeze enc1 pretrained embedding weights.</td>
</tr>
<tr>
<td></td>
<td><strong>Conditional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: True or False</td>
</tr>
<tr>
<td></td>
<td>Default value: True</td>
</tr>
<tr>
<td>enc1_layers</td>
<td>The number of layers in the enc1 encoder.</td>
</tr>
<tr>
<td></td>
<td><strong>Conditional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto or 1 ≤ integer ≤ 4</td>
</tr>
<tr>
<td></td>
<td>• For hcnn, auto means 4.</td>
</tr>
<tr>
<td></td>
<td>• For bilstm, auto means 1.</td>
</tr>
<tr>
<td></td>
<td>• For pooled_embedding, auto ignores the number of layers.</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>enc1_max_seq_len</td>
<td>The maximum sequence length for the enc1 encoder.</td>
</tr>
<tr>
<td></td>
<td><strong>Conditional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $1 \leq \text{integer} \leq 5000$</td>
</tr>
<tr>
<td>enc1_pretrained_embedding_file</td>
<td>The name of the enc1 pretrained token embedding file in the auxiliary data channel.</td>
</tr>
<tr>
<td></td>
<td><strong>Conditional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String with alphanumeric characters, underscore, or period. [A-Za-z0-9_]</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;&quot; (empty string)</td>
</tr>
<tr>
<td>enc1_token_embedding_dim</td>
<td>The output dimension of the enc1 token embedding layer.</td>
</tr>
<tr>
<td></td>
<td><strong>Conditional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $2 \leq \text{integer} \leq 1000$</td>
</tr>
<tr>
<td></td>
<td>Default value: 300</td>
</tr>
<tr>
<td>enc1_vocab_file</td>
<td>The vocabulary file for mapping pretrained enc1 token embeddings to vocabulary IDs.</td>
</tr>
<tr>
<td></td>
<td><strong>Conditional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String with alphanumeric characters, underscore, or period. [A-Za-z0-9_]</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;&quot; (empty string)</td>
</tr>
<tr>
<td>enc1_vocab_size</td>
<td>The vocabulary size of enc0 tokens.</td>
</tr>
<tr>
<td></td>
<td><strong>Conditional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $2 \leq \text{integer} \leq 3000000$</td>
</tr>
<tr>
<td>epochs</td>
<td>The number of epochs to run for training.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $1 \leq \text{integer} \leq 100$</td>
</tr>
<tr>
<td></td>
<td>Default value: 30</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The learning rate for training.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $1.0 \times 10^{-6} \leq \text{float} \leq 1.0$</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0004</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The batch size that the dataset is split into for an optimizer during training.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $1 \leq \text{integer} \leq 10000$</td>
</tr>
<tr>
<td></td>
<td>Default value: 32</td>
</tr>
<tr>
<td>mlp_activation</td>
<td>The type of activation function for the multilayer perceptron (MLP) layer.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: tanh, relu, or linear</td>
</tr>
<tr>
<td></td>
<td>• tanh: Hyperbolic tangent</td>
</tr>
<tr>
<td></td>
<td>• relu: Rectified linear unit (ReLU)</td>
</tr>
<tr>
<td></td>
<td>• linear: Linear function</td>
</tr>
<tr>
<td></td>
<td>Default value: linear</td>
</tr>
<tr>
<td>mlp_dim</td>
<td>The dimension of the output from MLP layers.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $2 \leq \text{integer} \leq 10000$</td>
</tr>
<tr>
<td></td>
<td>Default value: 512</td>
</tr>
<tr>
<td>mlp_layers</td>
<td>The number of MLP layers in the network.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $0 \leq \text{integer} \leq 10$</td>
</tr>
<tr>
<td></td>
<td>Default value: 2</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>negative_sampling_rate</td>
<td>The ratio of negative samples, generated to assist in training the algorithm, to positive samples that are provided by users. Negative samples represent data that is unlikely to occur in reality and are labelled negatively for training. They facilitate training a model to discriminate between the positive samples observed and the negative samples that are not. To specify the ratio of negative samples to positive samples used for training, set the value to a positive integer. For example, if you train the algorithm on input data in which all of the samples are positive and set negative_sampling_rate to 2, the Object2Vec algorithm internally generates two negative samples per positive sample. If you don't want to generate or use negative samples during training, set the value to 0.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: $0 \leq \text{integer}$</td>
</tr>
<tr>
<td></td>
<td>Default value: 0 (off)</td>
</tr>
<tr>
<td>num_classes</td>
<td>The number of classes for classification training. Amazon SageMaker ignores this hyperparameter for regression problems.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: $2 \leq \text{integer} \leq 30$</td>
</tr>
<tr>
<td></td>
<td>Default value: 2</td>
</tr>
<tr>
<td>optimizer</td>
<td>The optimizer type.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: adadelta, adagrad, adam, sgd, or rmsprop.</td>
</tr>
<tr>
<td></td>
<td>• adadelta: A per-dimension learning rate method for gradient descent</td>
</tr>
<tr>
<td></td>
<td>• adagrad: The adaptive gradient algorithm</td>
</tr>
<tr>
<td></td>
<td>• adam: The adaptive moment estimation algorithm</td>
</tr>
<tr>
<td></td>
<td>• sgd: Stochastic gradient descent</td>
</tr>
<tr>
<td></td>
<td>• rmsprop: Root mean square propagation</td>
</tr>
<tr>
<td></td>
<td>Default value: adam</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>output_layer</td>
<td>The type of output layer where you specify that the task is regression or classification.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: softmax or mean_squared_error</td>
</tr>
<tr>
<td></td>
<td>• softmax: The Softmax function used for classification.</td>
</tr>
<tr>
<td></td>
<td>• mean_squared_error: The MSE used for regression.</td>
</tr>
<tr>
<td></td>
<td>Default value: softmax</td>
</tr>
<tr>
<td>tied_token_embedding_weight</td>
<td>Whether to use a shared embedding layer for both encoders. If the inputs to both encoders use the same token-level units, use a shared token embedding layer. For example, for a collection of documents, if one encoder encodes sentences and another encodes whole documents, you can use a shared token embedding layer. That's because both sentences and documents are composed of word tokens from the same vocabulary.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: True or False</td>
</tr>
<tr>
<td></td>
<td>Default value: False</td>
</tr>
<tr>
<td>token_embedding_storage_type</td>
<td>The mode of gradient update used during training: when the dense mode is used, the optimizer calculates the full gradient matrix for the token embedding layer even if most rows of the gradient are zero-valued. When sparse mode is used, the optimizer only stores rows of the gradient that are actually being used in the mini-batch. If you want the algorithm to perform lazy gradient updates, which calculate the gradients only in the non-zero rows and which speed up training, specify row_sparse. Setting the value to row_sparse constrains the values available for other hyperparameters, as follows:</td>
</tr>
<tr>
<td></td>
<td>• The optimizer hyperparameter must be set to adam, adagrad, or sgd. Otherwise, the algorithm throws a CustomerValueError.</td>
</tr>
<tr>
<td></td>
<td>• The algorithm automatically disables bucketing, setting the bucket_width hyperparameter to 0.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: dense or row_sparse</td>
</tr>
<tr>
<td></td>
<td>Default value: dense</td>
</tr>
</tbody>
</table>
### Tune an Object2Vec Model

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. For the objective metric, you use one of the metrics that the algorithm computes. Automatic model tuning searches the chosen hyperparameters to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see [Perform Automatic Model Tuning with SageMaker](p. 2436).

### Metrics Computed by the Object2Vec Algorithm

The Object2Vec algorithm has both classification and regression metrics. The `output_layer` type determines which metric you can use for automatic model tuning.

#### Regressor Metrics Computed by the Object2Vec Algorithm

The algorithm reports a mean squared error regressor metric, which is computed during testing and validation. When tuning the model for regression tasks, choose this metric as the objective.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test:mean_squared_error</td>
<td>Mean Square Error</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:mean_squared_error</td>
<td>Mean Square Error</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

#### Classification Metrics Computed by the Object2Vec Algorithm

The Object2Vec algorithm reports accuracy and cross-entropy classification metrics, which are computed during test and validation. When tuning the model for classification tasks, choose one of these as the objective.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test:accuracy</td>
<td>Accuracy</td>
<td>Maximize</td>
</tr>
<tr>
<td>test:cross_entropy</td>
<td>Cross-entropy</td>
<td>Minimize</td>
</tr>
<tr>
<td>validation:accuracy</td>
<td>Accuracy</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:cross_entropy</td>
<td>Cross-entropy</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

### Tunable Object2Vec Hyperparameters

You can tune the following hyperparameters for the Object2Vec algorithm.
<table>
<thead>
<tr>
<th>Hyperparameter Name</th>
<th>Hyperparameter Type</th>
<th>Recommended Ranges and Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>dropout</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 1.0</td>
</tr>
<tr>
<td>early_stopping_pat</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 5</td>
</tr>
<tr>
<td>early_stopping_tol</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.001, MaxValue: 0.1</td>
</tr>
<tr>
<td>enc_dim</td>
<td>IntegerParameterRange</td>
<td>MinValue: 4, MaxValue: 4096</td>
</tr>
<tr>
<td>enc0_cnn_filter_width</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 5</td>
</tr>
<tr>
<td>enc0_layers</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 4</td>
</tr>
<tr>
<td>enc0_token_embedding_dim</td>
<td>IntegerParameterRange</td>
<td>MinValue: 5, MaxValue: 300</td>
</tr>
<tr>
<td>enc1_cnn_filter_width</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 5</td>
</tr>
<tr>
<td>enc1_layers</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 4</td>
</tr>
<tr>
<td>enc1_token_embedding_dim</td>
<td>IntegerParameterRange</td>
<td>MinValue: 5, MaxValue: 300</td>
</tr>
<tr>
<td>epochs</td>
<td>IntegerParameterRange</td>
<td>MinValue: 4, MaxValue: 20</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-6, MaxValue: 1.0</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 8192</td>
</tr>
<tr>
<td>mlp_activation</td>
<td>CategoricalParameterRanges</td>
<td>[tanh, relu, linear]</td>
</tr>
<tr>
<td>mlp_dim</td>
<td>IntegerParameterRange</td>
<td>MinValue: 16, MaxValue: 1024</td>
</tr>
<tr>
<td>mlp_layers</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 4</td>
</tr>
<tr>
<td>optimizer</td>
<td>CategoricalParameterRanges</td>
<td>[adagrad, adam, rmsprop, sgd, adadelta]</td>
</tr>
<tr>
<td>weight_decay</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 1.0</td>
</tr>
</tbody>
</table>
Data Formats for Object2Vec Training

Input: JSON Lines Request Format

Content-type: application/jsonlines

```json
{"label": 0, "in0": [6, 17, 606, 19, 53, 67, 52, 12, 5, 10, 15, 10178, 7, 33, 652, 80, 15, 69, 821, 4], "in1": [16, 21, 13, 45, 14, 9, 80, 59, 164, 4]}
{"label": 1, "in0": [22, 1016, 32, 13, 25, 11, 5, 64, 573, 45, 5, 80, 15, 67, 21, 7, 9, 107, 4], "in1": [22, 32, 13, 25, 1016, 573, 3252, 4]}
{"label": 1, "in0": [774, 14, 21, 206], "in1": [21, 366, 125]}
```

The "in0" and "in1" are the inputs for encoder0 and encoder1, respectively. The same format is valid for both classification and regression problems. For regression, the field "label" can accept real valued inputs.

Data Formats for Object2Vec Inference

GPU optimization: Classification or Regression

Due to GPU memory scarcity, the INFERENC_PREFERRED_MODE environment variable can be specified to optimize on whether the classification/regression or the section called "Output: Encoder Embeddings" (p. 2103) inference network is loaded into GPU. If the majority of your inference is for classification or regression, specify INFERENC_PREFERRED_MODE=classification. The following is a Batch Transform example of using 4 instances of p3.2xlarge that optimizes for classification/regression inference:

```python
transformer = o2v.transformer(instance_count=4,
                              instance_type="ml.p2.xlarge",
                              max_concurrent_transforms=2,
                              max_payload=1, # 1MB
                              strategy='MultiRecord',
                              env={'INFERENCE_PREFERRED_MODE': 'classification'}, # only useful with GPU
                              output_path=output_s3_path)
```

Input: Classification or Regression Request Format

Content-type: application/json

```json
{
  "instances" : [
    {"in0": [6, 17, 606, 19, 53, 67, 52, 12, 5, 10, 15, 10178, 7, 33, 652, 80, 15, 69, 821, 4], "in1": [16, 21, 13, 45, 14, 9, 80, 59, 164, 4]},
    {"in0": [22, 1016, 32, 13, 25, 11, 5, 64, 573, 45, 5, 80, 15, 67, 21, 7, 9, 107, 4],
      "in1": [22, 32, 13, 25, 1016, 573, 3252, 4]},
    {"in0": [774, 14, 21, 206], "in1": [21, 366, 125]}
  ]
}
```

Content-type: application/jsonlines

```jsonlines
{"in0": [6, 17, 606, 19, 53, 67, 52, 12, 5, 10, 15, 10178, 7, 33, 652, 80, 15, 69, 821, 4], "in1": [16, 21, 13, 45, 14, 9, 80, 59, 164, 4]}
{"in0": [22, 1016, 32, 13, 25, 11, 5, 64, 573, 45, 5, 80, 15, 67, 21, 7, 9, 107, 4], "in1": [22, 32, 13, 25, 1016, 573, 3252, 4]}
{"in0": [774, 14, 21, 206], "in1": [21, 366, 125]}
```

For classification problems, the length of the scores vector corresponds to num_classes. For regression problems, the length is 1.
Output: Classification or Regression Response Format

Accept: application/json

```
{
    "predictions": [
        {
            "scores": [
                0.6533935070037842,
                0.07582679390907288,
                0.2707797586917877
            ],
        },
        {
            "scores": [
                0.026291321963071823,
                0.6577019095420837,
                0.31600672006607056
            ]
        }
    ]
}
```

Accept: application/jsonlines

```
{"scores":[0.195667684078216,0.395351558923721,0.408980727195739]}
{"scores":[0.251988261938095,0.258233487606048,0.489778339862823]}
{"scores":[0.280087798833847,0.368331134319305,0.351581096649169]}
```

In both the classification and regression formats, the scores apply to individual labels.

**Encoder Embeddings for Object2Vec**

**GPU optimization: Encoder Embeddings**

An embedding is a mapping from discrete objects, such as words, to vectors of real numbers.

Due to GPU memory scarcity, the `INFERENCE_PREFERRED_MODE` environment variable can be specified to optimize on whether the the section called "Inference Formats: Scoring" (p. 2101) or the encoder embedding inference network is loaded into GPU. If the majority of your inference is for encoder embeddings, specify `INFERENCE_PREFERRED_MODE=embedding`. The following is a Batch Transform example of using 4 instances of p3.2xlarge that optimizes for encoder embedding inference:

```
transformer = o2v.transformer(instance_count=4,
    instance_type="ml.p2.xlarge",
    max_concurrent_transforms=2,
    max_payload=1,  # 1MB
    strategy='MultiRecord',
    env={'INFERENCE_PREFERRED_MODE': 'embedding'},  # only useful with GPU
    output_path=output_s3_path)
```

**Input: Encoder Embeddings**

Content-type: application/json; infer_max_seqlen=<FWD-LENGTH>,<BCK-LENGTH>

Where `<FWD-LENGTH>` and `<BCK-LENGTH>` are integers in the range [1,5000] and define the maximum sequence lengths for the forward and backward encoder.

```
{
    "instances" : [
```
Use Built-in Algorithms

Amazon SageMaker developer guide provides built-in algorithms for various applications.

**Input/Output Interface for the Sequence-to-Sequence Algorithm**

This interface allows developers to connect their applications to SageMaker's sequence-to-sequence models.

**EC2 Instance Recommendation for the Sequence-to-Sequence Algorithm**

Guidance on choosing the appropriate EC2 instance type for running sequence-to-sequence models.

**Sequence-to-Sequence Sample Notebooks**

Examples and sample notebooks for developers to experiment with sequence-to-sequence algorithms.

---

Amazon SageMaker Sequence to Sequence is a supervised learning algorithm where the input is a sequence of tokens (for example, text, audio) and the output generated is another sequence of tokens. Example applications include: machine translation (input a sentence from one language and predict what that sentence would be in another language), text summarization (input a longer string of words and predict a shorter string of words that is a summary), speech-to-text (audio clips converted into output sentences in tokens). Recently, problems in this domain have been successfully modeled with deep neural networks that show a significant performance boost over previous methodologies. Amazon SageMaker seq2seq uses Recurrent Neural Networks (RNNs) and Convolutional Neural Network (CNN) models with attention as encoder-decoder architectures.

**Topics**

- Input/Output Interface for the Sequence-to-Sequence Algorithm (p. 2104)
- EC2 Instance Recommendation for the Sequence-to-Sequence Algorithm (p. 2105)
- Sequence-to-Sequence Sample Notebooks (p. 2105)
• How Sequence-to-Sequence Works (p. 2105)
• Sequence-to-Sequence Hyperparameters (p. 2106)
• Tune a Sequence-to-Sequence Model (p. 2114)

Input/Output Interface for the Sequence-to-Sequence Algorithm

Training

SageMaker seq2seq expects data in RecordIO-Protobuf format. However, the tokens are expected as integers, not as floating points, as is usually the case.

A script to convert data from tokenized text files to the protobuf format is included in the seq2seq example notebook. In general, it packs the data into 32-bit integer tensors and generates the necessary vocabulary files, which are needed for metric calculation and inference.

After preprocessing is done, the algorithm can be invoked for training. The algorithm expects three channels:

• **train**: It should contain the training data (for example, the train.rec file generated by the preprocessing script).
• **validation**: It should contain the validation data (for example, the val.rec file generated by the preprocessing script).
• **vocab**: It should contain two vocabulary files (vocab.src.json and vocab.trg.json)

If the algorithm doesn't find data in any of these three channels, training results in an error.

Inference

For hosted endpoints, inference supports two data formats. To perform inference using space separated text tokens, use the application/json format. Otherwise, use the recordio-protobuf format to work with the integer encoded data. Both modes support batching of input data. application/json format also allows you to visualize the attention matrix.

• **application/json**: Expects the input in JSON format and returns the output in JSON format. Both content and accept types should be application/json. Each sequence is expected to be a string with whitespace separated tokens. This format is recommended when the number of source sequences in the batch is small. It also supports the following additional configuration options:

  configuration: {attention_matrix: true}: Returns the attention matrix for the particular input sequence.

• **application/x-recordio-protobuf**: Expects the input in recordio-protobuf format and returns the output in recordio-protobuf format. Both content and accept types should be applications/x-recordio-protobuf. For this format, the source sequences must be converted into a list of integers for subsequent protobuf encoding. This format is recommended for bulk inference.

For batch transform, inference supports JSON Lines format. Batch transform expects the input in JSON Lines format and returns the output in JSON Lines format. Both content and accept types should be application/jsonlines. The format for input is as follows:

```
content-type: application/jsonlines

{"source": "source_sequence_0"}
{"source": "source_sequence_1"}
```

The format for response is as follows:
accept: application/jsonlines

{"target": "predicted_sequence_0"
{"target": "predicted_sequence_1"

For additional details on how to serialize and deserialize the inputs and outputs to specific formats for inference, see the Sequence-to-Sequence Sample Notebooks (p. 2105).

**EC2 Instance Recommendation for the Sequence-to-Sequence Algorithm**

The Amazon SageMaker seq2seq algorithm only supports on GPU instance types and can only train on a single machine. However, you can use instances with multiple GPUs. The seq2seq algorithm supports P2, P3, G4dn, and G5 GPU instance families.

**Sequence-to-Sequence Sample Notebooks**

For a sample notebook that shows how to use the SageMaker Sequence to Sequence algorithm to train a English-German translation model, see Machine Translation English-German Example Using SageMaker Seq2Seq. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. The topic modeling example notebooks using the NTM algorithms are located in the Introduction to Amazon algorithms section. To open a notebook, click on its Use tab and select Create copy.

**How Sequence-to-Sequence Works**

Typically, a neural network for sequence-to-sequence modeling consists of a few layers, including:

- **An embedding layer.** In this layer, the input matrix, which is input tokens encoded in a sparse way (for example, one-hot encoded) are mapped to a dense feature layer. This is required because a high-dimensional feature vector is more capable of encoding information regarding a particular token (word for text corpora) than a simple one-hot-encoded vector. It is also a standard practice to initialize this embedding layer with a pre-trained word vector like FastText or Glove or to initialize it randomly and learn the parameters during training.

- **An encoder layer.** After the input tokens are mapped into a high-dimensional feature space, the sequence is passed through an encoder layer to compress all the information from the input embedding layer (of the entire sequence) into a fixed-length feature vector. Typically, an encoder is made of RNN-type networks like long short-term memory (LSTM) or gated recurrent units (GRU). (Colah's blog explains LSTM in a great detail.)

- **A decoder layer.** The decoder layer takes this encoded feature vector and produces the output sequence of tokens. This layer is also usually built with RNN architectures (LSTM and GRU).

The whole model is trained jointly to maximize the probability of the target sequence given the source sequence. This model was first introduced by Sutskever et al. in 2014.

**Attention mechanism.** The disadvantage of an encoder-decoder framework is that model performance decreases as and when the length of the source sequence increases because of the limit of how much information the fixed-length encoded feature vector can contain. To tackle this problem, in 2015, Bahdanau et al. proposed the attention mechanism. In an attention mechanism, the decoder tries to find the location in the encoder sequence where the most important information could be located and uses that information and previously decoded words to predict the next token in the sequence.

For more in details, see the whitepaper Effective Approaches to Attention-based Neural Machine Translation by Luong, et al. that explains and simplifies calculations for various attention mechanisms. Additionally, the whitepaper Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation by Wu, et al. describes Google's architecture for machine translation, which uses skip connections between encoder and decoder layers.
Sequence-to-Sequence Hyperparameters

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch_size</td>
<td>Mini batch size for gradient descent.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: positive integer</td>
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<tr>
<td></td>
<td>Default value: 64</td>
</tr>
<tr>
<td>beam_size</td>
<td>Length of the beam for beam search. Used during training for computing bleu and used during inference.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: positive integer</td>
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<tr>
<td></td>
<td>Default value: 5</td>
</tr>
<tr>
<td>bleu_sample_size</td>
<td>Number of instances to pick from validation dataset to decode and compute bleu score during training. Set to -1 to use full validation set (if bleu is chosen as optimized_metric).</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: integer</td>
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<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>bucket_width</td>
<td>Returns (source,target) buckets up to (max_seq_len_source, max_seq_len_target). The longer side of the data uses steps of bucket_width while the shorter side uses steps scaled down by the average target/source length ratio. If one sided reaches its maximum length before the other, width of extra buckets on that side is fixed to that side of max_len.</td>
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<td></td>
<td><strong>Optional</strong></td>
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<td></td>
<td>Valid values: positive integer</td>
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<tr>
<td></td>
<td>Default value: 10</td>
</tr>
<tr>
<td>bucketing_enabled</td>
<td>Set to false to disable bucketing, unroll to maximum length.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: true or false</td>
</tr>
<tr>
<td></td>
<td>Default value: true</td>
</tr>
<tr>
<td>checkpoint_frequency_num_batches</td>
<td>Checkpoint and evaluate every x batches. This checkpointing hyperparameter is passed to the SageMaker's seq2seq algorithm for early stopping and retrieving the best model. The algorithm's checkpointing runs locally in the algorithm's training container and is not</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
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<tr>
<td>checkpoint_threshold</td>
<td>Maximum number of checkpoints model is allowed to not improve in optimized_metric on validation dataset before training is stopped. This checkpointing hyperparameter is passed to the SageMaker's seq2seq algorithm for early stopping and retrieving the best model. The algorithm's checkpointing runs locally in the algorithm's training container and is not compatible with SageMaker checkpointing. The algorithm temporarily saves checkpoints to a local path and stores the best model artifact to the model output path in S3 after the training job has stopped.</td>
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<td>Optional</td>
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<td>Valid values: positive integer</td>
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<td>Default value: 3</td>
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<tr>
<td>clip_gradient</td>
<td>Clip absolute gradient values greater than this. Set to negative to disable.</td>
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<tr>
<td></td>
<td>Optional</td>
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<td></td>
<td>Valid values: float</td>
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<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>cnn_activation_type</td>
<td>The cnn activation type to be used.</td>
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<tr>
<td></td>
<td>Optional</td>
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<tr>
<td></td>
<td>Valid values: String. One of glu, relu, softrelu, sigmoid, or tanh.</td>
</tr>
<tr>
<td></td>
<td>Default value: glu</td>
</tr>
<tr>
<td>cnn_hidden_dropout</td>
<td>Dropout probability for dropout between convolutional layers.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
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<td></td>
<td>Valid values: Float. Range in [0,1].</td>
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<td>Default value: 0</td>
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<td>Parameter Name</td>
<td>Description</td>
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<tr>
<td>cnn_kernel_width_decoder</td>
<td>Kernel width for the cnn decoder.</td>
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<td></td>
<td>Optional</td>
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<td></td>
<td>Valid values: positive integer</td>
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<td>Default value: 5</td>
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<tr>
<td>cnn_kernel_width_encoder</td>
<td>Kernel width for the cnn encoder.</td>
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<td>Optional</td>
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<td></td>
<td>Valid values: positive integer</td>
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<td></td>
<td>Default value: 3</td>
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<tr>
<td>cnn_num_hidden</td>
<td>Number of cnn hidden units for encoder and decoder.</td>
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<td></td>
<td>Optional</td>
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<td></td>
<td>Valid values: positive integer</td>
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<td></td>
<td>Default value: 512</td>
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<tr>
<td>decoder_type</td>
<td>Decoder type.</td>
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<td></td>
<td>Optional</td>
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<td></td>
<td>Valid values: String. Either rnn or cnn.</td>
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<td></td>
<td>Default value: rnn</td>
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<tr>
<td>embed_dropout_source</td>
<td>Dropout probability for source side embeddings.</td>
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<tr>
<td></td>
<td>Optional</td>
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<td></td>
<td>Valid values: Float. Range in [0,1].</td>
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<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>embed_dropout_target</td>
<td>Dropout probability for target side embeddings.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
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<tr>
<td></td>
<td>Valid values: Float. Range in [0,1].</td>
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<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>encoder_type</td>
<td>Encoder type. The rnn architecture is based on attention mechanism by Bahdanau et al. and cnn architecture is based on Gehring et al.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
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<td></td>
<td>Valid values: String. Either rnn or cnn.</td>
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<tr>
<td></td>
<td>Default value: rnn</td>
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<tr>
<td>Parameter Name</td>
<td>Description</td>
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</tr>
<tr>
<td>fixed_rate_lr_half_life</td>
<td>Half life for learning rate in terms of number of checkpoints for fixed_rate_* schedulers.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
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<td></td>
<td>Valid values: positive integer</td>
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<td></td>
<td>Default value: 10</td>
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<tr>
<td>learning_rate</td>
<td>Initial learning rate.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: float</td>
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<td></td>
<td>Default value: 0.0003</td>
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<tr>
<td>loss_type</td>
<td>Loss function for training.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: String. cross-entropy</td>
</tr>
<tr>
<td></td>
<td>Default value: cross-entropy</td>
</tr>
<tr>
<td>lr_scheduler_type</td>
<td>Learning rate scheduler type. plateau_reduce means reduce the learning rate whenever optimized_metric on validation_accuracy plateaus. inv_t is inverse time decay. learning_rate/(1+decay_rate*t)</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. One of plateau_reduce, fixed_rate_inv_t, or fixed_rate_inv_sqrt_t.</td>
</tr>
<tr>
<td></td>
<td>Default value: plateau_reduce</td>
</tr>
<tr>
<td>max_num_batches</td>
<td>Maximum number of updates/batches to process. -1 for infinite.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: integer</td>
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<tr>
<td></td>
<td>Default value: -1</td>
</tr>
<tr>
<td>max_num_epochs</td>
<td>Maximum number of epochs to pass through training data before fitting is stopped. Training continues until this number of epochs even if validation accuracy is not improving if this parameter is passed. Ignored if not passed.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: Positive integer and less than or equal to max_num_epochs.</td>
</tr>
<tr>
<td></td>
<td>Default value: none</td>
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<tr>
<td>Parameter Name</td>
<td>Description</td>
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</tr>
<tr>
<td>max_seq_len_source</td>
<td>Maximum length for the source sequence length. Sequences longer than this length are truncated to this length.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: positive integer</td>
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<tr>
<td></td>
<td>Default value: 100</td>
</tr>
<tr>
<td>max_seq_len_target</td>
<td>Maximum length for the target sequence length. Sequences longer than this length are truncated to this length.</td>
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<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: positive integer</td>
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<tr>
<td></td>
<td>Default value: 100</td>
</tr>
<tr>
<td>min_num_epochs</td>
<td>Minimum number of epochs the training must run before it is stopped via early_stopping conditions.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<td></td>
<td>Valid values: positive integer</td>
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<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>momentum</td>
<td>Momentum constant used for sgd. Don't pass this parameter if you are using adam or rmsprop.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: float</td>
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<tr>
<td></td>
<td>Default value: none</td>
</tr>
<tr>
<td>num_embed_source</td>
<td>Embedding size for source tokens.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: positive integer</td>
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<tr>
<td></td>
<td>Default value: 512</td>
</tr>
<tr>
<td>num_embed_target</td>
<td>Embedding size for target tokens.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<td></td>
<td>Valid values: positive integer</td>
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<td>Default value: 512</td>
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<tr>
<td>Parameter Name</td>
<td>Description</td>
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<tr>
<td><code>num_layers_decoder</code></td>
<td>Number of layers for Decoder \textit{rnn} or \textit{cnn}.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<td></td>
<td>Valid values: positive integer</td>
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<td></td>
<td>Default value: 1</td>
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<tr>
<td><code>num_layers_encoder</code></td>
<td>Number of layers for Encoder \textit{rnn} or \textit{cnn}.</td>
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<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: positive integer</td>
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<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td><code>optimized_metric</code></td>
<td>Metrics to optimize with early stopping.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: String. One of perplexity, accuracy, or bleu.</td>
</tr>
<tr>
<td></td>
<td>Default value: perplexity</td>
</tr>
<tr>
<td><code>optimizer_type</code></td>
<td>Optimizer to choose from.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: String. One of adam, sgd, or rmsprop.</td>
</tr>
<tr>
<td></td>
<td>Default value: adam</td>
</tr>
<tr>
<td><code>plateau_reduce_lr_factor</code></td>
<td>Factor to multiply learning rate with (for plateau_reduce).</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: float</td>
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<tr>
<td></td>
<td>Default value: 0.5</td>
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<tr>
<td><code>plateau_reduce_lr_threshold</code></td>
<td>For plateau_reduce scheduler, multiply learning rate with reduce factor if</td>
</tr>
<tr>
<td></td>
<td>\textit{optimized_metric} didn't improve for this many checkpoints.</td>
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<tr>
<td></td>
<td><strong>Optional</strong></td>
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<tr>
<td></td>
<td>Valid values: positive integer</td>
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<td>Default value: 3</td>
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<tr>
<td>Parameter Name</td>
<td>Description</td>
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<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><code>rnn_attention_in_upper_layers</code></td>
<td>Pass the attention to upper layers of <code>rnn</code>, like Google NMT paper. Only applicable if more than one layer is used.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: boolean (true or false)</td>
</tr>
<tr>
<td></td>
<td>Default value: true</td>
</tr>
<tr>
<td><code>rnn_attention_num_hidden</code></td>
<td>Number of hidden units for attention layers. defaults to <code>rnn_num_hidden</code>.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>rnn_num_hidden</code></td>
</tr>
<tr>
<td><code>rnn_attention_type</code></td>
<td>Attention model for encoders. <code>mlp</code> refers to concat and <code>bilinear</code> refers to general from the Luong et al. paper.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. One of <code>dot</code>, <code>fixed</code>, <code>mlp</code>, or <code>bilinear</code>.</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>mlp</code></td>
</tr>
<tr>
<td><code>rnn_cell_type</code></td>
<td>Specific type of <code>rnn</code> architecture.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. Either <code>lstm</code> or <code>gru</code>.</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>lstm</code></td>
</tr>
<tr>
<td><code>rnn_decoder_state_init</code></td>
<td>How to initialize <code>rnn</code> decoder states from encoders.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. One of <code>last</code>, <code>avg</code>, or <code>zero</code>.</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>last</code></td>
</tr>
<tr>
<td><code>rnn_first_residual_layer</code></td>
<td>First <code>rnn</code> layer to have a residual connection, only applicable if number of layers in encoder or decoder is more than 1.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 2</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><code>rnn_num_hidden</code></td>
<td>The number of <code>rnn</code> hidden units for encoder and decoder. This must be a multiple of 2 because the algorithm uses bi-directional Long Term Short Term Memory (LSTM) by default.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive even integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 1024</td>
</tr>
<tr>
<td><code>rnn_residual_connections</code></td>
<td>Add residual connection to stacked <code>rnn</code>. Number of layers should be more than 1.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: boolean (<code>true</code> or <code>false</code>)</td>
</tr>
<tr>
<td></td>
<td>Default value: false</td>
</tr>
<tr>
<td><code>rnn_decoder_hidden_dropout</code></td>
<td>Dropout probability for hidden state that combines the context with the <code>rnn</code> hidden state in the decoder.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range in <code>[0,1]</code>.</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td><code>training_metric</code></td>
<td>Metrics to track on training on validation data.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. Either <code>perplexity</code> or <code>accuracy</code>.</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>perplexity</code></td>
</tr>
<tr>
<td><code>weight_decay</code></td>
<td>Weight decay constant.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td><code>weight_init_scale</code></td>
<td>Weight initialization scale (for uniform and xavier initialization).</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float</td>
</tr>
<tr>
<td></td>
<td>Default value: 2.34</td>
</tr>
</tbody>
</table>
## Tune a Sequence-to-Sequence Model

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

### Metrics Computed by the Sequence-to-Sequence Algorithm

The sequence to sequence algorithm reports three metrics that are computed during training. Choose one of them as an objective to optimize when tuning the hyperparameter values.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>validation:accuracy</td>
<td>Accuracy computed on the validation dataset.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:bleu</td>
<td><strong>Bleu</strong> score computed on the validation dataset. Because BLEU computation is expensive, you can choose to compute BLEU on a random subsample of the validation dataset to speed up the overall training process. Use the <code>bleu_sample_size</code> parameter to specify the subsample.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:perplexity</td>
<td><strong>Perplexity</strong>, is a loss function computed on the validation dataset. Perplexity measures the cross-entropy between an empirical sample and the distribution predicted by a model and so provides a measure of how well a model predicts the sample values, Models that are good at predicting a sample have a low perplexity.</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

### Tunable Sequence-to-Sequence Hyperparameters

You can tune the following hyperparameters for the SageMaker Sequence to Sequence algorithm. The hyperparameters that have the greatest impact on sequence to sequence objective are:

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>weight_init_type</td>
<td>Type of weight initialization.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. Either <code>uniform</code> or <code>xavier</code>.</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>xavier</code></td>
</tr>
<tr>
<td>xavier_factor_type</td>
<td>Xavier factor type.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String. One of <code>in</code>, <code>out</code>, or <code>avg</code>.</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>in</code></td>
</tr>
</tbody>
</table>
metrics are: batch_size, optimizer_type, learning_rate, num_layers_encoder, and num_layers_decoder.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_layers_encoder</td>
<td>IntegerParameterRange</td>
<td>[1-10]</td>
</tr>
<tr>
<td>num_layers_decoder</td>
<td>IntegerParameterRange</td>
<td>[1-10]</td>
</tr>
<tr>
<td>batch_size</td>
<td>CategoricalParameterRange</td>
<td>[16,32,64,128,256,512,1024,2048]</td>
</tr>
<tr>
<td>optimizer_type</td>
<td>CategoricalParameterRange</td>
<td>['adam', 'sgd', 'rmsprop']</td>
</tr>
<tr>
<td>weight_init_type</td>
<td>CategoricalParameterRange</td>
<td>['xavier', 'uniform']</td>
</tr>
<tr>
<td>weight_init_scale</td>
<td>ContinuousParameterRange</td>
<td>For the xavier type: MinValue: 2.0, MaxValue: 3.0 For the uniform type: MinValue: -1.0, MaxValue: 1.0</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.00005, MaxValue: 0.2</td>
</tr>
<tr>
<td>weight_decay</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 0.1</td>
</tr>
<tr>
<td>momentum</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.5, MaxValue: 0.9</td>
</tr>
<tr>
<td>clip_gradient</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1.0, MaxValue: 5.0</td>
</tr>
<tr>
<td>rnn_num_hidden</td>
<td>CategoricalParameterRange</td>
<td>Applicable only to recurrent neural networks (RNNs). [128,256,512,1024,2048]</td>
</tr>
<tr>
<td>cnn_num_hidden</td>
<td>CategoricalParameterRange</td>
<td>Applicable only to convolutional neural networks (CNNs). [128,256,512,1024,2048]</td>
</tr>
<tr>
<td>num_embed_source</td>
<td>IntegerParameterRange</td>
<td>[256-512]</td>
</tr>
<tr>
<td>num_embed_target</td>
<td>IntegerParameterRange</td>
<td>[256-512]</td>
</tr>
<tr>
<td>embed_dropout_source</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 0.5</td>
</tr>
<tr>
<td>embed_dropout_target</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 0.5</td>
</tr>
<tr>
<td>rnn_decoder_hidden_dropout</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 0.5</td>
</tr>
<tr>
<td>cnn_hidden_dropout</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 0.5</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Parameter Type</td>
<td>Recommended Ranges</td>
</tr>
<tr>
<td>------------------------</td>
<td>----------------------------</td>
<td>--------------------------------------------------------</td>
</tr>
<tr>
<td>lr_scheduler_type</td>
<td>CategoricalParameterRange</td>
<td>['plateau_reduce', 'fixed_rate_inv_t', 'fixed_rate_inv_sqrt_t']</td>
</tr>
<tr>
<td>plateau_reduce_lr_factor</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.1, MaxValue: 0.5</td>
</tr>
<tr>
<td>plateau_reduce_lr_threshold</td>
<td>IntegerParameterRange</td>
<td>[1-5]</td>
</tr>
<tr>
<td>fixed_rate_lr_half_life</td>
<td>IntegerParameterRange</td>
<td>[10-30]</td>
</tr>
</tbody>
</table>

**Text Classification - TensorFlow**

The Amazon SageMaker Text Classification - TensorFlow algorithm is a supervised learning algorithm that supports transfer learning with many pretrained models from the TensorFlow Hub. Use transfer learning to fine-tune one of the available pretrained models on your own dataset, even if a large amount of text data is not available. The text classification algorithm takes a text string as input and outputs a probability for each of the class labels. Training datasets must be in CSV format.

**Topics**
- How to use the SageMaker Text Classification - TensorFlow algorithm (p. 2116)
- Input and output interface for the Text Classification - TensorFlow algorithm (p. 2117)
- Amazon EC2 instance recommendation for the Text Classification - TensorFlow algorithm (p. 2118)
- Text Classification - TensorFlow sample notebooks (p. 2119)
- How Text Classification - TensorFlow Works (p. 2119)
- TensorFlow Hub Models (p. 2119)
- Text Classification - TensorFlow Hyperparameters (p. 2122)
- Tune a Text Classification - TensorFlow model (p. 2125)

**How to use the SageMaker Text Classification - TensorFlow algorithm**

You can use Text Classification - TensorFlow as an Amazon SageMaker built-in algorithm. The following section describes how to use Text Classification - TensorFlow with the SageMaker Python SDK. For information on how to use Text Classification - TensorFlow from the Amazon SageMaker Studio UI, see SageMaker JumpStart (p. 45).

The Text Classification - TensorFlow algorithm supports transfer learning using any of the compatible pretrained TensorFlow models. For a list of all available pretrained models, see TensorFlow Hub Models (p. 2119). Every pretrained model has a unique model_id. The following example uses BERT Base Uncased (model_id: tensorflow-tc-bert-en-uncased-L-12-H-768-A-12-2) to fine-tune on a custom dataset. The pretrained models are all pre-downloaded from the TensorFlow Hub and stored in Amazon S3 buckets so that training jobs can run in network isolation. Use these pre-generated model training artifacts to construct a SageMaker Estimator.

First, retrieve the Docker image URI, training script URI, and pretrained model URI. Then, change the hyperparameters as you see fit. You can see a Python dictionary of all available hyperparameters and their default values with hyperparameters.retrieve_default. For more information, see Text Classification - TensorFlow Hyperparameters (p. 2122). Use these values to construct a SageMaker Estimator.

**Note**
Default hyperparameter values are different for different models. For example, for larger models, the default batch size is smaller.
This example uses the SST2 dataset, which contains positive and negative movie reviews. We pre-downloaded the dataset and made it available with Amazon S3. To fine-tune your model, call .fit using the Amazon S3 location of your training dataset.

```python
from sagemaker import image_uris, model_uris, script_uris, hyperparameters
from sagemaker.estimator import Estimator

model_id, model_version = "tensorflow-tc-bert-en-uncased-L-12-H-768-A-12-2", "*
training_instance_type = "ml.p3.2xlarge"

# Retrieve the Docker image
train_image_uri =
    image_uris.retrieve(model_id=model_id, model_version=model_version, image_scope="training", instance_type=training_instance_type)

# Retrieve the training script
train_source_uri = script_uris.retrieve(model_id=model_id, model_version=model_version,
    script_scope="training")

# Retrieve the pretrained model tarball for transfer learning
train_model_uri = model_uris.retrieve(model_id=model_id, model_version=model_version,
    model_scope="training")

# Retrieve the default hyperparameters for fine-tuning the model
hyperparameters = hyperparameters.retrieve_default(model_id=model_id,
    model_version=model_version)

# [Optional] Override default hyperparameters with custom values
hyperparameters["epochs"] = "5"

# Sample training data is available in this bucket
training_data_bucket = f"jumpstart-cache-prod-{aws_region}"
training_data_prefix = "training-datasets/SST2/"

training_dataset_s3_path = f"s3://{training_data_bucket}/{training_data_prefix}"

output_bucket = sess.default_bucket()
output_prefix = "jumpstart-example-tc-training"
s3_output_location = f"s3://{output_bucket}/{output_prefix}/output"

# Create an Estimator instance
tf_tc_estimator = Estimator(  
    role=aws_role,  
    image_uri=train_image_uri,  
    source_dir=train_source_uri,  
    model_uri=train_model_uri,  
    entry_point="transfer_learning.py",  
    instance_count=1,  
    instance_type=training_instance_type,  
    max_run=360000,  
    hyperparameters=hyperparameters,  
    output_path=s3_output_location,
)

# Launch a training job
tf_tc_estimator.fit({"training": training_dataset_s3_path}, logs=True)
```

For more information about how to use the SageMaker Text Classification - TensorFlow algorithm for transfer learning on a custom dataset, see the Introduction to JumpStart - Text Classification notebook.

**Input and output interface for the Text Classification - TensorFlow algorithm**

Each of the pretrained models listed in TensorFlow Hub Models can be fine-tuned to any dataset made up of text sentences with any number of classes. The pretrained model attaches a classification layer to
the Text Embedding model and initializes the layer parameters to random values. The output dimension of the classification layer is determined based on the number of classes detected in the input data.

Be mindful of how to format your training data for input to the Text Classification - TensorFlow model.

• **Training data input format:** A directory containing a data.csv file. Each row of the first column should have integer class labels between 0 and the number of classes. Each row of the second column should have the corresponding text data.

The following is an example of an input CSV file. Note that the file should not have any header. The file should be hosted in an Amazon S3 bucket with a path similar to the following: s3://bucket_name/input_directory/. Note that the trailing / is required.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>hide new secretions from the parental units</td>
</tr>
<tr>
<td>0</td>
<td>contains no wit, only labored gags</td>
</tr>
<tr>
<td>1</td>
<td>that loves its characters and communicates something rather beautiful about human nature</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
</tbody>
</table>

**Incremental training**

You can seed the training of a new model with artifacts from a model that you trained previously with SageMaker. Incremental training saves training time when you want to train a new model with the same or similar data.

**Note**

You can only seed a SageMaker Text Classification - TensorFlow model with another Text Classification - TensorFlow model trained in SageMaker.

You can use any dataset for incremental training, as long as the set of classes remains the same. The incremental training step is similar to the fine-tuning step, but instead of starting with a pretrained model, you start with an existing fine-tuned model.

For more information on using incremental training with the SageMaker Text Classification - TensorFlow algorithm, see the [Introduction to JumpStart - Text Classification](https://sagemaker.amazon.com) sample notebook.

**Inference with the Text Classification - TensorFlow algorithm**

You can host the fine-tuned model that results from your TensorFlow Text Classification training for inference. Any raw text formats for inference must be content type application/x-text.

Running inference results in probability values, class labels for all classes, and the predicted label corresponding to the class index with the highest probability encoded in JSON format. The Text Classification - TensorFlow model processes a single string per request and outputs only one line. The following is an example of a JSON format response:

```json
accept: application/json;verbose

{"probabilities": [prob_0, prob_1, prob_2, ...],
 "labels": [label_0, label_1, label_2, ...],
 "predicted_label": predicted_label}
```

If `accept` is set to `application/json`, then the model only outputs probabilities.

**Amazon EC2 instance recommendation for the Text Classification - TensorFlow algorithm**

The Text Classification - TensorFlow algorithm supports all CPU and GPU instances for training, including:
We recommend GPU instances with more memory for training with large batch sizes. Both CPU (such as M5) and GPU (P2, P3, G4dn, or G5) instances can be used for inference. For a comprehensive list of SageMaker training and inference instances across AWS Regions, see Amazon SageMaker Pricing.

Text Classification - TensorFlow sample notebooks

For more information about how to use the SageMaker Text Classification - TensorFlow algorithm for transfer learning on a custom dataset, see the Introduction to JumpStart - Text Classification notebook.

For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. To open a notebook, choose its Use tab and choose Create copy.

How Text Classification - TensorFlow Works

The Text Classification - TensorFlow algorithm takes text as classifies it into one of the output class labels. Various deep learning networks such as MobileNet, ResNet, Inception, and EfficientNet are highly accurate for text classification. There are also deep learning networks that are trained on large text datasets, such as TextNet, which has more than 11 million texts with about 11,000 categories. After a network is trained with TextNet data, you can then fine-tune the network on a dataset with a particular focus to perform more specific text classification tasks. The Amazon SageMaker Text Classification - TensorFlow algorithm supports transfer learning on many pretrained models that are available in the TensorFlow Hub.

According to the number of class labels in your training data, a text classification layer is attached to the pretrained TensorFlow model of your choice. The classification layer consists of a dropout layer, a dense layer, and a fully connected layer with 2-norm regularization, and is initialized with random weights. You can change the hyperparameter values for the dropout rate of the dropout layer and the L2 regularization factor for the dense layer.

You can fine-tune either the entire network (including the pretrained model) or only the top classification layer on new training data. With this method of transfer learning, training with smaller datasets is possible.

TensorFlow Hub Models

The following pretrained models are available to use for transfer learning with the Text Classification - TensorFlow algorithm.

The following models vary significantly in size, number of model parameters, training time, and inference latency for any given dataset. The best model for your use case depends on the complexity of your fine-tuning dataset and any requirements that you have on training time, inference latency, or model accuracy.
<table>
<thead>
<tr>
<th>Model Name</th>
<th>model_id</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERT Base Uncased</td>
<td>tensorflow-tc-bert-en-uncased-L-12-H-768-A-12-2</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>BERT Base Cased</td>
<td>tensorflow-tc-bert-uncased-L-12-H-768-A-12-2</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>BERT Base Multilingual Cased</td>
<td>tensorflow-tc-bert-multi-cased-L-12-H-768-A-12-2</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Small BERT L-4_H-256_A-4</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-4-H-256-A-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Small BERT L-4_H-768_A-12</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-4-H-768-A-12</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Small BERT L-6_H-256_A-4</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-6-H-256-A-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Model Name</td>
<td>model_id</td>
<td>Source</td>
</tr>
<tr>
<td>-----------------------</td>
<td>---------------------------------------------------------------------------</td>
<td>-----------------------------</td>
</tr>
<tr>
<td>Small BERT L-6_H-768_A-12</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-6-H-768-A-12</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Small BERT L-8_H-768_A-12</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-8-H-768-A-12</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Small BERT L-10_H-256_A-4</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-10-H-256-A-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Small BERT L-10_H-768_A-12</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-10-H-768-A-12</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Small BERT L-12_H-256_A-4</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-12-H-256-A-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Small BERT L-12_H-768_A-12</td>
<td>tensorflow-tc-small-bert-bert-en-uncased-L-12-H-768-A-12</td>
<td>TensorFlow Hub link</td>
</tr>
</tbody>
</table>
Amazon SageMaker Developer Guide
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Model Name</th>
<th>model_id</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>BERT Large Cased</td>
<td>tensorflow-tc-bert-en-cased-L-24-H-1024-A-16-2</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>ALBERT Base</td>
<td>tensorflow-tc-albert-en-base</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>ELECTRA Small++</td>
<td>tensorflow-tc-electra-small-1</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>ELECTRA Base</td>
<td>tensorflow-tc-electra-base-1</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>BERT Base Wikipedia and BooksCorpus</td>
<td>tensorflow-tc-experts-bert-wiki-books-1</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>BERT Base MEDLINE/PubMed</td>
<td>tensorflow-tc-experts-bert-pubmed-1</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Talking Heads Base</td>
<td>tensorflow-tc-talking-heads-base</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Talking Heads Large</td>
<td>tensorflow-tc-talking-heads-large</td>
<td>TensorFlow Hub link</td>
</tr>
</tbody>
</table>

Text Classification - TensorFlow Hyperparameters

Hyperparameters are parameters that are set before a machine learning model begins learning. The following hyperparameters are supported by the Amazon SageMaker built-in Object Detection - TensorFlow algorithm. See Tune a Text Classification - TensorFlow model (p. 2125) for information on hyperparameter tuning.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch_size</td>
<td>The batch size for training. For training on instances with multiple GPUs, this batch size is used across the GPUs. Valid values: positive integer. Default value: 32.</td>
</tr>
<tr>
<td>beta_1</td>
<td>The beta1 for the &quot;adam&quot; and &quot;adamw&quot; optimizers. Represents the exponential decay rate for the first moment estimates. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.9.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| beta_2              | The beta2 for the "adam" and "adamw" optimizers. Represents the exponential decay rate for the second moment estimates. Ignored for other optimizers.  
                   | Valid values: float, range: [0.0, 1.0].  
                   | Default value: 0.999.                                                                                                                                                                                                                                                                                                                                          |
| dropout_rate        | The dropout rate for the dropout layer in the top classification layer. Used only when reinitialize_top_layer is set to "True".  
                   | Valid values: float, range: [0.0, 1.0].  
                   | Default value: 0.2                                                                                                                                                                                                                                                                                                                                             |
| early_stopping      | Set to "True" to use early stopping logic during training. If "False", early stopping is not used.  
                   | Valid values: string, either: ("True" or "False").  
                   | Default value: "False".                                                                                                                                                                                                                                                                                                                                       |
| early_stopping_min_delta | The minimum change needed to qualify as an improvement. An absolute change less than the value of early_stopping_min_delta does not qualify as improvement. Used only when early_stopping is set to "True".  
                   | Valid values: float, range: [0.0, 1.0].  
                   | Default value: 0.0.                                                                                                                                                                                                                                                                                                                                             |
| early_stopping_patience | The number of epochs to continue training with no improvement. Used only when early_stopping is set to "True".  
                   | Valid values: positive integer.  
                   | Default value: 5.                                                                                                                                                                                                                                                                                                                                               |
| epochs              | The number of training epochs.  
                   | Valid values: positive integer.  
                   | Default value: 10.                                                                                                                                                                                                                                                                                                                                               |
| epsilon             | The epsilon for "adam", "rmsprop", "adadelta", and "adagrad" optimizers. Usually set to a small value to avoid division by 0. Ignored for other optimizers.  
                   | Valid values: float, range: [0.0, 1.0].  
<pre><code>               | Default value: 1e-7.                                                                                                                                                                                                                                                                                                                                           |
</code></pre>
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>initial_accumulator_value</td>
<td>The starting value for the accumulators, or the per-parameter momentum values, for the &quot;adagrad&quot; optimizer. Ignored for other optimizers.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0001.</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The optimizer learning rate.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.001.</td>
</tr>
<tr>
<td>momentum</td>
<td>The momentum for the &quot;sgd&quot; and &quot;nesterov&quot; optimizers. Ignored for other optimizers.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.9.</td>
</tr>
<tr>
<td>optimizer</td>
<td>The optimizer type. For more information, see Optimizers in the TensorFlow documentation.</td>
</tr>
<tr>
<td></td>
<td>Valid values: string, any of the following: (&quot;adamw&quot;, &quot;adam&quot;, &quot;sgd&quot;, &quot;nesterov&quot;, &quot;rmsprop&quot;, &quot;adagrad&quot;, &quot;adadelta&quot;).</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;adam&quot;.</td>
</tr>
<tr>
<td>regularizers_l2</td>
<td>The L2 regularization factor for the dense layer in the classification layer. Used only when reinitialize_top_layer is set to &quot;True&quot;.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0001.</td>
</tr>
<tr>
<td>reinitialize_top_layer</td>
<td>If set to &quot;Auto&quot;, the top classification layer parameters are re-initialized during fine-tuning. For incremental training, top classification layer parameters are not re-initialized unless set to &quot;True&quot;.</td>
</tr>
<tr>
<td></td>
<td>Valid values: string, any of the following: (&quot;Auto&quot;, &quot;True&quot; or &quot;False&quot;).</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;Auto&quot;.</td>
</tr>
<tr>
<td>rho</td>
<td>The discounting factor for the gradient of the &quot;adadelta&quot; and &quot;rmsprop&quot; optimizers. Ignored for other optimizers.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.95.</td>
</tr>
</tbody>
</table>
### Parameter Name | Description
--- | ---
`train_only_on_top_layer` | If "True", only the top classification layer parameters are fine-tuned. If "False", all model parameters are fine-tuned.
Valid values: string, either: ("True" or "False").
Default value: "False".

`validation_split_ratio` | The fraction of training data to randomly split to create validation data. Only used if validation data is not provided through the validation channel.
Valid values: float, range: [0.0, 1.0].
Default value: 0.2.

`warmup_steps_fraction` | The fraction of the total number of gradient update steps, where the learning rate increases from 0 to the initial learning rate as a warm up. Only used with the adamw optimizer.
Valid values: float, range: [0.0, 1.0].
Default value: 0.1.

---

**Tune a Text Classification - TensorFlow model**

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see *Perform Automatic Model Tuning with SageMaker* (p. 2436).

**Metrics computed by the Text Classification - TensorFlow algorithm**

Refer to the following chart to find which metrics are computed by the Text Classification - TensorFlow algorithm.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
<th>Regex Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>validation:accuracy</code></td>
<td>The ratio of the number of correct predictions to the total number of predictions made.</td>
<td>Maximize</td>
<td><code>val_accuracy=([0-9\.]+)</code></td>
</tr>
</tbody>
</table>

**Tunable Text Classification - TensorFlow hyperparameters**

Tune a text classification model with the following hyperparameters. The hyperparameters that have the greatest impact on text classification objective metrics are: `batch_size`, `learning_rate`, and `optimizer`. Tune the optimizer-related hyperparameters, such as `momentum`, `regularizers_l2`, `beta_1`, `beta_2`, and `eps` based on the selected optimizer. For example, use `beta_1` and `beta_2` only when `adamw` or `adam` is the optimizer.
For more information about which hyperparameters are used for each optimizer, see Text Classification - TensorFlow Hyperparameters (p. 2122).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 4, MaxValue: 128</td>
</tr>
<tr>
<td>beta_1</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.999</td>
</tr>
<tr>
<td>beta_2</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.999</td>
</tr>
<tr>
<td>eps</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-8, MaxValue: 1.0</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.5</td>
</tr>
<tr>
<td>momentum</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
<tr>
<td>optimizer</td>
<td>CategoricalParameterRanges</td>
<td>['adamw', 'adam', 'sgd', 'rmsprop', 'nesterov', 'adagrad', 'adadelta']</td>
</tr>
<tr>
<td>regularizers_l2</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
<tr>
<td>train_only_on_top_layer</td>
<td>CategoricalParameterRanges</td>
<td>['True', 'False']</td>
</tr>
</tbody>
</table>

**Built-in SageMaker Algorithms for Time-Series Data**

SageMaker provides algorithms that are tailored to the analysis of time-series data for forecasting product demand, server loads, webpage requests, and more.

- **DeepAR Forecasting Algorithm (p. 2126)**—a supervised learning algorithm for forecasting scalar (one-dimensional) time series using recurrent neural networks (RNN).

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>DeepAR Forecasting</td>
<td>train and (optionally) test</td>
<td>File</td>
<td>JSON Lines or Parquet</td>
<td>GPU or CPU</td>
<td>Yes</td>
</tr>
</tbody>
</table>

**DeepAR Forecasting Algorithm**

The Amazon SageMaker DeepAR forecasting algorithm is a supervised learning algorithm for forecasting scalar (one-dimensional) time series using recurrent neural networks (RNN). Classical forecasting methods, such as autoregressive integrated moving average (ARIMA) or exponential smoothing (ETS), fit a single model to each individual time series. They then use that model to extrapolate the time series into the future.
In many applications, however, you have many similar time series across a set of cross-sectional units. For example, you might have time series groupings for demand for different products, server loads, and requests for webpages. For this type of application, you can benefit from training a single model jointly over all of the time series. DeepAR takes this approach. When your dataset contains hundreds of related time series, DeepAR outperforms the standard ARIMA and ETS methods. You can also use the trained model to generate forecasts for new time series that are similar to the ones it has been trained on.

The training input for the DeepAR algorithm is one or, preferably, more target time series that have been generated by the same process or similar processes. Based on this input dataset, the algorithm trains a model that learns an approximation of this process/processes and uses it to predict how the target time series evolves. Each target time series can be optionally associated with a vector of static (time-independent) categorical features provided by the cat field and a vector of dynamic (time-dependent) time series provided by the dynamic_feat field. SageMaker trains the DeepAR model by randomly sampling training examples from each target time series in the training dataset. Each training example consists of a pair of adjacent context and prediction windows with fixed predefined lengths. To control how far in the past the network can see, use the context_length hyperparameter. To control how far in the future predictions can be made, use the prediction_length hyperparameter. For more information, see How the DeepAR Algorithm Works (p. 2131).

Input/Output Interface for the DeepAR Algorithm

DeepAR supports two data channels. The required train channel describes the training dataset. The optional test channel describes a dataset that the algorithm uses to evaluate model accuracy after training. You can provide training and test datasets in JSON Lines format. Files can be in gzip or Parquet file format.

When specifying the paths for the training and test data, you can specify a single file or a directory that contains multiple files, which can be stored in subdirectories. If you specify a directory, DeepAR uses all files in the directory as inputs for the corresponding channel, except those that start with a period (.) and those named _SUCCESS. This ensures that you can directly use output folders produced by Spark jobs as input channels for your DeepAR training jobs.

By default, the DeepAR model determines the input format from the file extension (.json, .json.gz, or .parquet) in the specified input path. If the path does not end in one of these extensions, you must explicitly specify the format in the SDK for Python. Use the content_type parameter of the s3_input class.

The records in your input files should contain the following fields:

- **start**—A string with the format YYYY-MM-DD HH:MM:SS. The start timestamp can't contain time zone information.
- **target**—An array of floating-point values or integers that represent the time series. You can encode missing values as null literals, or as "NaN" strings in JSON, or as nan floating-point values in Parquet.
- **dynamic_feat** (optional)—An array of arrays of floating-point values or integers that represents the vector of custom feature time series (dynamic features). If you set this field, all records must have the
same number of inner arrays (the same number of feature time series). In addition, each inner array must be the same length as the associated target value plus prediction_length. Missing values are not supported in the features. For example, if target time series represents the demand of different products, an associated dynamic_feat might be a boolean time-series which indicates whether a promotion was applied (1) to the particular product or not (0):

```json
{"start": ..., "target": [1, 5, 10, 2], "dynamic_feat": [[0, 1, 1, 0]]}
```

- **cat** (optional)—An array of categorical features that can be used to encode the groups that the record belongs to. Categorical features must be encoded as a 0-based sequence of positive integers. For example, the categorical domain \{R, G, B\} can be encoded as \{0, 1, 2\}. All values from each categorical domain must be represented in the training dataset. That's because the DeepAR algorithm can forecast only for categories that have been observed during training. And, each categorical feature is embedded in a low-dimensional space whose dimensionality is controlled by the embedding_dimension hyperparameter. For more information, see DeepAR Hyperparameters (p. 2133).

If you use a JSON file, it must be in JSON Lines format. For example:

```json
["start": "2009-11-01 00:00:00", "target": [4.3, "NaN", 5.1, ...], "cat": [0, 1], "dynamic_feat": [[1.1, 1.2, 0.5, ...]]}
["start": "2012-01-30 00:00:00", "target": [1.0, -5.0, ...], "cat": [2, 3], "dynamic_feat": [[1.1, 2.05, ...]]}
["start": "1999-01-30 00:00:00", "target": [2.0, 1.0], "cat": [1, 4], "dynamic_feat": [[1.3, 0.4]]}
```

In this example, each time series has two associated categorical features and one time series features.

For Parquet, you use the same three fields as columns. In addition, "start" can be the datetime type. You can compress Parquet files using gzip (gzip) or the Snappy compression library (snappy).

If the algorithm is trained without cat and dynamic_feat fields, it learns a "global" model, that is a model that is agnostic to the specific identity of the target time series at inference time and is conditioned only on its shape.

If the model is conditioned on the cat and dynamic_feat feature data provided for each time series, the prediction will probably be influenced by the character of time series with the corresponding cat features. For example, if the target time series represents the demand of clothing items, you can associate a two-dimensional cat vector that encodes the type of item (e.g. 0 = shoes, 1 = dress) in the first component and the color of an item (e.g. 0 = red, 1 = blue) in the second component. A sample input would look as follows:

```json
{ "start": ..., "target": ..., "cat": [0, 0], ... } # red shoes
{ "start": ..., "target": ..., "cat": [1, 1], ... } # blue dress
```

At inference time, you can request predictions for targets with cat values that are combinations of the cat values observed in the training data, for example:

```json
{ "start": ..., "target": ..., "cat": [0, 1], ... } # blue shoes
{ "start": ..., "target": ..., "cat": [1, 0], ... } # red dress
```

The following guidelines apply to training data:

- The start time and length of the time series can differ. For example, in marketing, products often enter a retail catalog at different dates, so their start dates naturally differ. But all series must have the same frequency, number of categorical features, and number of dynamic features.
• Shuffle the training file with respect to the position of the time series in the file. In other words, the time series should occur in random order in the file.

• Make sure to set the start field correctly. The algorithm uses the start timestamp to derive the internal features.

• If you use categorical features (cat), all time series must have the same number of categorical features. If the dataset contains the cat field, the algorithm uses it and extracts the cardinality of the groups from the dataset. By default, cardinality is "auto". If the dataset contains the cat field, but you don’t want to use it, you can disable it by setting cardinality to "". If a model was trained using a cat feature, you must include it for inference.

• If your dataset contains the dynamic_feat field, the algorithm uses it automatically. All time series have to have the same number of feature time series. The time points in each of the feature time series correspond one-to-one to the time points in the target. In addition, the entry in the dynamic_feat field should have the same length as the target. If the dataset contains the dynamic_feat field, but you don’t want to use it, disable it by setting num_dynamic_feat to "". If the model was trained with the dynamic_feat field, you must provide this field for inference. In addition, each of the features has to have the length of the provided target plus the prediction_length. In other words, you must provide the feature value in the future.

If you specify optional test channel data, the DeepAR algorithm evaluates the trained model with different accuracy metrics. The algorithm calculates the root mean square error (RMSE) over the test data as follows:

$$RMSE = \sqrt{\frac{1}{nT} \sum_{i,t} (\hat{y}_{i,t} - y_{i,t})^2}$$

$y_{i,t}$ is the true value of time series $i$ at the time $t$. $\hat{y}_{i,t}$ is the mean prediction. The sum is over all $n$ time series in the test set and over the last $T$ time points for each time series, where $T$ corresponds to the forecast horizon. You specify the length of the forecast horizon by setting the prediction_length hyperparameter. For more information, see DeepAR Hyperparameters (p. 2133).

In addition, the algorithm evaluates the accuracy of the forecast distribution using weighted quantile loss. For a quantile in the range [0, 1], the weighted quantile loss is defined as follows:

$$w_{\text{QuantileLoss}}(\tau) = 2 \sum_{i,t} \frac{Q_{i,t}^{(\tau)}}{|y_{i,t}|}, \quad \text{with} \quad Q_{i,t}^{(\tau)} = \begin{cases} (1 - \tau)|q_{i,t}^{(\tau)} - y_{i,t}| & \text{if } q_{i,t}^{(\tau)} > y_{i,t} \\ \tau|q_{i,t}^{(\tau)} - y_{i,t}| & \text{otherwise} \end{cases}$$

$q_{i,t}^{(\tau)}$ is the $\tau$-quantile of the distribution that the model predicts. To specify which quantiles to calculate loss for, set the test_quantiles hyperparameter. In addition to these, the average of the prescribed quantile losses is reported as part of the training logs. For information, see DeepAR Hyperparameters (p. 2133).

For inference, DeepAR accepts JSON format and the following fields:

• "instances", which includes one or more time series in JSON Lines format
• A name of "configuration", which includes parameters for generating the forecast

For more information, see DeepAR Inference Formats (p. 2138).

Best Practices for Using the DeepAR Algorithm

When preparing your time series data, follow these best practices to achieve the best results:
- Except for when splitting your dataset for training and testing, always provide the entire time series for training, testing, and when calling the model for inference. Regardless of how you set context_length, don't break up the time series or provide only a part of it. The model uses data points further back than the value set in context_length for the lagged values feature.

- When tuning a DeepAR model, you can split the dataset to create a training dataset and a test dataset. In a typical evaluation, you would test the model on the same time series used for training, but on the future prediction_length time points that follow immediately after the last time point visible during training. You can create training and test datasets that satisfy this criteria by using the entire dataset (the full length of all time series that are available) as a test set and removing the last prediction_length points from each time series for training. During training, the model doesn't see the target values for time points on which it is evaluated during testing. During testing, the algorithm withholds the last prediction_length points of each time series in the test set and generates a prediction. Then it compares the forecast with the withheld values. You can create more complex evaluations by repeating time series multiple times in the test set, but cutting them at different endpoints. With this approach, accuracy metrics are averaged over multiple forecasts from different time points. For more information, see Tune a DeepAR Model (p. 2137).

- Avoid using very large values (>400) for the prediction_length because it makes the model slow and less accurate. If you want to forecast further into the future, consider aggregating your data at a lower frequency. For example, use 5min instead of 1min.

- Because lags are used, a model can look further back in the time series than the value specified for context_length. Therefore, you don't need to set this parameter to a large value. We recommend starting with the value that you used for prediction_length.

- We recommend training a DeepAR model on as many time series as are available. Although a DeepAR model trained on a single time series might work well, standard forecasting algorithms, such as ARIMA or ETS, might provide more accurate results. The DeepAR algorithm starts to outperform the standard methods when your dataset contains hundreds of related time series. Currently, DeepAR requires that the total number of observations available across all training time series is at least 300.

**EC2 Instance Recommendations for the DeepAR Algorithm**

You can train DeepAR on both GPU and CPU instances and in both single and multi-machine settings. We recommend starting with a single CPU instance (for example, ml.c4.2xlarge or ml.c4.4xlarge), and switching to GPU instances and multiple machines only when necessary. Using GPUs and multiple machines improves throughput only for larger models (with many cells per layer and many layers) and for large mini-batch sizes (for example, greater than 512).

For inference, DeepAR supports only CPU instances.

Specifying large values for context_length, prediction_length, num_cells, num_layers, or mini_batch_size can create models that are too large for small instances. In this case, use a larger instance type or reduce the values for these parameters. This problem also frequently occurs when running hyperparameter tuning jobs. In that case, use an instance type large enough for the model tuning job and consider limiting the upper values of the critical parameters to avoid job failures.

**DeepAR Sample Notebooks**

For a sample notebook that shows how to prepare a time series dataset for training the SageMaker DeepAR algorithm and how to deploy the trained model for performing inferences, see Time series forecasting with DeepAR - Synthetic data as well as DeepAR demo on electricity dataset, which illustrates the advanced features of DeepAR on a real world dataset. For instructions on creating and accessing Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After creating and opening a notebook instance, choose the SageMaker Examples tab to see a list of all of the SageMaker examples. To open a notebook, choose its Use tab, and choose Create copy.
How the DeepAR Algorithm Works

During training, DeepAR accepts a training dataset and an optional test dataset. It uses the test dataset to evaluate the trained model. In general, the datasets don’t have to contain the same set of time series. You can use a model trained on a given training set to generate forecasts for the future of the target time series in the training set, and for other target time series. Both the training and the test datasets consist of one or, preferably, more target time series. Each target time series can optionally be associated with a vector of feature time series and a vector of categorical features. For more information, see Input/Output Interface for the DeepAR Algorithm (p. 2127).

For example, the following is an element of a training set indexed by $i$ which consists of a target time series, $Z_{i,t}$, and two associated feature time series, $X_{i,1,t}$ and $X_{i,2,t}$:

The target time series might contain missing values, which are represented by line breaks in the time series. DeepAR supports only feature time series that are known in the future. This allows you to run “what if?” scenarios. What happens, for example, if I change the price of a product in some way?

Each target time series can also be associated with a number of categorical features. You can use these features to encode which groupings a target time series belongs to. Categorical features allow the model to learn typical behavior for groups, which it can use to improve model accuracy. DeepAR implements this by learning an embedding vector for each group that captures the common properties of all time series in the group.

How Feature Time Series Work in the DeepAR Algorithm

To facilitate learning time-dependent patterns, such as spikes during weekends, DeepAR automatically creates feature time series based on the frequency of the target time series. It uses these derived feature time series with the custom feature time series that you provide during training and inference. The following figure shows two of these derived time series features: $u_{i,1,t}$ represents the hour of the day and $u_{i,2,t}$ the day of the week.
The DeepAR algorithm automatically generates these feature time series. The following table lists the derived features for the supported basic time frequencies.

<table>
<thead>
<tr>
<th>Frequency of the Time Series</th>
<th>Derived Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minute</td>
<td>minute-of-hour, hour-of-day, day-of-week, day-of-month, day-of-year</td>
</tr>
<tr>
<td>Hour</td>
<td>hour-of-day, day-of-week, day-of-month, day-of-year</td>
</tr>
<tr>
<td>Day</td>
<td>day-of-week, day-of-month, day-of-year</td>
</tr>
<tr>
<td>Week</td>
<td>day-of-week, week-of-year</td>
</tr>
<tr>
<td>Month</td>
<td>month-of-year</td>
</tr>
</tbody>
</table>

DeepAR trains a model by randomly sampling several training examples from each of the time series in the training dataset. Each training example consists of a pair of adjacent context and prediction windows with fixed predefined lengths. The context_length hyperparameter controls how far in the past the network can see, and the prediction_length hyperparameter controls how far in the future predictions can be made. During training, the algorithm ignores training set elements containing time series that are shorter than a specified prediction length. The following figure represents five samples with context lengths of 12 hours and prediction lengths of 6 hours drawn from element $i$. For brevity, we’ve omitted the feature time series $x_{i,t}$ and $u_{i,t}$.  

---

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To capture seasonality patterns, DeepAR also automatically feeds lagged values from the target time series. In the example with hourly frequency, for each time index, \( t = T \), the model exposes the \( z_{i,t} \) values, which occurred approximately one, two, and three days in the past.

For inference, the trained model takes as input target time series, which might or might not have been used during training, and forecasts a probability distribution for the next \( \text{prediction\_length} \) values. Because DeepAR is trained on the entire dataset, the forecast takes into account patterns learned from similar time series.

For information on the mathematics behind DeepAR, see DeepAR: Probabilistic Forecasting with Autoregressive Recurrent Networks.

### DeepAR Hyperparameters

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>context_length</td>
<td>The number of time-points that the model gets to see before making the prediction. The value for this parameter should be about the same as the ( \text{prediction_length} ). The model also receives lagged inputs from the target, so context_length can be much smaller than typical seasonalities. For example, a daily time series can have yearly seasonality. The model automatically includes a lag of one year, so the context length can be shorter than a year. The lag values that the model picks depend on the frequency of the time series. For example, lag values for daily frequency are previous week, 2 weeks, 3 weeks, 4 weeks, and year. Required. Valid values: Positive integer</td>
</tr>
<tr>
<td>epochs</td>
<td>The maximum number of passes over the training data. The optimal value depends on your data size and learning rate. See also ( \text{early_stopping_patience} ). Typical values range from 10 to 1000. Required. Valid values: Positive integer</td>
</tr>
<tr>
<td>prediction_length</td>
<td>The number of time-steps that the model is trained to predict, also called the forecast horizon. The trained model always generates forecasts with this length. It can’t generate longer forecasts. The</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
</tbody>
</table>
| prediction_length | fixed when a model is trained and it cannot be changed later. **Required**
| time_freq | granularity of the time series in the dataset. Use time_freq to select appropriate date features and lags. The model supports the following basic frequencies. It also supports multiples of these basic frequencies. For example, 5min specifies a frequency of 5 minutes. **Required**
| cardinality | When using the categorical features (cat), cardinality is an array specifying the number of categories (groups) per categorical feature. Set this to auto to infer the cardinality from the data. The auto mode also works when no categorical features are used in the dataset. This is the recommended setting for the parameter. Set cardinality to ignore to force DeepAR to not use categorical features, even if they are present in the data. To perform additional data validation, it is possible to explicitly set this parameter to the actual value. For example, if two categorical features are provided where the first has 2 and the other has 3 possible values, set this to [2, 3]. For more information on how to use categorical features, see the data-section on the main documentation page of DeepAR. **Optional**
| dropout_rate | The dropout rate to use during training. The model uses zoneout regularization. For each iteration, a random subset of hidden neurons are not updated. Typical values are less than 0.2. **Optional**

Valid values: Positive integer
Valid values: An integer followed by M, W, D, H, or min. For example, 5min.
Valid values: auto, ignore, array of positive integers, empty string, or
Valid values: float
Default value: auto
Default value: 0.1
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>early_stopping_patience</td>
<td>If this parameter is set, training stops when no progress is made within the specified number of epochs. The model that has the lowest loss is returned as the final model. Optional Valid values: integer</td>
</tr>
<tr>
<td>embedding_dimension</td>
<td>Size of embedding vector learned per categorical feature (same value is used for all categorical features). The DeepAR model can learn group-level time series patterns when a categorical grouping feature is provided. To do this, the model learns an embedding vector of size embedding_dimension for each group, capturing the common properties of all time series in the group. A larger embedding_dimension allows the model to capture more complex patterns. However, because increasing the embedding_dimension increases the number of parameters in the model, more training data is required to accurately learn these parameters. Typical values for this parameter are between 10-100. Optional Valid values: positive integer Default value: 10</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The learning rate used in training. Typical values range from 1e-4 to 1e-1. Optional Valid values: float Default value: 1e-3</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>likelihood</td>
<td>The model generates a probabilistic forecast, and can provide quantiles of the distribution and return samples. Depending on your data, select an appropriate likelihood (noise model) that is used for uncertainty estimates. The following likelihoods can be selected:</td>
</tr>
<tr>
<td></td>
<td>• <em>gaussian</em>: Use for real-valued data.</td>
</tr>
<tr>
<td></td>
<td>• <em>beta</em>: Use for real-valued targets between 0 and 1 inclusive.</td>
</tr>
<tr>
<td></td>
<td>• <em>negative-binomial</em>: Use for count data (non-negative integers).</td>
</tr>
<tr>
<td></td>
<td>• <em>student-T</em>: An alternative for real-valued data that works well for bursty data.</td>
</tr>
<tr>
<td></td>
<td>• <em>deterministic-L1</em>: A loss function that does not estimate uncertainty and only learns a point forecast.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: One of <em>gaussian</em>, <em>beta</em>, <em>negative-binomial</em>, <em>student-T</em>, or <em>deterministic-L1</em>.</td>
</tr>
<tr>
<td></td>
<td>Default value: <em>student-T</em></td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The size of mini-batches used during training. Typical values range from 32 to 512.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 128</td>
</tr>
<tr>
<td>num_cells</td>
<td>The number of cells to use in each hidden layer of the RNN. Typical values range from 30 to 100.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 40</td>
</tr>
<tr>
<td>num_dynamic_feat</td>
<td>The number of dynamic_feat provided in the data. Set this to auto to infer the number of dynamic features from the data. The auto mode also works when no dynamic features are used in the dataset. This is the recommended setting for the parameter.</td>
</tr>
<tr>
<td></td>
<td>To force DeepAR to not use dynamic features, even if they are present in the data, set num_dynamic_feat to ignore.</td>
</tr>
<tr>
<td></td>
<td>To perform additional data validation, it is possible to explicitly set this parameter to the actual integer value. For example, if two dynamic features are provided, set this to 2.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: auto, ignore, positive integer, or empty string</td>
</tr>
<tr>
<td></td>
<td>Default value: auto</td>
</tr>
</tbody>
</table>
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
<th>Optional</th>
<th>Valid values:</th>
<th>Default value</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_eval_samples</td>
<td>The number of samples that are used per time-series when calculating test accuracy metrics. This parameter does not have any influence on the training or the final model. In particular, the model can be queried with a different number of samples. This parameter only affects the reported accuracy scores on the test channel after training. Smaller values result in faster evaluation, but then the evaluation scores are typically worse and more uncertain. When evaluating with higher quantiles, for example 0.95, it may be important to increase the number of evaluation samples.</td>
<td>Optional</td>
<td>integer</td>
<td>100</td>
</tr>
<tr>
<td>num_layers</td>
<td>The number of hidden layers in the RNN. Typical values range from 1 to 4.</td>
<td>Optional</td>
<td>positive integer</td>
<td>2</td>
</tr>
<tr>
<td>test_quantiles</td>
<td>Quantiles for which to calculate quantile loss on the test channel.</td>
<td>Optional</td>
<td>array of floats</td>
<td>[0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9]</td>
</tr>
</tbody>
</table>

Tune a DeepAR Model

Automatic model tuning, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

Metrics Computed by the DeepAR Algorithm

The DeepAR algorithm reports three metrics, which are computed during training. When tuning a model, choose one of these as the objective. For the objective, use either the forecast accuracy on a provided test channel (recommended) or the training loss. For recommendations for the training/test split for the DeepAR algorithm, see Best Practices for Using the DeepAR Algorithm (p. 2129).

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test:RMSE</td>
<td>The root mean square error between the forecast and the actual target computed on the test set.</td>
<td>Minimize</td>
</tr>
</tbody>
</table>
### Use Built-in Algorithms

**Metric Name**

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test:mean_wQuantileLoss</td>
<td>The average overall quantile losses computed on the test set. To control which quantiles are used, set the test_quantiles hyperparameter.</td>
<td>Minimize</td>
</tr>
<tr>
<td>train:final_loss</td>
<td>The training negative log-likelihood loss averaged over the last training epoch for the model.</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

### Tunable Hyperparameters for the DeepAR Algorithm

Tune a DeepAR model with the following hyperparameters. The hyperparameters that have the greatest impact, listed in order from the most to least impactful, on DeepAR objective metrics are: epochs, context_length, mini_batch_size, learning_rate, and num_cells.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>epochs</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 1000</td>
</tr>
<tr>
<td>context_length</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 200</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 32, MaxValue: 1028</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-5, MaxValue: 1e-1</td>
</tr>
<tr>
<td>num_cells</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 30, MaxValue: 200</td>
</tr>
<tr>
<td>num_layers</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 8</td>
</tr>
<tr>
<td>dropout_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.00, MaxValue: 0.2</td>
</tr>
<tr>
<td>embedding_dimension</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 50</td>
</tr>
</tbody>
</table>

### DeepAR Inference Formats

#### DeepAR JSON Request Formats

Query a trained model by using the model’s endpoint. The endpoint takes the following JSON request format.

In the request, the instances field corresponds to the time series that should be forecast by the model.

If the model was trained with categories, you must provide a cat for each instance. If the model was trained without the cat field, it should be omitted.

If the model was trained with a custom feature time series (dynamic_feat), you have to provide the same number of dynamic_feat values for each instance. Each of them should have a length given by length(target) + prediction_length, where the last prediction_length values correspond to
the time points in the future that will be predicted. If the model was trained without custom feature time series, the field should not be included in the request.

```json
{
  "instances": [
    {
      "start": "2009-11-01 00:00:00",
      "target": [4.0, 10.0, "NaN", 100.0, 113.0],
      "cat": [0, 1],
      "dynamic_feat": [[1.0, 1.1, 2.1, 0.5, 3.1, 4.1, 1.2, 5.0, ...]]
    },
    {
      "start": "2012-01-30",
      "target": [1.0],
      "cat": [2, 1],
      "dynamic_feat": [[2.0, 3.1, 4.5, 1.5, 1.8, 3.2, 0.1, 3.0, ...]]
    },
    {
      "start": "1999-01-30",
      "target": [2.0, 1.0],
      "cat": [1, 3],
      "dynamic_feat": [[1.0, 0.1, -2.5, 0.3, 2.0, -1.2, -0.1, -3.0, ...]]
    }
  ],
  "configuration": {
    "num_samples": 50,
    "output_types": ["mean", "quantiles", "samples"],
    "quantiles": ["0.5", "0.9"]
  }
}
```

The `configuration` field is optional. `configuration.num_samples` sets the number of sample paths that the model generates to estimate the mean and quantiles. `configuration.output_types` describes the information that will be returned in the request. Valid values are "mean", "quantiles" and "samples". If you specify "quantiles", each of the quantile values in `configuration.quantiles` is returned as a time series. If you specify "samples", the model also returns the raw samples used to calculate the other outputs.

**DeepAR JSON Response Formats**

The following is the format of a response, where `[...]` are arrays of numbers:

```json
{
  "predictions": [
    {
      "quantiles": {
        "0.9": [...],
        "0.5": [...]
      },
      "samples": [...],
      "mean": [...]}
    },
    {
      "quantiles": {
        "0.9": [...],
        "0.5": [...]
      },
      "samples": [...],
      "mean": [...]}
    },
    {
      "quantiles": {
        "0.9": [...],
        "0.5": [...]
      },
      "samples": [...],
      "mean": [...]}
  }
}
```
DeepAR has a response timeout of 60 seconds. When passing multiple time series in a single request, the forecasts are generated sequentially. Because the forecast for each time series typically takes about 300 to 1000 milliseconds or longer, depending on the model size, passing too many time series in a single request can cause time outs. It's better to send fewer time series per request and send more requests. Because the DeepAR algorithm uses multiple workers per instance, you can achieve much higher throughput by sending multiple requests in parallel.

By default, DeepAR uses one worker per CPU for inference, if there is sufficient memory per CPU. If the model is large and there isn't enough memory to run a model on each CPU, the number of workers is reduced. The number of workers used for inference can be overwitten using the environment variable `MODEL_SERVER_WORKERS`. For example, by setting `MODEL_SERVER_WORKERS=1` when calling the SageMaker `CreateModel` API.

**Batch Transform with the DeepAR Algorithm**

DeepAR forecasting supports getting inferences by using batch transform from data using the JSON Lines format. In this format, each record is represented on a single line as a JSON object, and lines are separated by newline characters. The format is identical to the JSON Lines format used for model training. For information, see *Input/Output Interface for the DeepAR Algorithm* (p. 2127). For example:

```json
{"start": "2009-11-01 00:00:00", "target": [4.3, "NaN", 5.1, ...], "cat": [0, 1],
"dynamic_feat": [[1.1, 1.2, 0.5, ..]]}
{"start": "2012-01-30 00:00:00", "target": [1.0, -5.0, ...], "cat": [2, 3], "dynamic_feat":
[[1.1, 2.05, ...]]}
{"start": "1999-01-30 00:00:00", "target": [2.0, 1.0], "cat": [1, 4], "dynamic_feat":
[[1.3, 0.4]]}
```

**Note**

When creating the transformation job with `CreateTransformJob`, set the `BatchStrategy` value to `SingleRecord` and set the `SplitType` value in the `TransformInput` configuration to `Line`, as the default values currently cause runtime failures.

Similar to the hosted endpoint inference request format, the `cat` and the `dynamic_feat` fields for each instance are required if both of the following are true:

- The model is trained on a dataset that contained both the `cat` and the `dynamic_feat` fields.
- The corresponding cardinality and `num_dynamic_feat` values used in the training job are not set to "".

Unlike hosted endpoint inference, the configuration field is set once for the entire batch inference job using an environment variable named `DEEPAR_INFERENCE_CONFIG`. The value of `DEEPAR_INFERENCE_CONFIG` can be passed when the model is created by calling `CreateTransformJob` API. If `DEEPAR_INFERENCE_CONFIG` is missing in the container environment, the inference container uses the following default:

```json
{
"num_samples": 100,
"output_types": ["mean", "quantiles"],
"quantiles": ["0.1", "0.2", "0.3", "0.4", "0.5", "0.6", "0.7", "0.8", "0.9"]
}
```
The output is also in JSON Lines format, with one line per prediction, in an order identical to the instance order in the corresponding input file. Predictions are encoded as objects identical to the ones returned by responses in online inference mode. For example:

```json
{ "quantiles": { "0.1": [...], "0.2": [...] }, "samples": [...], "mean": [...] }
```

Note that in the `TransformInput` configuration of the SageMaker `CreateTransformJob` request clients must explicitly set the `AssembleWith` value to `Line`, as the default value `None` concatenates all JSON objects on the same line.

For example, here is a SageMaker `CreateTransformJob` request for a DeepAR job with a custom `DEEPAR_INFERENCE_CONFIG`:

```json
{
  "BatchStrategy": "SingleRecord",
  "Environment": {
    "DEEPAR_INFERENCE_CONFIG": "{ "num_samples": 200, "output_types": ["mean"] }",
    ...
  },
  "TransformInput": {
    "SplitType": "Line",
    ...
  },
  "TransformOutput": {
    "AssembleWith": "Line",
    ...
  }
}
```

### Unsupervised Built-in SageMaker Algorithms

Amazon SageMaker provides several built-in algorithms that can be used for a variety of unsupervised learning tasks such as clustering, dimension reduction, pattern recognition, and anomaly detection.

- **IP Insights (p. 2142)**—learns the usage patterns for IPv4 addresses. It is designed to capture associations between IPv4 addresses and various entities, such as user IDs or account numbers.
- **K-Means Algorithm (p. 2151)**—finds discrete groupings within data, where members of a group are as similar as possible to one another and as different as possible from members of other groups.
- **Principal Component Analysis (PCA) Algorithm (p. 2159)**—reduces the dimensionality (number of features) within a dataset by projecting data points onto the first few principal components. The objective is to retain as much information or variation as possible. For mathematicians, principal components are eigenvectors of the data's covariance matrix.
- **Random Cut Forest (RCF) Algorithm (p. 2163)**—detects anomalous data points within a data set that diverge from otherwise well-structured or patterned data.

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>IP Insights</td>
<td>train and validation</td>
<td>File</td>
<td>CSV</td>
<td>CPU or GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>K-Means</td>
<td>train and test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU or GPUCommon (single GPU)</td>
<td>No</td>
</tr>
</tbody>
</table>
IP Insights

Amazon SageMaker IP Insights is an unsupervised learning algorithm that learns the usage patterns for IPv4 addresses. It is designed to capture associations between IPv4 addresses and various entities, such as user IDs or account numbers. You can use it to identify a user attempting to log into a web service from an anomalous IP address, for example. Or you can use it to identify an account that is attempting to create computing resources from an unusual IP address. Trained IP Insight models can be hosted at an endpoint for making real-time predictions or used for processing batch transforms.

SageMaker IP insights ingests historical data as (entity, IPv4 Address) pairs and learns the IP usage patterns of each entity. When queried with an (entity, IPv4 Address) event, a SageMaker IP Insights model returns a score that infers how anomalous the pattern of the event is. For example, when a user attempts to log in from an IP address, if the IP Insights score is high enough, a web login server might decide to trigger a multi-factor authentication system. In more advanced solutions, you can feed the IP Insights score into another machine learning model. For example, you can combine the IP Insight score with other features to rank the findings of another security system, such as those from Amazon GuardDuty.

The SageMaker IP Insights algorithm can also learn vector representations of IP addresses, known as *embeddings*. You can use vector-encoded embeddings as features in downstream machine learning tasks that use the information observed in the IP addresses. For example, you can use them in tasks such as measuring similarities between IP addresses in clustering and visualization tasks.

**Topics**

- Input/Output Interface for the IP Insights Algorithm (p. 2142)
- EC2 Instance Recommendation for the IP Insights Algorithm (p. 2143)
- IP Insights Sample Notebooks (p. 2144)
- How IP Insights Works (p. 2144)
- IP Insights Hyperparameters (p. 2145)
- Tune an IP Insights Model (p. 2147)
- IP Insights Data Formats (p. 2149)

**Input/Output Interface for the IP Insights Algorithm**

**Training and Validation**

The SageMaker IP Insights algorithm supports training and validation data channels. It uses the optional validation channel to compute an area-under-curve (AUC) score on a predefined negative sampling strategy. The AUC metric validates how well the model discriminates between positive and negative samples. Training and validation data content types need to be in *text/csv* format. The first column of the CSV data is an opaque string that provides a unique identifier for the entity. The second column

### Algorithm Table

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>GPU or CPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Random Cut Forest</td>
<td>train and (optionally) test</td>
<td>File or Pipe</td>
<td>recordIO-protobuf or CSV</td>
<td>CPU</td>
<td>Yes</td>
</tr>
</tbody>
</table>
is an IPv4 address in decimal-dot notation. IP Insights currently supports only File mode. For more information and some examples, see IP Insights Training Data Formats (p. 2149).

Inference

For inference, IP Insights supports text/csv, application/json, and application/jsonlines data content types. For more information about the common data formats for inference provided by SageMaker, see Common Data Formats for Inference (p. 1963). IP Insights inference returns output formatted as either application/json or application/jsonlines. Each record in the output data contains the corresponding dot_product (or compatibility score) for each input data point. For more information and some examples, see IP Insights Inference Data Formats (p. 2149).

EC2 Instance Recommendation for the IP Insights Algorithm

The SageMaker IP Insights algorithm can run on both GPU and CPU instances. For training jobs, we recommend using GPU instances. However, for certain workloads with large training datasets, distributed CPU instances might reduce training costs. For inference, we recommend using CPU instances. IP Insights supports P2, P3, G4dn, and G5 GPU families.

GPU Instances for the IP Insights Algorithm

IP Insights supports all available GPUs. If you need to speed up training, we recommend starting with a single GPU instance, such as ml.p3.2xlarge, and then moving to a multi-GPU environment, such as ml.p3.8xlarge and ml.p3.16xlarge. Multi-GPUs automatically divide the mini batches of training data across themselves. If you switch from a single GPU to multiple GPUs, the mini_batch_size is divided equally into the number of GPUs used. You may want to increase the value of the mini_batch_size to compensate for this.

CPU Instances for the IP Insights Algorithm

The type of CPU instance that we recommend depends largely on the instance’s available memory and the model size. The model size is determined by two hyperparameters: vector_dim and num_entity_vectors. The maximum supported model size is 8 GB. The following table lists typical EC2 instance types that you would deploy based on these input parameters for various model sizes.

<table>
<thead>
<tr>
<th>vector_dim \ num_entity_vectors</th>
<th>10,000</th>
<th>50,000</th>
<th>100,000</th>
<th>500,000</th>
<th>1,000,000</th>
<th>5,000,000</th>
<th>10,000,000</th>
<th>50,000,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>32</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.2xlarge</td>
<td>ml.m5.4xlarge</td>
<td></td>
</tr>
<tr>
<td>64</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.2xlarge</td>
<td>ml.m5.2xlarge</td>
<td></td>
</tr>
<tr>
<td>128</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.2xlarge</td>
<td>ml.m5.2xlarge</td>
<td>ml.m5.4xlarge</td>
<td></td>
</tr>
<tr>
<td>256</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.2xlarge</td>
<td>ml.m5.4xlarge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>512</td>
<td>ml.m5.large</td>
<td>ml.m5.large</td>
<td>ml.m5.2xlarge</td>
<td>ml.m5.5xlarge</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1024</td>
<td>ml.m5.large</td>
<td>ml.m5.2xlarge</td>
<td>ml.m5.5xlarge</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2048</td>
<td>ml.m5.large</td>
<td>ml.m5.5xlarge</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The values for the mini_batch_size, num_ip_encoder_layers, random_negative_sampling_rate, and shuffled_negative_sampling_rate hyperparameters also affect the amount of memory required. If these values are large, you might need to use a larger instance type than normal.
IP Insights Sample Notebooks

For a sample notebook that shows how to train the SageMaker IP Insights algorithm and perform inferences with it, see An Introduction to the SageMaker IP Insights Algorithm. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After creating a notebook instance, choose the SageMaker Examples tab to see a list of all the SageMaker examples. To open a notebook, choose its Use tab and choose Create copy.

How IP Insights Works

Amazon SageMaker IP Insights is an unsupervised algorithm that consumes observed data in the form of (entity, IPv4 address) pairs that associates entities with IP addresses. IP Insights determines how likely it is that an entity would use a particular IP address by learning latent vector representations for both entities and IP addresses. The distance between these two representations can then serve as the proxy for how likely this association is.

The IP Insights algorithm uses a neural network to learn the latent vector representations for entities and IP addresses. Entities are first hashed to a large but fixed hash space and then encoded by a simple embedding layer. Character strings such as user names or account IDs can be fed directly into IP Insights as they appear in log files. You don't need to preprocess the data for entity identifiers. You can provide entities as an arbitrary string value during both training and inference. The hash size should be configured with a value that is high enough to ensure that the number of collisions, which occur when distinct entities are mapped to the same latent vector, remain insignificant. For more information about how to select appropriate hash sizes, see Feature Hashing for Large Scale Multitask Learning. For representing IP addresses, on the other hand, IP Insights uses a specially designed encoder network to uniquely represent each possible IPv4 address by exploiting the prefix structure of IP addresses.

During training, IP Insights automatically generates negative samples by randomly pairing entities and IP addresses. These negative samples represent data that is less likely to occur in reality. The model is trained to discriminate between positive samples that are observed in the training data and these generated negative samples. More specifically, the model is trained to minimize the cross entropy, also known as the log loss, defined as follows:

\[ L = \frac{1}{N} \sum_n [y_n \log p_n + (1 - y_n) \log (1 - p_n)] \]

\( y_n \) is the label that indicates whether the sample is from the real distribution governing observed data (\( y_n = 1 \)) or from the distribution generating negative samples (\( y_n = 0 \)). \( p_n \) is the probability that the sample is from the real distribution, as predicted by the model.

Generating negative samples is an important process that is used to achieve an accurate model of the observed data. If negative samples are extremely unlikely, for example, if all of the IP addresses in negative samples are 10.0.0.0, then the model trivially learns to distinguish negative samples and fails to accurately characterize the actual observed dataset. To keep negative samples more realistic, IP Insights generates negative samples both by randomly generating IP addresses and randomly picking IP addresses from training data. You can configure the type of negative sampling and the rates at which negative samples are generated with the random_negative_sampling_rate and shuffled_negative_sampling_rate hyperparameters.

Given an nth (entity, IP address pair), the IP Insights model outputs a score, \( S_n \), that indicates how compatible the entity is with the IP address. This score corresponds to the log odds ratio for a given (entity, IP address) of the pair coming from a real distribution as compared to coming from a negative distribution. It is defined as follows:

\[ S_n = \log \left( \frac{P_{real}(n)}{P_{neg}(n)} \right) \]

The score is essentially a measure of the similarity between the vector representations of the nth entity and IP address. It can be interpreted as how much more likely it would be to observe this event in reality.
than in a randomly generated dataset. During training, the algorithm uses this score to calculate an estimate of the probability of a sample coming from the real distribution, $p_n$, to use in the cross entropy minimization, where:

$$p_n = \frac{1}{1 + e^{-s_n}}$$

### IP Insights Hyperparameters

In the `CreateTransformJob` request, you specify the training algorithm. You can also specify algorithm-specific hyperparameters as string-to-string maps. The following table lists the hyperparameters for the Amazon SageMaker IP Insights algorithm.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>num_entity_vectors</code></td>
<td>The number of entity vector representations (entity embedding vectors) to train. Each entity in the training set is randomly assigned to one of these vectors using a hash function. Because of hash collisions, it might be possible to have multiple entities assigned to the same vector. This would cause the same vector to represent multiple entities. This generally has a negligible effect on model performance, as long as the collision rate is not too severe. To keep the collision rate low, set this value as high as possible. However, the model size, and, therefore, the memory requirement, for both training and inference, scales linearly with this hyperparameter. We recommend that you set this value to twice the number of unique entity identifiers. Required Valid values: $1 \leq \text{positive integer} \leq 250,000,000$</td>
</tr>
<tr>
<td><code>vector_dim</code></td>
<td>The size of embedding vectors to represent entities and IP addresses. The larger the value, the more information that can be encoded using these representations. In practice, model size scales linearly with this parameter and limits how large the dimension can be. In addition, using vector representations that are too large can cause the model to overfit, especially for small training datasets. Overfitting occurs when a model doesn't learn any pattern in the data but effectively memorizes the training data and, therefore, cannot generalize well and performs poorly during inference. The recommended value is 128. Required Valid values: $4 \leq \text{positive integer} \leq 4096$</td>
</tr>
<tr>
<td><code>batch_metrics_publish_interval</code></td>
<td>The interval (every X batches) at which the Apache MXNet Speedometer function prints the training speed of the network (samples/second). Optional Valid values: positive integer $\geq 1$ Default value: 1,000</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>epochs</td>
<td>The number of passes over the training data. The optimal value depends on your data size and learning rate. Typical values range from 5 to 100.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer ≥ 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 10</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The learning rate for the optimizer. IP Insights use a gradient-descent-based Adam optimizer. The learning rate effectively controls the step size to update model parameters at each iteration. Too large a learning rate can cause the model to diverge because the training is likely to overshoot a minima. On the other hand, too small a learning rate slows down convergence. Typical values range from 1e-4 to 1e-1.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 1e-6 ≤ float ≤ 10.0</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.001</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The number of examples in each mini batch. The training procedure processes data in mini batches. The optimal value depends on the number of unique account identifiers in the dataset. In general, the larger the mini_batch_size, the faster the training and the greater the number of possible shuffled-negative-sample combinations. However, with a large mini_batch_size, the training is more likely to converge to a poor local minimum and perform relatively worse for inference.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 1 ≤ positive integer ≤ 500000</td>
</tr>
<tr>
<td></td>
<td>Default value: 10,000</td>
</tr>
<tr>
<td>num_ip_encoder_layers</td>
<td>The number of fully connected layers used to encode the IP address embedding. The larger the number of layers, the greater the model's capacity to capture patterns among IP addresses. However, using a large number of layers increases the chance of overfitting.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 ≤ positive integer ≤ 100</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>random_negative_sampling_rate</td>
<td>The number of random negative samples, R, to generate per input example. The training procedure relies on negative samples to prevent the vector representations of the model collapsing to a single point. Random negative sampling generates R random IP addresses for each input account in the mini batch. The sum of the random_negative_sampling_rate (R) and shuffled_negative_sampling_rate (S) must be in the interval: 1 ≤ R + S ≤ 500.</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: 0 ≤ positive integer ≤ 500</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>shuffled_negative_sampling_rate</td>
<td>The number of shuffled negative samples, S, to generate per input example. In some cases, it helps to use more realistic negative samples that are randomly picked from the training data itself. This kind of negative sampling is achieved by shuffling the data within a mini batch. Shuffled negative sampling generates S negative IP addresses by shuffling the IP address and account pairings within a mini batch. The sum of the random_negative_sampling_rate (R) and shuffled_negative_sampling_rate (S) must be in the interval: 1 ≤ R + S ≤ 500.</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: 0 ≤ positive integer ≤ 500</td>
</tr>
<tr>
<td></td>
<td>Default value: 1</td>
</tr>
<tr>
<td>weight_decay</td>
<td>The weight decay coefficient. This parameter adds an L2 regularization factor that is required to prevent the model from overfitting the training data.</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: 0.0 ≤ float ≤ 10.0</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.00001</td>
</tr>
</tbody>
</table>

**Tune an IP Insights Model**

*Automatic model tuning*, also called hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).
Metrics Computed by the IP Insights Algorithm

The Amazon SageMaker IP Insights algorithm is an unsupervised learning algorithm that learns associations between IP addresses and entities. The algorithm trains a discriminator model, which learns to separate observed data points (positive samples) from randomly generated data points (negative samples). Automatic model tuning on IP Insights helps you find the model that can most accurately distinguish between unlabeled validation data and automatically generated negative samples. The model accuracy on the validation dataset is measured by the area under the receiver operating characteristic curve. This validation:discriminator_auc metric can take values between 0.0 and 1.0, where 1.0 indicates perfect accuracy.

The IP Insights algorithm computes a validation:discriminator_auc metric during validation, the value of which is used as the objective function to optimize for hyperparameter tuning.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>validation:discriminator_auc</td>
<td>Area under the receiver operating characteristic curve on the validation dataset. The validation dataset is not labeled. Area Under the Curve (AUC) is a metric that describes the model's ability to discriminate validation data points from randomly generated data points.</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

Tunable IP Insights Hyperparameters

You can tune the following hyperparameters for the SageMaker IP Insights algorithm.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>epochs</td>
<td>IntegerParameterRange</td>
<td>MinValue: 1, MaxValue: 100</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-4, MaxValue: 0.1</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 100, MaxValue: 50000</td>
</tr>
<tr>
<td>num_entity_vectors</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 10000, MaxValue: 100000</td>
</tr>
<tr>
<td>num_ip_encoder_layers</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 10</td>
</tr>
<tr>
<td>random_negative_sampling</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 0, MaxValue: 10</td>
</tr>
<tr>
<td>shuffled_negative_sampling</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 0, MaxValue: 10</td>
</tr>
<tr>
<td>vector_dim</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 8, MaxValue: 256</td>
</tr>
<tr>
<td>weight_decay</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 1.0</td>
</tr>
</tbody>
</table>
IP Insights Data Formats

This section provides examples of the available input and output data formats used by the IP Insights algorithm during training and inference.

Topics

- IP Insights Training Data Formats (p. 2149)
- IP Insights Inference Data Formats (p. 2149)

IP Insights Training Data Formats

The following are the available data input formats for the IP Insights algorithm. Amazon SageMaker built-in algorithms adhere to the common input training format described in Common Data Formats for Training (p. 1959). However, the SageMaker IP Insights algorithm currently supports only the CSV data input format.

IP Insights Training Data Input Formats

INPUT: CSV

The CSV file must have two columns. The first column is an opaque string that corresponds to an entity's unique identifier. The second column is the IPv4 address of the entity's access event in decimal-dot notation.

<table>
<thead>
<tr>
<th>content-type: text/csv</th>
</tr>
</thead>
<tbody>
<tr>
<td>entity_id_1, 192.168.1.2</td>
</tr>
<tr>
<td>entity_id_2, 10.10.1.2</td>
</tr>
</tbody>
</table>

IP Insights Inference Data Formats

The following are the available input and output formats for the IP Insights algorithm. Amazon SageMaker built-in algorithms adhere to the common input inference format described in Common Data Formats for Inference (p. 1963). However, the SageMaker IP Insights algorithm does not currently support RecordIO format.

IP Insights Input Request Formats

INPUT: CSV Format

The CSV file must have two columns. The first column is an opaque string that corresponds to an entity's unique identifier. The second column is the IPv4 address of the entity's access event in decimal-dot notation.

<table>
<thead>
<tr>
<th>content-type: text/csv</th>
</tr>
</thead>
<tbody>
<tr>
<td>entity_id_1, 192.168.1.2</td>
</tr>
<tr>
<td>entity_id_2, 10.10.1.2</td>
</tr>
</tbody>
</table>

INPUT: JSON Format

JSON data can be provided in different formats. IP Insights follows the common SageMaker formats. For more information about inference formats, see Common Data Formats for Inference (p. 1963).

| content-type: application/json |
Use Built-in Algorithms

INPUT: JSONLINES Format

The JSON Lines content type is useful for running batch transform jobs. For more information on SageMaker inference formats, see Common Data Formats for Inference (p. 1963). For more information on running batch transform jobs, see Use Batch Transform (p. 2955).

IP Insights Output Response Formats

OUTPUT: JSON Response Format

The default output of the SageMaker IP Insights algorithm is the dot_product between the input entity and IP address. The dot_product signifies how compatible the model considers the entity and IP address. The dot_product is unbounded. To make predictions about whether an event is anomalous, you need to set a threshold based on your defined distribution. For information about how to use the dot_product for anomaly detection, see the An Introduction to the SageMaker IP Insights Algorithm.

Advanced users can access the model's learned entity and IP embeddings by providing the additional content-type parameter verbose=True to the Accept heading. You can use the entity_embedding and ip_embedding for debugging, visualizing, and understanding the model. Additionally, you can use these embeddings in other machine learning techniques, such as classification or clustering.
K-Means Algorithm

K-means is an unsupervised learning algorithm. It attempts to find discrete groupings within data, where members of a group are as similar as possible to one another and as different as possible from members of other groups. You define the attributes that you want the algorithm to use to determine similarity.

Amazon SageMaker uses a modified version of the web-scale k-means clustering algorithm. Compared with the original version of the algorithm, the version used by Amazon SageMaker is more accurate. Like the original algorithm, it scales to massive datasets and delivers improvements in training time. To do this, the version used by Amazon SageMaker streams mini-batches (small, random subsets) of the training data. For more information about mini-batch k-means, see Web-scale k-means Clustering.

The k-means algorithm expects tabular data, where rows represent the observations that you want to cluster, and the columns represent attributes of the observations. The $n$ attributes in each row represent a point in $n$-dimensional space. The Euclidean distance between these points represents the similarity of the corresponding observations. The algorithm groups observations with similar attribute values (the points corresponding to these observations are closer together). For more information about how k-means works in Amazon SageMaker, see How K-Means Clustering Works (p. 2152).

Topics
- Input/Output Interface for the K-Means Algorithm (p. 2151)
- EC2 Instance Recommendation for the K-Means Algorithm (p. 2152)
- K-Means Sample Notebooks (p. 2152)
- How K-Means Clustering Works (p. 2152)
- K-Means Hyperparameters (p. 2155)
- Tune a K-Means Model (p. 2157)
- K-Means Response Formats (p. 2158)

Input/Output Interface for the K-Means Algorithm

For training, the k-means algorithm expects data to be provided in the train channel (recommended S3DataDistributionType=ShardedByS3Key), with an optional test channel (recommended S3DataDistributionType=FullyReplicated) to score the data on. Both recordIO-wrapped-protobuf and CSV formats are supported for training. You can use either File mode or Pipe mode to train models on data that is formatted as recordIO-wrapped-protobuf or as CSV.

For inference, text/csv, application/json, and application/x-recordio-protobuf are supported. k-means returns a closest_cluster label and the distance_to_cluster for each observation.

For more information on input and output file formats, see K-Means Response Formats (p. 2158) for inference and the K-Means Sample Notebooks (p. 2152). The k-means algorithm does not support
multiple instance learning, in which the training set consists of labeled “bags”, each of which is a collection of unlabeled instances.

**EC2 Instance Recommendation for the K-Means Algorithm**

We recommend training k-means on CPU instances. You can train on GPU instances, but should limit GPU training to single-GPU instances (such as ml.g4dn.xlarge) because only one GPU is used per instance. The k-means algorithm supports P2, P3, G4dn, and G5 instances for training and inference.

**K-Means Sample Notebooks**

For a sample notebook that uses the SageMaker K-means algorithm to segment the population of counties in the United States by attributes identified using principle component analysis, see Analyze US census data for population segmentation using Amazon SageMaker. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. To open a notebook, click on its Use tab and select Create copy.

**How K-Means Clustering Works**

K-means is an algorithm that trains a model that groups similar objects together. The k-means algorithm accomplishes this by mapping each observation in the input dataset to a point in the \( n \)-dimensional space (where \( n \) is the number of attributes of the observation). For example, your dataset might contain observations of temperature and humidity in a particular location, which are mapped to points \((t, h)\) in 2-dimensional space.

**Note**

Clustering algorithms are unsupervised. In unsupervised learning, labels that might be associated with the objects in the training dataset aren't used.

In k-means clustering, each cluster has a center. During model training, the k-means algorithm uses the distance of the point that corresponds to each observation in the dataset to the cluster centers as the basis for clustering. You choose the number of clusters \( (k) \) to create.

For example, suppose that you want to create a model to recognize handwritten digits and you choose the MNIST dataset for training. The dataset provides thousands of images of handwritten digits (0 through 9). In this example, you might choose to create 10 clusters, one for each digit \((0, 1, ..., 9)\). As part of model training, the k-means algorithm groups the input images into 10 clusters.

Each image in the MNIST dataset is a 28x28-pixel image, with a total of 784 pixels. Each image corresponds to a point in a 784-dimensional space, similar to a point in a 2-dimensional space \((x, y)\). To find a cluster to which a point belongs, the k-means algorithm finds the distance of that point from all of the cluster centers. It then chooses the cluster with the closest center as the cluster to which the image belongs.

**Note**

Amazon SageMaker uses a customized version of the algorithm where, instead of specifying that the algorithm create \( k \) clusters, you might choose to improve model accuracy by specifying extra cluster centers \((K = k \times x)\). However, the algorithm ultimately reduces these to \( k \) clusters.

In SageMaker, you specify the number of clusters when creating a training job. For more information, see CreateTrainingJob. In the request body, you add the HyperParameters string map to specify the \( k \) and extra_center_factor strings.

The following is a summary of how k-means works for model training in SageMaker:

1. It determines the initial \( K \) cluster centers.
Note
In the following topics, K clusters refer to k * x, where you specify k and x when creating a model training job.

2. It iterates over input training data and recalculates cluster centers.
3. It reduces resulting clusters to k (if the data scientist specified the creation of k*x clusters in the request).

The following sections also explain some of the parameters that a data scientist might specify to configure a model training job as part of the "HyperParameters" string map.

Topics
• Step 1: Determine the Initial Cluster Centers (p. 2153)
• Step 2: Iterate over the Training Dataset and Calculate Cluster Centers (p. 2154)
• Step 3: Reduce the Clusters from K to k (p. 2154)

Step 1: Determine the Initial Cluster Centers

When using k-means in SageMaker, the initial cluster centers are chosen from the observations in a small, randomly sampled batch. Choose one of the following strategies to determine how these initial cluster centers are selected:

• The random approach—Randomly choose K observations in your input dataset as cluster centers. For example, you might choose a cluster center that points to the 784-dimensional space that corresponds to any 10 images in the MNIST training dataset.

• The k-means++ approach, which works as follows:
  1. Start with one cluster and determine its center. You randomly select an observation from your training dataset and use the point corresponding to the observation as the cluster center. For example, in the MNIST dataset, randomly choose a handwritten digit image. Then choose the point in the 784-dimensional space that corresponds to the image as your cluster center. This is cluster center 1.
  2. Determine the center for cluster 2. From the remaining observations in the training dataset, pick an observation at random. Choose one that is different than the one you previously selected. This observation corresponds to a point that is far away from cluster center 1. Using the MNIST dataset as an example, you do the following:
    • For each of the remaining images, find the distance of the corresponding point from cluster center 1. Square the distance and assign a probability that is proportional to the square of the distance. That way, an image that is different from the one that you previously selected has a higher probability of getting selected as cluster center 2.
    • Choose one of the images randomly, based on probabilities assigned in the previous step. The point that corresponds to the image is cluster center 2.
  3. Repeat Step 2 to find cluster center 3. This time, find the distances of the remaining images from cluster center 2.
  4. Repeat the process until you have the K cluster centers.

To train a model in SageMaker, you create a training job. In the request, you provide configuration information by specifying the following "HyperParameters" string maps:

• To specify the number of clusters to create, add the k string.
• For greater accuracy, add the optional extra_center_factor string.
• To specify the strategy that you want to use to determine the initial cluster centers, add the init_method string and set its value to random or k-means++.
For more information about the SageMaker k-means estimator, see K-means in the Amazon SageMaker Python SDK documentation.

You now have an initial set of cluster centers.

**Step 2: Iterate over the Training Dataset and Calculate Cluster Centers**

The cluster centers that you created in the preceding step are mostly random, with some consideration for the training dataset. In this step, you use the training dataset to move these centers toward the true cluster centers. The algorithm iterates over the training dataset, and recalculates the $K$ cluster centers.

1. Read a mini-batch of observations (a small, randomly chosen subset of all records) from the training dataset and do the following.

   **Note**
   When creating a model training job, you specify the batch size in the mini_batch_size string in the HyperParameters string map.

   a. Assign all of the observations in the mini-batch to one of the clusters with the closest cluster center.

   b. Calculate the number of observations assigned to each cluster. Then, calculate the proportion of new points assigned per cluster.

   For example, consider the following clusters:

   Cluster $c1 = 100$ previously assigned points. You added 25 points from the mini-batch in this step.

   Cluster $c2 = 150$ previously assigned points. You added 40 points from the mini-batch in this step.

   Cluster $c3 = 450$ previously assigned points. You added 5 points from the mini-batch in this step.

   Calculate the proportion of new points assigned to each of clusters as follows:

   $p1 = \text{proportion of points assigned to } c1 = \frac{25}{100+25}$
   $p2 = \text{proportion of points assigned to } c2 = \frac{40}{150+40}$
   $p3 = \text{proportion of points assigned to } c3 = \frac{5}{450+5}$

   c. Compute the center of the new points added to each cluster:

   $d1 = \text{center of the new points added to cluster } 1$
   $d2 = \text{center of the new points added to cluster } 2$
   $d3 = \text{center of the new points added to cluster } 3$

   d. Compute the weighted average to find the updated cluster centers as follows:

   $\text{Center of cluster } 1 = ((1 - p1) \times \text{center of cluster } 1) + (p1 \times d1)$
   $\text{Center of cluster } 2 = ((1 - p2) \times \text{center of cluster } 2) + (p2 \times d2)$
   $\text{Center of cluster } 3 = ((1 - p3) \times \text{center of cluster } 3) + (p3 \times d3)$

2. Read the next mini-batch, and repeat Step 1 to recalculate the cluster centers.

3. For more information about mini-batch k-means, see Web-Scale k-means Clustering.

**Step 3: Reduce the Clusters from $K$ to $k$**

If the algorithm created $K$ clusters—($K = k \times x$) where $x$ is greater than 1—then it reduces the $K$ clusters to $k$ clusters. (For more information, see extra_center_factor in the preceding discussion.) It does this
by applying Lloyd's method with kmeans++ initialization to the $K$ cluster centers. For more information about Lloyd's method, see k-means clustering.

**K-Means Hyperparameters**

In the `CreateTrainingJob` request, you specify the training algorithm that you want to use. You can also specify algorithm-specific hyperparameters as string-to-string maps. The following table lists the hyperparameters for the k-means training algorithm provided by Amazon SageMaker. For more information about how k-means clustering works, see How K-Means Clustering Works (p. 2152).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>feature_dim</code></td>
<td>The number of features in the input data. Required Valid values: Positive integer</td>
</tr>
<tr>
<td><code>k</code></td>
<td>The number of required clusters. Required Valid values: Positive integer</td>
</tr>
<tr>
<td><code>epochs</code></td>
<td>The number of passes done over the training data. Optional Valid values: Positive integer Default value: 1</td>
</tr>
<tr>
<td><code>eval_metrics</code></td>
<td>A JSON list of metric types used to report a score for the model. Allowed values are msd for Means Square Deviation and ssd for Sum of Square Distance. If test data is provided, the score is reported for each of the metrics requested. Optional Valid values: Either <code>&quot;msd&quot;</code> or <code>&quot;ssd&quot;</code> or <code>&quot;msd&quot;, &quot;ssd&quot;</code>. Default value: <code>&quot;msd&quot;</code></td>
</tr>
<tr>
<td><code>extra_center_factor</code></td>
<td>The algorithm creates $K$ centers = num_clusters * extra_center_factor as it runs and reduces the number of centers from $K$ to $k$ when finalizing the model. Optional Valid values: Either a positive integer or auto. Default value: auto</td>
</tr>
<tr>
<td><code>half_life_time_size</code></td>
<td>Used to determine the weight given to an observation when computing a cluster mean. This weight decays exponentially as more points are observed. When a point is first observed, it is assigned a weight of 1 when computing the cluster mean. The decay constant for the exponential decay function is chosen so that</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| after observing half_life_time_size points, its weight is 1/2. If set to 0, there is no decay. | Optional  
Valid values: Non-negative integer  
Default value: 0 |
| init_method      | Method by which the algorithm chooses the initial cluster centers. The standard k-means approach chooses them at random. An alternative k-means++ method chooses the first cluster center at random. Then it spreads out the position of the remaining initial clusters by weighting the selection of centers with a probability distribution that is proportional to the square of the distance of the remaining data points from existing centers.  
Optional  
Valid values: Either random or kmeans++.  
Default value: random |
| local_lloyd_init_method | The initialization method for Lloyd's expectation-maximization (EM) procedure used to build the final model containing k centers.  
Optional  
Valid values: Either random or kmeans++.  
Default value: kmeans++ |
| local_lloyd_max_iter | The maximum number of iterations for Lloyd's expectation-maximization (EM) procedure used to build the final model containing k centers.  
Optional  
Valid values: Positive integer  
Default value: 300 |
| local_lloyd_num_trials | The number of times the Lloyd's expectation-maximization (EM) procedure with the least loss is run when building the final model containing k centers.  
Optional  
Valid values: Either a positive integer or auto.  
Default value: auto |
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>local_lloyd_tol</td>
<td>The tolerance for change in loss for early stopping of Lloyd's expectation-maximization (EM) procedure used to build the final model containing k centers.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float. Range in [0, 1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0001</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The number of observations per mini-batch for the data iterator.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 5000</td>
</tr>
</tbody>
</table>

### Tune a K-Means Model

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

The Amazon SageMaker k-means algorithm is an unsupervised algorithm that groups data into clusters whose members are as similar as possible. Because it is unsupervised, it doesn't use a validation dataset that hyperparameters can optimize against. But it does take a test dataset and emits metrics that depend on the squared distance between the data points and the final cluster centroids at the end of each training run. To find the model that reports the tightest clusters on the test dataset, you can use a hyperparameter tuning job. The clusters optimize the similarity of their members.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

### Metrics Computed by the K-Means Algorithm

The k-means algorithm computes the following metrics during training. When tuning a model, choose one of these metrics as the objective metric.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>test:msd</td>
<td>Mean squared distances between each record in the test set and the closest center of the model.</td>
<td>Minimize</td>
</tr>
<tr>
<td>test:ssd</td>
<td>Sum of the squared distances between each record in the test set and the closest center of the model.</td>
<td>Minimize</td>
</tr>
</tbody>
</table>

### Tunable K-Means Hyperparameters

Tune the Amazon SageMaker k-means model with the following hyperparameters. The hyperparameters that have the greatest impact on k-means objective metrics are: mini_batch_size,
extra_center_factor, and init_method. Tuning the hyperparameter epochs generally results in minor improvements.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>epochs</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue:10</td>
</tr>
<tr>
<td>extra_center_factor</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 4, MaxValue:10</td>
</tr>
<tr>
<td>init_method</td>
<td>CategoricalParameterRanges</td>
<td>['kmeans++', 'random']</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 3000, MaxValue:15000</td>
</tr>
</tbody>
</table>

K-Means Response Formats

All SageMaker built-in algorithms adhere to the common input inference format described in Common Data Formats - Inference. This topic contains a list of the available output formats for the SageMaker k-means algorithm.

JSON Response Format

```json
{
    "predictions": [
        {
            "closest_cluster": 1.0,
            "distance_to_cluster": 3.0,
        },
        {
            "closest_cluster": 2.0,
            "distance_to_cluster": 5.0,
        },
        ...
    ]
}
```

JSONLINES Response Format

```json
{"closest_cluster": 1.0, "distance_to_cluster": 3.0}
{"closest_cluster": 2.0, "distance_to_cluster": 5.0}
```

RECORDIO Response Format

```json
[Record = {
    features = {},
    label = {
        'closest_cluster': {
            keys: [],
            values: [1.0, 2.0]  # float32
        },
        'distance_to_cluster': {
            keys: [],
            values: [3.0, 5.0]  # float32
        }
    }
}
```

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CSV Response Format

The first value in each line corresponds to closest_cluster.

The second value in each line corresponds to distance_to_cluster.

1.0, 3.0
2.0, 5.0

Principal Component Analysis (PCA) Algorithm

PCA is an unsupervised machine learning algorithm that attempts to reduce the dimensionality (number of features) within a dataset while still retaining as much information as possible. This is done by finding a new set of features called components, which are composites of the original features that are uncorrelated with one another. They are also constrained so that the first component accounts for the largest possible variability in the data, the second component the second most variability, and so on.

In Amazon SageMaker, PCA operates in two modes, depending on the scenario:

- **regular**: For datasets with sparse data and a moderate number of observations and features.
- **randomized**: For datasets with both a large number of observations and features. This mode uses an approximation algorithm.

PCA uses tabular data.

The rows represent observations you want to embed in a lower dimensional space. The columns represent features that you want to find a reduced approximation for. The algorithm calculates the covariance matrix (or an approximation thereof in a distributed manner), and then performs the singular value decomposition on this summary to produce the principal components.

Topics

- Input/Output Interface for the PCA Algorithm (p. 2159)
- EC2 Instance Recommendation for the PCA Algorithm (p. 2160)
- PCA Sample Notebooks (p. 2160)
- How PCA Works (p. 2160)
- PCA Hyperparameters (p. 2161)
- PCA Response Formats (p. 2162)

Input/Output Interface for the PCA Algorithm

For training, PCA expects data provided in the train channel, and optionally supports a dataset passed to the test dataset, which is scored by the final algorithm. Both recordIO-wrapped-protobuf and CSV formats are supported for training. You can use either File mode or Pipe mode to train models on data that is formatted as recordIO-wrapped-protobuf or as CSV.

For inference, PCA supports text/csv, application/json, and application/x-recordio-protobuf. Results are returned in either application/json or application/x-recordio-protobuf format with a vector of “projections.”
For more information on input and output file formats, see PCA Response Formats (p. 2162) for inference and the PCA Sample Notebooks (p. 2160).

EC2 Instance Recommendation for the PCA Algorithm

PCA supports CPU and GPU instances for training and inference. Which instance type is most performant depends heavily on the specifics of the input data. For GPU instances, PCA supports P2, P3, G4dn, and G5.

PCA Sample Notebooks

For a sample notebook that shows how to use the SageMaker Principal Component Analysis algorithm to analyze the images of handwritten digits from zero to nine in the MNIST dataset, see An Introduction to PCA with MNIST. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. The topic modeling example notebooks using the NTM algorithms are located in the Introduction to Amazon algorithms section. To open a notebook, click on its Use tab and select Create copy.

How PCA Works

Principal Component Analysis (PCA) is a learning algorithm that reduces the dimensionality (number of features) within a dataset while still retaining as much information as possible.

PCA reduces dimensionality by finding a new set of features called components, which are composites of the original features, but are uncorrelated with one another. The first component accounts for the largest possible variability in the data, the second component the second most variability, and so on.

It is an unsupervised dimensionality reduction algorithm. In unsupervised learning, labels that might be associated with the objects in the training dataset aren't used.

Given the input of a matrix with rows $x_1, \ldots, x_n$ each of dimension $1 \times d$, the data is partitioned into mini-batches of rows and distributed among the training nodes (workers). Each worker then computes a summary of its data. The summaries of the different workers are then unified into a single solution at the end of the computation.

Modes

The Amazon SageMaker PCA algorithm uses either of two modes to calculate these summaries, depending on the situation:

- **regular**: for datasets with sparse data and a moderate number of observations and features.
- **randomized**: for datasets with both a large number of observations and features. This mode uses an approximation algorithm.

As the algorithm’s last step, it performs the singular value decomposition on the unified solution, from which the principal components are then derived.

Mode 1: Regular

The workers jointly compute both $\sum x_i^T x_i$ and $\sum x_i$.

Note

Because $x_i$ are $1 \times d$ row vectors, $x_i^T x_i$ is a matrix (not a scalar). Using row vectors within the code allows us to obtain efficient caching.
The covariance matrix is computed as $\sum x_i^T x_i - (1/n)(\sum x_i)^T \sum x_i$, and its top `num_components` singular vectors form the model.

**Note**

If `subtract_mean` is `False`, we avoid computing and subtracting $\sum x_i$.

Use this algorithm when the dimension $d$ of the vectors is small enough so that $d^2$ can fit in memory.

**Mode 2: Randomized**

When the number of features in the input dataset is large, we use a method to approximate the covariance metric. For every mini-batch $X_i$ of dimension $b * d$, we randomly initialize a $(num\_components + extra\_components) \times b$ matrix that we multiply by each mini-batch, to create a $(num\_components + extra\_components) \times d$ matrix. The sum of these matrices is computed by the workers, and the servers perform SVD on the final $(num\_components + extra\_components) \times d$ matrix. The top right $num\_components$ singular vectors of it are the approximation of the top singular vectors of the input matrix.

Let $\ell = num\_components + extra\_components$. Given a mini-batch $X_i$ of dimension $b * d$, the worker draws a random matrix $H_i$ of dimension $\ell \times b$. Depending on whether the environment uses a GPU or CPU and the dimension size, the matrix is either a random sign matrix where each entry is $\pm 1$ or a FJLT (fast Johnson Lindenstrauss transform; for information, see FJLT Transforms and the follow-up papers). The worker then computes $H_i X_i$ and maintains $B = \sum H_i X_i$. The worker also maintains $h^T$, the sum of columns of $H_1, \ldots, H_T$ (T being the total number of mini-batches), and $s$, the sum of all input rows. After processing the entire shard of data, the worker sends the server $B$, $h$, $s$, and $n$ (the number of input rows).

Denote the different inputs to the server as $B^i, h^i, s^i, n^i$. The server computes $B, h, s, n$ the sums of the respective inputs. It then computes $C = B - (1/n)h^T s$, and finds its singular value decomposition. The top-right singular vectors and singular values of $C$ are used as the approximate solution to the problem.

**PCA Hyperparameters**

In the `CreateTrainingJob` request, you specify the training algorithm. You can also specify algorithm-specific HyperParameters as string-to-string maps. The following table lists the hyperparameters for the PCA training algorithm provided by Amazon SageMaker. For more information about how PCA works, see *How PCA Works* (p. 2160).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>feature_dim</code></td>
<td>Input dimension.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td><code>mini_batch_size</code></td>
<td>Number of rows in a mini-batch.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td><code>num_components</code></td>
<td>The number of principal components to compute.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>algorithm_mode</td>
<td>Mode for computing the principal components.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: <em>regular</em> or <em>randomized</em></td>
</tr>
<tr>
<td></td>
<td>Default value: <em>regular</em></td>
</tr>
<tr>
<td>extra_components</td>
<td>As the value increases, the solution becomes more accurate but the runtime</td>
</tr>
<tr>
<td></td>
<td>and memory consumption increase linearly. The default, -1, means the</td>
</tr>
<tr>
<td></td>
<td>maximum of 10 and num_components.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Non-negative integer or -1</td>
</tr>
<tr>
<td></td>
<td>Default value: -1</td>
</tr>
<tr>
<td>subtract_mean</td>
<td>Indicates whether the data should be unbiased both during training and</td>
</tr>
<tr>
<td></td>
<td>at inference.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: One of <em>true</em> or <em>false</em></td>
</tr>
<tr>
<td></td>
<td>Default value: <em>true</em></td>
</tr>
</tbody>
</table>

### PCA Response Formats

All Amazon SageMaker built-in algorithms adhere to the common input inference format described in [Common Data Formats - Inference](#). This topic contains a list of the available output formats for the SageMaker PCA algorithm.

#### JSON Response Format

Accept—application/json

```json
{
   "projections": [
       {
           "projection": [1.0, 2.0, 3.0, 4.0, 5.0]
        },
        {
           "projection": [6.0, 7.0, 8.0, 9.0, 0.0]
        },
        ....
    ]
}
```

#### JSONLINES Response Format

Accept—application/jsonlines

```json
{
   "projection": [1.0, 2.0, 3.0, 4.0, 5.0]  
}{
   "projection": [6.0, 7.0, 8.0, 9.0, 0.0]  
}
Random Cut Forest (RCF) Algorithm

Amazon SageMaker Random Cut Forest (RCF) is an unsupervised algorithm for detecting anomalous data points within a data set. These are observations which diverge from otherwise well-structured or patterned data. Anomalies can manifest as unexpected spikes in time series data, breaks in periodicity, or unclassifiable data points. They are easy to describe in that, when viewed in a plot, they are often easily distinguishable from the "regular" data. Including these anomalies in a data set can drastically increase the complexity of a machine learning task since the "regular" data can often be described with a simple model.

With each data point, RCF associates an anomaly score. Low score values indicate that the data point is considered "normal." High values indicate the presence of an anomaly in the data. The definitions of "low" and "high" depend on the application but common practice suggests that scores beyond three standard deviations from the mean score are considered anomalous.

While there are many applications of anomaly detection algorithms to one-dimensional time series data such as traffic volume analysis or sound volume spike detection, RCF is designed to work with arbitrary-dimensional input. Amazon SageMaker RCF scales well with respect to number of features, data set size, and number of instances.

Topics
- Input/Output Interface for the RCF Algorithm (p. 2163)
- Instance Recommendations for the RCF Algorithm (p. 2164)
- RCF Sample Notebooks (p. 2164)
- How RCF Works (p. 2165)
- RCF Hyperparameters (p. 2167)
- Tune an RCF Model (p. 2168)
- RCF Response Formats (p. 2169)

Input/Output Interface for the RCF Algorithm

Amazon SageMaker Random Cut Forest supports the train and test data channels. The optional test channel is used to compute accuracy, precision, recall, and F1-score metrics on labeled data. Train and
test data content types can be either application/x-recordio-protobuf or text/csv formats. For the test data, when using text/csv format, the content must be specified as text/csv;label_size=1 where the first column of each row represents the anomaly label: "1" for an anomalous data point and "0" for a normal data point. You can use either File mode or Pipe mode to train RCF models on data that is formatted as recordIO-wrapped-protobuf or as CSV.

The train channel only supports S3DataDistributionType=ShardedByS3Key and the test channel only supports S3DataDistributionType=FullyReplicated. The following example specifies the S3 distribution type for the train channel using the Amazon SageMaker Python SDK.

Note
The sagemaker.inputs.s3_input method was renamed to sagemaker.inputs.TrainingInput in SageMaker Python SDK v2.

```python
import sagemaker

# specify Random Cut Forest training job information and hyperparameters
rcf = sagemaker.estimator.Estimator(...)

# explicitly specify "ShardedByS3Key" distribution type
train_data = sagemaker.inputs.TrainingInput(
    s3_data=s3_training_data_location,
    content_type='text/csv;label_size=0',
    distribution='ShardedByS3Key')

# run the training job on input data stored in S3
rcf.fit({'train': train_data})
```

To avoid common errors around execution roles, ensure that you have the execution roles required, AmazonSageMakerFullAccess and AmazonEC2ContainerRegistryFullAccess. To avoid common errors around your image not existing or its permissions being incorrect, ensure that your ECR image is not larger then the allocated disk space on the training instance. To avoid this, run your training job on an instance that has sufficient disk space. In addition, if your ECR image is from a different AWS account's Elastic Container Service (ECS) repository, and you do not set repository permissions to grant access, this will result in an error. See the ECR repository permissions for more information on setting a repository policy statement.

See the S3DataSource for more information on customizing the S3 data source attributes. Finally, in order to take advantage of multi-instance training the training data must be partitioned into at least as many files as instances.

For inference, RCF supports application/x-recordio-protobuf, text/csv and application/json input data content types. See the Common Data Formats for Built-in Algorithms (p. 1959) documentation for more information. RCF inference returns application/x-recordio-protobuf or application/json formatted output. Each record in these output data contains the corresponding anomaly scores for each input data point. See Common Data Formats--Inference for more information.

For more information on input and output file formats, see RCF Response Formats (p. 2169) for inference and the RCF Sample Notebooks (p. 2164).

Instance Recommendations for the RCF Algorithm
For training, we recommend the m1.m4, m1.c4, and m1.c5 instance families. For inference we recommend using a m1.c5.x1 instance type in particular, for maximum performance as well as minimized cost per hour of usage. Although the algorithm could technically run on GPU instance types it does not take advantage of GPU hardware.

RCF Sample Notebooks
For an example of how to train an RCF model and perform inferences with it, see the An Introduction to SageMaker Random Cut Forests notebook. For instructions how to create and access Jupyter notebook
instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. To open a notebook, click on its Use tab and select Create copy.

How RCF Works

Amazon SageMaker Random Cut Forest (RCF) is an unsupervised algorithm for detecting anomalous data points within a dataset. These are observations which diverge from otherwise well-structured or patterned data. Anomalies can manifest as unexpected spikes in time series data, breaks in periodicity, or unclassifiable data points. They are easy to describe in that, when viewed in a plot, they are often easily distinguishable from the "regular" data. Including these anomalies in a dataset can drastically increase the complexity of a machine learning task since the "regular" data can often be described with a simple model.

The main idea behind the RCF algorithm is to create a forest of trees where each tree is obtained using a partition of a sample of the training data. For example, a random sample of the input data is first determined. The random sample is then partitioned according to the number of trees in the forest. Each tree is given such a partition and organizes that subset of points into a k-d tree. The anomaly score assigned to a data point by the tree is defined as the expected change in complexity of the tree as a result adding that point to the tree; which, in approximation, is inversely proportional to the resulting depth of the point in the tree. The random cut forest assigns an anomaly score by computing the average score from each constituent tree and scaling the result with respect to the sample size. The RCF algorithm is based on the one described in reference [1].

Sample Data Randomly

The first step in the RCF algorithm is to obtain a random sample of the training data. In particular, suppose we want a sample of size $K$ from $N$ total data points. If the training data is small enough, the entire dataset can be used, and we could randomly draw elements from this set. However, frequently the training data is too large to fit all at once, and this approach isn’t feasible. Instead, we use a technique called reservoir sampling.

Reservoir sampling is an algorithm for efficiently drawing random samples from a dataset $S = \{S_1, \ldots, S_N\}$ where the elements in the dataset can only be observed one at a time or in batches. In fact, reservoir sampling works even when $N$ is not known a priori. If only one sample is requested, such as when $K = 1$, the algorithm is like this:

**Algorithm: Reservoir Sampling**

- Input: dataset or data stream $S = \{S_1, \ldots, S_N\}$
- Initialize the random sample $X = S_1$
- For each observed sample $S_n, n = 2, \ldots, N$:
  - Pick a uniform random number $\xi \in [0, 1]$
  - If $\xi < 1/n$
    - Set $X = S_n$
- Return $X$

This algorithm selects a random sample such that $P(X = S_n) = 1/N$ for all $n = 1, \ldots, N$. When $K > 1$ the algorithm is more complicated. Additionally, a distinction must be made between random sampling that is with and without replacement. RCF performs an augmented reservoir sampling without replacement on the training data based on the algorithms described in [2].

Train a RCF Model and Produce Inferences

The next step in RCF is to construct a random cut forest using the random sample of data. First, the sample is partitioned into a number of equal-sized partitions equal to the number of trees in the forest.
Then, each partition is sent to an individual tree. The tree recursively organizes its partition into a binary tree by partitioning the data domain into bounding boxes.

This procedure is best illustrated with an example. Suppose a tree is given the following two-dimensional dataset. The corresponding tree is initialized to the root node:

![A two-dimensional dataset where the majority of data lies in a cluster (blue) except for one anomalous data point (orange). The tree is initialized with a root node.](image)

The RCF algorithm organizes these data in a tree by first computing a bounding box of the data, selecting a random dimension (giving more weight to dimensions with higher "variance"), and then randomly determining the position of a hyperplane "cut" through that dimension. The two resulting subspaces define their own sub tree. In this example, the cut happens to separate a lone point from the remainder of the sample. The first level of the resulting binary tree consists of two nodes, one which will consist of the subtree of points to the left of the initial cut and the other representing the single point on the right.
A random cut partitioning the two-dimensional dataset. An anomalous data point is more likely to lie isolated in a bounding box at a smaller tree depth than other points.

Bounding boxes are then computed for the left and right halves of the data and the process is repeated until every leaf of the tree represents a single data point from the sample. Note that if the lone point is sufficiently far away then it is more likely that a random cut would result in point isolation. This observation provides the intuition that tree depth is, loosely speaking, inversely proportional to the anomaly score.

When performing inference using a trained RCF model the final anomaly score is reported as the average across scores reported by each tree. Note that it is often the case that the new data point does not already reside in the tree. To determine the score associated with the new point the data point is inserted into the given tree and the tree is efficiently (and temporarily) reassembled in a manner equivalent to the training process described above. That is, the resulting tree is as if the input data point were a member of the sample used to construct the tree in the first place. The reported score is inversely proportional to the depth of the input point within the tree.

Choose Hyperparameters

The primary hyperparameters used to tune the RCF model are num_trees and num_samples_per_tree. Increasing num_trees has the effect of reducing the noise observed in anomaly scores since the final score is the average of the scores reported by each tree. While the optimal value is application-dependent we recommend using 100 trees to begin with as a balance between score noise and model complexity. Note that inference time is proportional to the number of trees. Although training time is also affected it is dominated by the reservoir sampling algorithm described above.

The parameter num_samples_per_tree is related to the expected density of anomalies in the dataset. In particular, num_samples_per_tree should be chosen such that 1/num_samples_per_tree approximates the ratio of anomalous data to normal data. For example, if 256 samples are used in each tree then we expect our data to contain anomalies 1/256 or approximately 0.4% of the time. Again, an optimal value for this hyperparameter is dependent on the application.

References


RCF Hyperparameters

In the CreateTrainingJob request, you specify the training algorithm. You can also specify algorithm-specific hyperparameters as string-to-string maps. The following table lists the hyperparameters for the Amazon SageMaker RCF algorithm. For more information, including recommendations on how to choose hyperparameters, see How RCF Works (p. 2165).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>feature_dim</td>
<td>The number of features in the data set. (If you use the Random Cut Forest estimator, this value is calculated for you and need not be specified.) Required</td>
</tr>
<tr>
<td></td>
<td>Valid values: Positive integer (min: 1, max: 10000)</td>
</tr>
</tbody>
</table>
Use Built-in Algorithms

Parameter Name | Description
--- | ---
**eval_metrics** | A list of metrics used to score a labeled test data set. The following metrics can be selected for output:
- **accuracy** - returns fraction of correct predictions.
- **precision_recall_fscore** - returns the positive and negative precision, recall, and F1-scores.

Optional
Valid values: a list with possible values taken from accuracy or precision_recall_fscore.
Default value: Both accuracy, precision_recall_fscore are calculated.

**num_samples_per_tree** | Number of random samples given to each tree from the training data set.
Optional
Valid values: Positive integer (min: 1, max: 2048)
Default value: 256

**num_trees** | Number of trees in the forest.
Optional
Valid values: Positive integer (min: 50, max: 1000)
Default value: 100

Tune an RCF Model

*Automatic model tuning*, also known as hyperparameter tuning or hyperparameter optimization, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

The Amazon SageMaker RCF algorithm is an unsupervised anomaly-detection algorithm that requires a labeled test dataset for hyperparameter optimization. RCF calculates anomaly scores for test data points and then labels the data points as anomalous if their scores are beyond three standard deviations from the mean score. This is known as the three-sigma limit heuristic. The F1-score is based on the difference between calculated labels and actual labels. The hyperparameter tuning job finds the model that maximizes that score. The success of hyperparameter optimization depends on the applicability of the three-sigma limit heuristic to the test dataset.

For more information about model tuning, see [Perform Automatic Model Tuning with SageMaker](p. 2436).

**Metrics Computed by the RCF Algorithm**

The RCF algorithm computes the following metric during training. When tuning the model, choose this metric as the objective metric.
### Tunable RCF Hyperparameters

You can tune a RCF model with the following hyperparameters.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_samples_per_tree</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 2048</td>
</tr>
<tr>
<td>num_trees</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 50, MaxValue: 1000</td>
</tr>
</tbody>
</table>

### RCF Response Formats

All Amazon SageMaker built-in algorithms adhere to the common input inference format described in **Common Data Formats - Inference**. Note that SageMaker Random Cut Forest supports both dense and sparse JSON and RecordIO formats. This topic contains a list of the available output formats for the SageMaker RCF algorithm.

#### JSON Response Format

ACCEPT: application/json.

```
{
    "scores": [
        {"score": 0.02},
        {"score": 0.25}
    ]
}
```

#### JSONLINES Response Format

ACCEPT: application/jsonlines.

```
{"score": 0.02},
```

Use Built-in Algorithms

**RECORDIO Response Format**

ACCEPT: application/x-recordio-protobuf.

```json
[
    Record = {
        features = {},
        label = {
            'score': {
                keys: [],
                values: [0.25]  # float32
            }
        }
    },
    Record = {
        features = {},
        label = {
            'score': {
                keys: [],
                values: [0.25]  # float32
            }
        }
    }
]
```
values: [0.23] # float32

Built-in SageMaker Algorithms for Computer Vision

SageMaker provides image processing algorithms that are used for image classification, object detection, and computer vision.

- **Image Classification - MXNet (p. 2172)**—uses example data with answers (referred to as a *supervised algorithm*). Use this algorithm to classify images.
- **Image Classification - TensorFlow (p. 2183)**—uses pretrained TensorFlow Hub models to fine-tune for specific tasks (referred to as a *supervised algorithm*). Use this algorithm to classify images.
- **Object Detection - MXNet (p. 2196)**—detects and classifies objects in images using a single deep neural network. It is a supervised learning algorithm that takes images as input and identifies all instances of objects within the image scene.
- **Object Detection - TensorFlow (p. 2207)**—detects bounding boxes and object labels in an image. It is a supervised learning algorithm that supports transfer learning with available pretrained TensorFlow models.
- **Semantic Segmentation Algorithm (p. 2215)**—provides a fine-grained, pixel-level approach to developing computer vision applications.

<table>
<thead>
<tr>
<th>Algorithm name</th>
<th>Channel name</th>
<th>Training input mode</th>
<th>File type</th>
<th>Instance class</th>
<th>Parallelizable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image Classification - MXNet</td>
<td>train and validation, (optionally) train_lst, validation_lst, and model</td>
<td>File or Pipe</td>
<td>recordIO or image files (.jpg or .png)</td>
<td>GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Image Classification - TensorFlow</td>
<td>training and validation</td>
<td>File</td>
<td>image files (.jpg, jpeg, or .png)</td>
<td>CPU or GPU</td>
<td>Yes (only across multiple GPUs on a single instance)</td>
</tr>
<tr>
<td>Algorithm name</td>
<td>Channel name</td>
<td>Training input mode</td>
<td>File type</td>
<td>Instance class</td>
<td>Parallelizable</td>
</tr>
<tr>
<td>----------------------</td>
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</tr>
<tr>
<td>Object Detection</td>
<td>train and validation, (optionally) train_annotation, validation_annotation, and model</td>
<td>File or Pipe</td>
<td>recordIO or image files (.jpg or .png)</td>
<td>GPU</td>
<td>Yes</td>
</tr>
<tr>
<td>Object Detection - TensorFlow</td>
<td>training and validation</td>
<td>File</td>
<td>image files (.jpg, .jpeg, or .png)</td>
<td>GPU</td>
<td>Yes (only across multiple GPUs on a single instance)</td>
</tr>
<tr>
<td>Semantic Segmentation</td>
<td>train and validation, train_annotation, validation_annotation, and (optionally) label_map and model</td>
<td>File or Pipe</td>
<td>Image files</td>
<td>GPU (single instance only)</td>
<td>No</td>
</tr>
</tbody>
</table>

**Image Classification - MXNet**

The Amazon SageMaker image classification algorithm is a supervised learning algorithm that supports multi-label classification. It takes an image as input and outputs one or more labels assigned to that image. It uses a convolutional neural network that can be trained from scratch or trained using transfer learning when a large number of training images are not available.

The recommended input format for the Amazon SageMaker image classification algorithms is Apache MXNet RecordIO. However, you can also use raw images in .jpg or .png format. Refer to [this discussion](#) for a broad overview of efficient data preparation and loading for machine learning systems.

**Note**

To maintain better interoperability with existing deep learning frameworks, this differs from the protobuf data formats commonly used by other Amazon SageMaker algorithms.

For more information on convolutional networks, see:

- Deep residual learning for image recognition [Kaiming He, et al., 2016 IEEE Conference on Computer Vision and Pattern Recognition](#)
- ImageNet image database
- Image classification with Gluon-CV and MXNet

**Topics**

- Input/Output Interface for the Image Classification Algorithm (p. 2173)
- EC2 Instance Recommendation for the Image Classification Algorithm (p. 2175)
- Image Classification Sample Notebooks (p. 2175)
- How Image Classification Works (p. 2175)
- Image Classification Hyperparameters (p. 2176)
- Tune an Image Classification Model (p. 2182)
Input/Output Interface for the Image Classification Algorithm

The SageMaker Image Classification algorithm supports both RecordIO (application/x-recordio) and image (image/png, image/jpeg, and application/x-image) content types for training in file mode, and supports the RecordIO (application/x-recordio) content type for training in pipe mode. However, you can also train in pipe mode using the image files (image/png, image/jpeg, and application/x-image), without creating RecordIO files, by using the augmented manifest format.

Distributed training is supported for file mode and pipe mode. When using the RecordIO content type in pipe mode, you must set the S3DataDistributionType of the S3DataSource to FullyReplicated. The algorithm supports a fully replicated model where your data is copied onto each machine.

The algorithm supports image/png, image/jpeg, and application/x-image for inference.

Train with RecordIO Format

If you use the RecordIO format for training, specify both train and validation channels as values for the InputDataConfig parameter of the CreateTrainingJob request. Specify one RecordIO (.rec) file in the train channel and one RecordIO file in the validation channel. Set the content type for both channels to application/x-recordio.

Train with Image Format

If you use the Image format for training, specify train, validation, train_lst, and validation_lst channels as values for the InputDataConfig parameter of the CreateTrainingJob request. Specify the individual image data (.jpg or .png files) for the train and validation channels. Specify one .lst file in each of the train_lst and validation_lst channels. Set the content type for all four channels to application/x-image.

Note

SageMaker reads the training and validation data separately from different channels, so you must store the training and validation data in different folders.

A .lst file is a tab-separated file with three columns that contains a list of image files. The first column specifies the image index, the second column specifies the class label index for the image, and the third column specifies the relative path of the image file. The image index in the first column must be unique across all of the images. The set of class label indices are numbered successively and the numbering should start with 0. For example, 0 for the cat class, 1 for the dog class, and so on for additional classes.

The following is an example of a .lst file:

```
5      1   your_image_directory/train_img_dog1.jpg
1000   0   your_image_directory/train_img_cat1.jpg
22     1   your_image_directory/train_img_dog2.jpg
```

For example, if your training images are stored in s3://<your_bucket>/train/class_dog, s3://<your_bucket>/train/class_cat, and so on, specify the path for your train channel as s3://<your_bucket>/train, which is the top-level directory for your data. In the .lst file, specify the relative path for an individual file named train_image_dog1.jpg in the class_dog class directory as class_dog/train_image_dog1.jpg. You can also store all your image files under one subdirectory inside the train directory. In that case, use that subdirectory for the relative path. For example, s3://<your_bucket>/train/your_image_directory.

Train with Augmented Manifest Image Format

The augmented manifest format enables you to do training in Pipe mode using image files without needing to create RecordIO files. You need to specify both train and validation channels as values for the InputDataConfig parameter of the CreateTrainingJob request. While using the format, an S3 manifest file needs to be generated that contains the list of images and their corresponding
annotations. The manifest file format should be in **JSON Lines** format in which each line represents one sample. The images are specified using the 'source-ref' tag that points to the S3 location of the image. The annotations are provided under the "AttributeNames" parameter value as specified in the `CreateTrainingJob` request. It can also contain additional metadata under the metadata tag, but these are ignored by the algorithm. In the following example, the "AttributeNames" are contained in the list of image and annotation references ['"source-ref", "class"']. The corresponding label value is "0" for the first image and "1" for the second image:

```
{"source-ref":"s3://image/filename1.jpg", "class":"0"}
{"source-ref":"s3://image/filename2.jpg", "class":"1", "class-metadata": {"class-name": "cat", "type": "groundtruth/image-classification"}}
```

The order of "AttributeNames" in the input files matters when training the ImageClassification algorithm. It accepts piped data in a specific order, with image first, followed by label. So the "AttributeNames" in this example are provided with "source-ref" first, followed by "class". When using the ImageClassification algorithm with Augmented Manifest, the value of the `RecordWrapperType` parameter must be "RecordIO".

Multi-label training is also supported by specifying a JSON array of values. The `num_classes` hyperparameter must be set to match the total number of classes. There are two valid label formats: multi-hot and class-id.

In the multi-hot format, each label is a multi-hot encoded vector of all classes, where each class takes the value of 0 or 1. In the following example, there are three classes. The first image is labeled with classes 0 and 2, while the second image is labeled with class 2 only:

```
{"image-ref": "s3://mybucket/sample01/image1.jpg", "class": ":[1, 0, 1]"}
{"image-ref": "s3://mybucket/sample02/image2.jpg", "class": ":[0, 0, 1]"}
```

In the class-id format, each label is a list of the class ids, from [0, num_classes), which apply to the data point. The previous example would instead look like this:

```
{"image-ref": "s3://mybucket/sample01/image1.jpg", "class": ":[0, 2]"}
{"image-ref": "s3://mybucket/sample02/image2.jpg", "class": ":[2]"}
```

The multi-hot format is the default, but can be explicitly set in the content type with the `label-format` parameter: "application/x-recordio; label-format=multi-hot". The class-id format, which is the format outputted by GroundTruth, must be set explicitly: "application/x-recordio; label-format=class-id".

For more information on augmented manifest files, see [Provide Dataset Metadata to Training Jobs with an Augmented Manifest File](p. 2700).

**Incremental Training**

You can also seed the training of a new model with the artifacts from a model that you trained previously with SageMaker. Incremental training saves training time when you want to train a new model with the same or similar data. SageMaker image classification models can be seeded only with another built-in image classification model trained in SageMaker.

To use a pretrained model, in the `CreateTrainingJob` request, specify the `ChannelName` as "model" in the `InputDataConfig` parameter. Set the `ContentType` for the model channel to `application/x-sagemaker-model`. The input hyperparameters of both the new model and the pretrained model that you upload to the model channel must have the same settings for the `num_layers`, `image_shape` and `num_classes` input parameters. These parameters define the network architecture. For the pretrained model file, use the compressed model artifacts (in .tar.gz format) output by SageMaker. You can use either RecordIO or image formats for input data.
For a sample notebook that shows how to use incremental training with the SageMaker image classification algorithm, see the End-to-End Incremental Training Image Classification Example. For more information on incremental training and for instructions on how to use it, see Incremental Training in Amazon SageMaker (p. 2677).

Inference with the Image Classification Algorithm

The generated models can be hosted for inference and support encoded .jpg and .png image formats as image/png, image/jpeg, and application/x-image content-type. The input image is resized automatically. The output is the probability values for all classes encoded in JSON format, or in JSON Lines text format for batch transform. The image classification model processes a single image per request and so outputs only one line in the JSON or JSON Lines format. The following is an example of a response in JSON Lines format:

```
accept: application/jsonlines

{"prediction": [prob_0, prob_1, prob_2, prob_3, ...]}
```

For more details on training and inference, see the image classification sample notebook instances referenced in the introduction.

EC2 Instance Recommendation for the Image Classification Algorithm

For image classification, we support P2, P3, G4dn, and G5 instances. We recommend using GPU instances with more memory for training with large batch sizes. You can also run the algorithm on multi-GPU and multi-machine settings for distributed training. Both CPU (such as C4) and GPU (P2, P3, G4dn, or G5) instances can be used for inference.

Image Classification Sample Notebooks

For a sample notebook that uses the SageMaker image classification algorithm to train a model on the caltech-256 dataset and then to deploy it to perform inferences, see the End-to-End Multiclass Image Classification Example. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. The example image classification notebooks are located in the Introduction to Amazon algorithms section. To open a notebook, click on its Use tab and select Create copy.

How Image Classification Works

The image classification algorithm takes an image as input and classifies it into one of the output categories. Deep learning has revolutionized the image classification domain and has achieved great performance. Various deep learning networks such as ResNet [1], DenseNet, inception, and so on, have been developed to be highly accurate for image classification. At the same time, there have been efforts to collect labeled image data that are essential for training these networks. ImageNet[2] is one such large dataset that has more than 11 million images with about 11,000 categories. Once a network is trained with ImageNet data, it can then be used to generalize with other datasets as well, by simple re-adjustment or fine-tuning. In this transfer learning approach, a network is initialized with weights (in this example, trained on ImageNet), which can be later fine-tuned for an image classification task in a different dataset.

Image classification in Amazon SageMaker can be run in two modes: full training and transfer learning. In full training mode, the network is initialized with random weights and trained on user data from scratch. In transfer learning mode, the network is initialized with pre-trained weights and just the top fully connected layer is initialized with random weights. Then, the whole network is fine-tuned with new data. In this mode, training can be achieved even with a smaller dataset. This is because the network is already trained and therefore can be used in cases without sufficient training data.
Image Classification Hyperparameters

Hyperparameters are parameters that are set before a machine learning model begins learning. The following hyperparameters are supported by the Amazon SageMaker built-in Image Classification algorithm. See Tune an Image Classification Model (p. 2182) for information on image classification hyperparameter tuning.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_classes</td>
<td>Number of output classes. This parameter defines the dimensions of the network output and is typically set to the number of classes in the dataset. Besides multi-class classification, multi-label classification is supported too. Please refer to Input/Output Interface for the Image Classification Algorithm (p. 2173) for details on how to work with multi-label classification with augmented manifest files. Required Valid values: positive integer</td>
</tr>
<tr>
<td>num_training_samples</td>
<td>Number of training examples in the input dataset. If there is a mismatch between this value and the number of samples in the training set, then the behavior of the lr_scheduler_step parameter is undefined and distributed training accuracy might be affected. Required Valid values: positive integer</td>
</tr>
</tbody>
</table>
| augmentation_type    | Data augmentation type. The input images can be augmented in multiple ways as specified below.  
  - **crop**: Randomly crop the image and flip the image horizontally  
  - **crop_color**: In addition to ‘crop’, three random values in the range [-36, 36], [-50, 50], and [-50, 50] are added to the corresponding Hue-Saturation-Lightness channels respectively  
  - **crop_color_transform**: In addition to crop_color, random transformations, including rotation, shear, and aspect ratio variations are applied to the image. The maximum angle of rotation is 10 degrees, the maximum shear ratio is 0.1, and the maximum aspect changing ratio is 0.25. Optional Valid values: crop, crop_color, or crop_color_transform. Default value: no default value |
<p>| beta_1               | The beta1 for adam, that is the exponential decay rate for the first moment estimates. Optional Valid values: float. Range in [0, 1].                                                                                                                                          |</p>
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Default value: 0.9</td>
</tr>
<tr>
<td>beta_2</td>
<td>The beta2 for adam, that is the exponential decay rate for the second moment estimates.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: float. Range in [0, 1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.999</td>
</tr>
<tr>
<td>checkpoint_frequency</td>
<td>Period to store model parameters (in number of epochs).</td>
</tr>
<tr>
<td></td>
<td>Note that all checkpoint files are saved as part of the final model file &quot;model.tar.gz&quot; and uploaded to S3 to the specified model location. This increases the size of the model file proportionally to the number of checkpoints saved during training.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer no greater than epochs.</td>
</tr>
<tr>
<td></td>
<td>Default value: no default value (Save checkpoint at the epoch that has the best validation accuracy)</td>
</tr>
<tr>
<td>early_stopping</td>
<td>True to use early stopping logic during training. False not to use it.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: True or False</td>
</tr>
<tr>
<td></td>
<td>Default value: False</td>
</tr>
<tr>
<td>early_stopping_min_epochs</td>
<td>The minimum number of epochs that must be run before the early stopping logic can be invoked. It is used only when early_stopping = True.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 10</td>
</tr>
<tr>
<td>early_stopping_patience</td>
<td>The number of epochs to wait before ending training if no improvement is made in the relevant metric. It is used only when early_stopping = True.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 5</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
</tbody>
</table>
| `early_stopping_tolerance`     | Relative tolerance to measure an improvement in accuracy validation metric. If the ratio of the improvement in accuracy divided by the previous best accuracy is smaller than the `early_stopping_tolerance` value set, early stopping considers there is no improvement. It is used only when `early_stopping` = True. Optional  
Valid values: $0 \leq \text{float} \leq 1$  
Default value: 0.0 |
| `epochs`                       | Number of training epochs. Optional  
Valid values: positive integer  
Default value: 30 |
| `eps`                          | The epsilon for `adam` and `rmsprop`. It is usually set to a small value to avoid division by 0. Optional  
Valid values: float. Range in [0, 1].  
Default value: $1e^{-8}$ |
| `gamma`                        | The gamma for `rmsprop`, the decay factor for the moving average of the squared gradient. Optional  
Valid values: float. Range in [0, 1].  
Default value: 0.9 |
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>image_shape</strong></td>
<td>The input image dimensions, which is the same size as the input layer of the network. The format is defined as 'num_channels, height, width'. The image dimension can take on any value as the network can handle varied dimensions of the input. However, there may be memory constraints if a larger image dimension is used. Pretrained models can use only a fixed 224 x 224 image size. Typical image dimensions for image classification are '3,224,224'. This is similar to the ImageNet dataset. For training, if any input image is smaller than this parameter in any dimension, training fails. If an image is larger, a portion of the image is cropped, with the cropped area specified by this parameter. If hyperparameter augmentation_type is set, random crop is taken; otherwise, central crop is taken. At inference, input images are resized to the image_shape that was used during training. Aspect ratio is not preserved, and images are not cropped. <strong>Optional</strong> Valid values: string Default value: ‘3,224,224’</td>
</tr>
<tr>
<td><strong>kv_store</strong></td>
<td>Weight update synchronization mode during distributed training. The weight updates can be updated either synchronously or asynchronously across machines. Synchronous updates typically provide better accuracy than asynchronous updates but can be slower. See distributed training in MXNet for more details. This parameter is not applicable to single machine training. • dist_sync: The gradients are synchronized after every batch with all the workers. With dist_sync, batch-size now means the batch size used on each machine. So if there are n machines and we use batch size b, then dist_sync behaves like local with batch size n*b • dist_async: Performs asynchronous updates. The weights are updated whenever gradients are received from any machine and the weight updates are atomic. However, the order is not guaranteed. <strong>Optional</strong> Valid values: dist_sync or dist_async Default value: no default value</td>
</tr>
<tr>
<td><strong>learning_rate</strong></td>
<td>Initial learning rate. <strong>Optional</strong> Valid values: float. Range in [0, 1]. Default value: 0.1</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>lr_scheduler_factor</td>
<td>The ratio to reduce learning rate used in conjunction with the lr_scheduler_step parameter, defined as $lr_{new} = lr_{old} \times lr_{scheduler_factor}$.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float. Range in [0, 1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.1</td>
</tr>
<tr>
<td>lr_scheduler_step</td>
<td>The epochs at which to reduce the learning rate. As explained in the lr_scheduler_factor parameter, the learning rate is reduced by lr_scheduler_factor at these epochs. For example, if the value is set to &quot;10, 20&quot;, then the learning rate is reduced by lr_scheduler_factor after 10th epoch and again by lr_scheduler_factor after 20th epoch. The epochs are delimited by &quot;,&quot;.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: string</td>
</tr>
<tr>
<td></td>
<td>Default value: no default value</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The batch size for training. In a single-machine multi-GPU setting, each GPU handles mini_batch_size/num_gpu training samples. For the multi-machine training in dist_sync mode, the actual batch size is mini_batch_size*number of machines. See MXNet docs for more details.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 32</td>
</tr>
<tr>
<td>momentum</td>
<td>The momentum for sgd and nag, ignored for other optimizers.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float. Range in [0, 1].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.9</td>
</tr>
<tr>
<td>multi_label</td>
<td>Flag to use for multi-label classification where each sample can be assigned multiple labels. Average accuracy across all classes is logged.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 or 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 0</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td>num_layers</td>
<td>Number of layers for the network. For data with large image size (for example, 224x224 - like ImageNet), we suggest selecting the number of layers from the set [18, 34, 50, 101, 152, 200]. For data with small image size (for example, 28x28 - like CIFAR), we suggest selecting the number of layers from the set [20, 32, 44, 56, 110]. The number of layers in each set is based on the ResNet paper. For transfer learning, the number of layers defines the architecture of base network and hence can only be selected from the set [18, 34, 50, 101, 152, 200].</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer in [18, 34, 50, 101, 152, 200] or [20, 32, 44, 56, 110]</td>
</tr>
<tr>
<td></td>
<td>Default value: 152</td>
</tr>
<tr>
<td>optimizer</td>
<td>The optimizer type. For more details of the parameters for the optimizers, please refer to MXNet's API.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: One of sgd, adam, rmsprop, or nag.</td>
</tr>
<tr>
<td></td>
<td>• sgd: Stochastic gradient descent</td>
</tr>
<tr>
<td></td>
<td>• adam: Adaptive momentum estimation</td>
</tr>
<tr>
<td></td>
<td>• rmsprop: Root mean square propagation</td>
</tr>
<tr>
<td></td>
<td>• nag: Nesterov accelerated gradient</td>
</tr>
<tr>
<td></td>
<td>Default value: sgd</td>
</tr>
<tr>
<td>precision_dtype</td>
<td>The precision of the weights used for training. The algorithm can use either single precision (float32) or half precision (float16) for the weights. Using half-precision for weights results in reduced memory consumption.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: float32 or float16</td>
</tr>
<tr>
<td></td>
<td>Default value: float32</td>
</tr>
<tr>
<td>resize</td>
<td>The number of pixels in the shortest side of an image after resizing it for training. If the parameter is not set, then the training data is used without resizing. The parameter should be larger than both the width and height components of image_shape to prevent training failure.</td>
</tr>
<tr>
<td></td>
<td>Required when using image content types</td>
</tr>
<tr>
<td></td>
<td>Optional when using the RecordIO content type</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: no default value</td>
</tr>
</tbody>
</table>
### Parameter Name | Description
--- | ---
top_k | Reports the top-k accuracy during training. This parameter has to be greater than 1, since the top-1 training accuracy is the same as the regular training accuracy that has already been reported. **Optional**

Valid values: positive integer larger than 1.

Default value: no default value

use_pretrained_model | Flag to use pre-trained model for training. If set to 1, then the pretrained model with the corresponding number of layers is loaded and used for training. Only the top FC layer are reinitialized with random weights. Otherwise, the network is trained from scratch. **Optional**

Valid values: 0 or 1

Default value: 0

use_weighted_loss | Flag to use weighted cross-entropy loss for multi-label classification (used only when multi_label = 1), where the weights are calculated based on the distribution of classes. **Optional**

Valid values: 0 or 1

Default value: 0

weight_decay | The coefficient weight decay for sgd and nag, ignored for other optimizers. **Optional**

Valid values: float. Range in [0, 1].

Default value: 0.0001

---

### Tune an Image Classification Model

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

### Metrics Computed by the Image Classification Algorithm

The image classification algorithm is a supervised algorithm. It reports an accuracy metric that is computed during training. When tuning the model, choose this metric as the objective metric.
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Metric Name | Description | Optimization Direction
---|---|---
validation:accuracy | The ratio of the number of correct predictions to the total number of predictions made. | Maximize

Tunable Image Classification Hyperparameters

Tune an image classification model with the following hyperparameters. The hyperparameters that have the greatest impact on image classification objective metrics are: mini_batch_size, learning_rate, and optimizer. Tune the optimizer-related hyperparameters, such as momentum, weight_decay, beta_1, beta_2, eps, and gamma, based on the selected optimizer. For example, use beta_1 and beta_2 only when adam is the optimizer.

For more information about which hyperparameters are used in each optimizer, see Image Classification Hyperparameters (p. 2176).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>beta_1</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.999</td>
</tr>
<tr>
<td>beta_2</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.999</td>
</tr>
<tr>
<td>eps</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-8, MaxValue: 1.0</td>
</tr>
<tr>
<td>gamma</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-8, MaxValue: 0.999</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.5</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 8, MaxValue: 512</td>
</tr>
<tr>
<td>momentum</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
<tr>
<td>optimizer</td>
<td>CategoricalParameterRanges</td>
<td>['sgd', 'adam', 'rmsprop', 'nag']</td>
</tr>
<tr>
<td>weight_decay</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
</tbody>
</table>

Image Classification - TensorFlow

The Amazon SageMaker Image Classification - TensorFlow algorithm is a supervised learning algorithm that supports transfer learning with many pretrained models from the TensorFlow Hub. Use transfer learning to fine-tune one of the available pretrained models on your own dataset, even if a large amount of image data is not available. The image classification algorithm takes an image as input and outputs a probability for each provided class label. Training datasets must consist of images in .jpg, .jpeg, or .png format.

Topics
- How to use the SageMaker Image Classification - TensorFlow algorithm (p. 2184)
How to use the SageMaker Image Classification - TensorFlow algorithm

You can use Image Classification - TensorFlow as an Amazon SageMaker built-in algorithm. The following section describes how to use Image Classification - TensorFlow with the SageMaker Python SDK. For information on how to use Image Classification - TensorFlow from the Amazon SageMaker Studio UI, see SageMaker JumpStart (p. 45).

The Image Classification - TensorFlow algorithm supports transfer learning using any of the compatible pretrained TensorFlow Hub models. For a list of all available pretrained models, see TensorFlow Hub Models (p. 2187). Every pretrained model has a unique model_id. The following example uses MobileNet V2 1.00 224 (model_id: tensorflow-ic-imagenet-mobilenet-v2-100-224-classification-4) to fine-tune on a custom dataset. The pretrained models are all pre-downloaded from the TensorFlow Hub and stored in Amazon S3 buckets so that training jobs can run in network isolation. Use these pre-generated model training artifacts to construct a SageMaker Estimator.

First, retrieve the Docker image URI, training script URI, and pretrained model URI. Then, change the hyperparameters as you see fit. You can see a Python dictionary of all available hyperparameters and their default values with hyperparameters.retrieve_default. For more information, see Image Classification - TensorFlow Hyperparameters (p. 2192). Use these values to construct a SageMaker Estimator.

**Note**
Default hyperparameter values are different for different models. For larger models, the default batch size is smaller and the train_only_on_top hyperparameter is set to "True".

This example uses the tf_flowers dataset, which contains five classes of flower images. We pre-downloaded the dataset from TensorFlow under the Apache 2.0 license and made it available with Amazon S3. To fine-tune your model, call .fit using the Amazon S3 location of your training dataset.

```python
from sagemaker import image_uris, model_uris, script_uris, hyperparameters
from sagemaker.estimator import Estimator

model_id, model_version = "tensorflow-ic-imagenet-mobilenet-v2-100-224-classification-4", 
"*
training_instance_type = "ml.p3.2xlarge"

# Retrieve the Docker image
train_image_uri = image_uris.retrieve(model_id=model_id, model_version=model_version, image_scope="training", instance_type=None)

# Retrieve the training script
train_source_uri = script_uris.retrieve(model_id=model_id, model_version=model_version, script_scope="training")

# Retrieve the pretrained model tarball for transfer learning
train_model_uri = model_uris.retrieve(model_id=model_id, model_version=model_version, model_scope="training")

# Retrieve the default hyper-parameters for fine-tuning the model
hyperparameters = hyperparameters.retrieve_default(model_id=model_id, model_version=model_version)
```

from sagemaker import image_uris, model_uris, script_uris, hyperparameters
from sagemaker.estimator import Estimator

model_id, model_version = "tensorflow-ic-imagenet-mobilenet-v2-100-224-classification-4", 
"*
training_instance_type = "ml.p3.2xlarge"

# Retrieve the Docker image
train_image_uri = image_uris.retrieve(model_id=model_id, model_version=model_version, image_scope="training", instance_type=None)

# Retrieve the training script
train_source_uri = script_uris.retrieve(model_id=model_id, model_version=model_version, script_scope="training")

# Retrieve the pretrained model tarball for transfer learning
train_model_uri = model_uris.retrieve(model_id=model_id, model_version=model_version, model_scope="training")

# Retrieve the default hyper-parameters for fine-tuning the model
hyperparameters = hyperparameters.retrieve_default(model_id=model_id, model_version=model_version)
# [Optional] Override default hyperparameters with custom values
hyperparameters["epochs"] = "5"

# The sample training data is available in the following S3 bucket
training_data_bucket = f"jumpstart-cache-prod-{aws_region}"
training_data_prefix = "training-datasets/tf_flowers/"

training_dataset_s3_path = f"s3://{training_data_bucket}/{training_data_prefix}"

output_bucket = sess.default_bucket()
output_prefix = "jumpstart-example-ic-training"
s3_output_location = f"s3://{output_bucket}/{output_prefix}/output"

# Create SageMaker Estimator instance
tf_ic_estimator = Estimator(
    role=aws_role,
    image_uri=train_image_uri,
    source_dir=train_source_uri,
    model_uri=train_model_uri,
    entry_point="transfer_learning.py",
    instance_count=1,
    instance_type=training_instance_type,
    max_run=360000,
    hyperparameters=hyperparameters,
    output_path=s3_output_location,
)

# Use S3 path of the training data to launch SageMaker TrainingJob
tf_ic_estimator.fit({"training": training_dataset_s3_path}, logs=True)

Input and output interface for the Image Classification - TensorFlow algorithm

Each of the pretrained models listed in TensorFlow Hub Models can be fine-tuned to any dataset with
any number of image classes. Be mindful of how to format your training data for input to the Image
Classification - TensorFlow model.

- **Training data input format**: Your training data should be a directory with as many subdirectories as
the number of classes. Each subdirectory should contain images belonging to that class in .jpg, .jpeg,
or .png format.

The following is an example of an input directory structure. This example dataset has two
classes: roses and dandelion. The image files in each class folder can have any name. The
input directory should be hosted in an Amazon S3 bucket with a path similar to the following:
s3://bucket_name/input_directory/. Note that the trailing / is required.

```
input_directory
|-- roses
   |-- abc.jpg
   |-- def.jpg
|-- dandelion
   |-- ghi.jpg
   |-- jkl.jpg
```

Trained models output label mapping files that map class folder names to the indices in the list of
output class probabilities. This mapping is in alphabetical order. For example, in the preceding example,
the dandelion class is index 0 and the roses class is index 1.

After training, you have a fine-tuned model that you can further train using incremental training
or deploy for inference. The Image Classification - TensorFlow algorithm automatically adds a pre-
processing and post-processing signature to the fine-tuned model so that it can take in images as input

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and return class probabilities. The ﬁle mapping class indices to class labels is saved along with the
models.

Incremental training
You can seed the training of a new model with artifacts from a model that you trained previously with
SageMaker. Incremental training saves training time when you want to train a new model with the same
or similar data.

Note

You can only seed a SageMaker Image Classiﬁcation - TensorFlow model with another Image
You can use any dataset for incremental training, as long as the set of classes remains the same. The
incremental training step is similar to the ﬁne-tuning step, but instead of starting with a pretrained
model, you start with an existing ﬁne-tuned model. For an example of incremental training with the

Inference with the Image Classiﬁcation - TensorFlow algorithm
You can host the ﬁne-tuned model that results from your TensorFlow Image Classiﬁcation training
for inference. Any input image for inference must be in .jpg, .jpeg, or .png format and be content
type application/x-image. The Image Classiﬁcation - TensorFlow algorithm resizes input images
automatically.
Running inference results in probability values, class labels for all classes, and the predicted label
corresponding to the class index with the highest probability encoded in JSON format. The Image
Classiﬁcation - TensorFlow model processes a single image per request and outputs only one line. The
following is an example of a JSON format response:
accept: application/json;verbose
{"probabilities": [prob_0, prob_1, prob_2, ...],
"labels":
[label_0, label_1, label_2, ...],
"predicted_label": predicted_label}

If accept is set to application/json, then the model only outputs probabilities. For more
information on training and inference with the Image Classiﬁcation - TensorFlow algorithm, see the
Introduction to SageMaker TensorFlow - Image Classiﬁcation sample notebook.

Amazon EC2 instance recommendation for the Image Classiﬁcation - TensorFlow algorithm
The Image Classiﬁcation - TensorFlow algorithm supports all CPU and GPU instances for training,
including:
• ml.p2.xlarge
• ml.p2.16xlarge
• ml.p3.2xlarge
• ml.p3.16xlarge
• ml.g4dn.xlarge
• ml.g4dn.16.xlarge
• ml.g5.xlarge
• ml.g5.48xlarge
We recommend GPU instances with more memory for training with large batch sizes. Both CPU (such as
M5) and GPU (P2, P3, G4dn, or G5) instances can be used for inference.

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**Image Classification - TensorFlow sample notebooks**

For more information about how to use the SageMaker Image Classification - TensorFlow algorithm for transfer learning on a custom dataset, see the Introduction to SageMaker TensorFlow - Image Classification notebook.

For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. To open a notebook, choose its Use tab and choose Create copy.

**How Image Classification - TensorFlow Works**

The Image Classification - TensorFlow algorithm takes an image as input and classifies it into one of the output class labels. Various deep learning networks such as MobileNet, ResNet, Inception, and EfficientNet are highly accurate for image classification. There are also deep learning networks that are trained on large image datasets, such as ImageNet, which has over 11 million images and almost 11,000 classes. After a network is trained with ImageNet data, you can then fine-tune the network on a dataset with a particular focus to perform more specific classification tasks. The Amazon SageMaker Image Classification - TensorFlow algorithm supports transfer learning on many pretrained models that are available in the TensorFlow Hub.

According to the number of class labels in your training data, a classification layer is attached to the pretrained TensorFlow Hub model of your choice. The classification layer consists of a dropout layer, a dense layer, and a fully-connected layer with 2-norm regularizer that is initialized with random weights. The model has hyperparameters for the dropout rate of the dropout layer and the L2 regularization factor for the dense layer. You can then fine-tune either the entire network (including the pretrained model) or only the top classification layer on new training data. With this method of transfer learning, training with smaller datasets is possible.

**TensorFlow Hub Models**

The following pretrained models are available to use for transfer learning with the Image Classification - TensorFlow algorithm.

The following models vary significantly in size, number of model parameters, training time, and inference latency for any given dataset. The best model for your use case depends on the complexity of your fine-tuning dataset and any requirements that you have on training time, inference latency, or model accuracy.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>model_id</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>MobileNet V2 1.00 224</td>
<td>tensorflow-ic-imagenet-mobilenet-v2-100-224-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>MobileNet V2 0.75 224</td>
<td>tensorflow-ic-imagenet-mobilenet-v2-075-224-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>MobileNet V2 0.50 224</td>
<td>tensorflow-ic-imagenet-mobilenet-v2-050-224-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>MobileNet V2 0.35 224</td>
<td>tensorflow-ic-imagenet-mobilenet-v2-035-224-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Model Name</td>
<td>model_id</td>
<td>Source</td>
</tr>
<tr>
<td>------------------------</td>
<td>---------------------------------------------------------------------------</td>
<td>----------------------------------</td>
</tr>
<tr>
<td>MobileNet V2 1.40 224</td>
<td>tensorflow-ic-imagenet-mobilenet-v2-140-224-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>MobileNet V2 1.30 224</td>
<td>tensorflow-ic-imagenet-mobilenet-v2-130-224-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>MobileNet V2</td>
<td>tensorflow-ic-tf2-preview-mobilenet-v2-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Inception V3</td>
<td>tensorflow-ic-imagenet-inception-v3-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Inception V2</td>
<td>tensorflow-ic-imagenet-inception-v2-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Inception V1</td>
<td>tensorflow-ic-imagenet-inception-v1-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Inception V3 Preview</td>
<td>tensorflow-ic-tf2-preview-inception-v3-classification-4</td>
<td>TensorFlow Hub link</td>
</tr>
<tr>
<td>Inception ResNet V2</td>
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</tr>
</tbody>
</table>
## Image Classification - TensorFlow Hyperparameters

Hyperparameters are parameters that are set before a machine learning model begins learning. The following hyperparameters are supported by the Amazon SageMaker built-in Image Classification - TensorFlow algorithm. See [Tune an Image Classification - TensorFlow model (p. 2195)](#) for information on hyperparameter tuning.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>augmentation</td>
<td>Set to &quot;True&quot; to apply augmentation_random_flip, augmentation_random_rotation, and augmentation_random_zoom to the training data. Valid values: string, either: (&quot;True&quot; or &quot;False&quot;). Default value: &quot;False&quot;.</td>
</tr>
<tr>
<td>augmentation_random_flip</td>
<td>Indicates which flip mode to use for data augmentation when augmentation is set to &quot;True&quot;. For more information, see RandomFlip in the TensorFlow documentation. Valid values: string, any of the following: (&quot;horizontal_and_vertical&quot;, &quot;vertical&quot;, or &quot;None&quot;). Default value: &quot;horizontal_and_vertical&quot;.</td>
</tr>
<tr>
<td>augmentation_random_rotation</td>
<td>Indicates how much rotation to use for data augmentation when augmentation is set to &quot;True&quot;. Values represent a fraction of $2\pi$. Positive values rotate counterclockwise while negative values rotate clockwise. 0 means no rotation. For more information, see RandomRotation in the TensorFlow documentation. Valid values: float, range: [-1.0, 1.0]. Default value: 0.2.</td>
</tr>
<tr>
<td>augmentation_random_zoom</td>
<td>Indicates how much vertical zoom to use for data augmentation when augmentation is set to &quot;True&quot;. Positive values zoom out while negative values zoom in. 0 means no zoom. For more information, see RandomZoom in the TensorFlow documentation. Valid values: float, range: [-1.0, 1.0]. Default value: 0.1.</td>
</tr>
<tr>
<td>batch_size</td>
<td>The batch size for training. For training on instances with multiple GPUs, this batch size is used across the GPUs. Valid values: positive integer. Default value: 32.</td>
</tr>
<tr>
<td>beta_1</td>
<td>The beta1 for the &quot;adam&quot; optimizer. Represents the exponential decay rate for the first moment estimates. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.9.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>beta_2</td>
<td>The beta2 for the &quot;adam&quot; optimizer. Represents the exponential decay rate for the second moment estimates. Ignored for other optimizers.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.999.</td>
</tr>
<tr>
<td>binary_mode</td>
<td>When binary_mode is set to &quot;True&quot;, the model returns a single probability number for the positive class and can use additional eval_metric options. Use only for binary classification problems.</td>
</tr>
<tr>
<td></td>
<td>Valid values: string, either: (&quot;True&quot; or &quot;False&quot;).</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;False&quot;.</td>
</tr>
<tr>
<td>dropout_rate</td>
<td>The dropout rate for the dropout layer in the top classification layer.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.2</td>
</tr>
<tr>
<td>early_stopping</td>
<td>Set to &quot;True&quot; to use early stopping logic during training. If &quot;False&quot;, early stopping is not used.</td>
</tr>
<tr>
<td></td>
<td>Valid values: string, either: (&quot;True&quot; or &quot;False&quot;).</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;False&quot;.</td>
</tr>
<tr>
<td>early_stopping_min_delta</td>
<td>The minimum change needed to qualify as an improvement. An absolute change less than the value of early_stopping_min_delta does not qualify as improvement. Used only when early_stopping is set to &quot;True&quot;.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float, range: [0.0, 1.0].</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0.</td>
</tr>
<tr>
<td>early_stopping_patience</td>
<td>The number of epochs to continue training with no improvement. Used only when early_stopping is set to &quot;True&quot;.</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer.</td>
</tr>
<tr>
<td></td>
<td>Default value: 5.</td>
</tr>
<tr>
<td>epochs</td>
<td>The number of training epochs.</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer.</td>
</tr>
<tr>
<td></td>
<td>Default value: 3.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>epsilon</td>
<td>The epsilon for &quot;adam&quot;, &quot;rmsprop&quot;, &quot;adadelta&quot;, and &quot;adagrad&quot; optimizers. Usually set to a small value to avoid division by 0. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 1e-7.</td>
</tr>
<tr>
<td>eval_metric</td>
<td>If binary_mode is set to &quot;False&quot;, eval_metric can only be &quot;accuracy&quot;. If binary_mode is &quot;True&quot;, select any of the valid values. For more information, see Metrics in the TensorFlow documentation. Valid values: string, any of the following: (&quot;accuracy&quot;, &quot;precision&quot;, &quot;recall&quot;, &quot;auc&quot;, or &quot;prc&quot;). Default value: &quot;accuracy&quot;.</td>
</tr>
<tr>
<td>image_resize_interpolation</td>
<td>Indicates interpolation method used when resizing images. For more information, see image.resize in the TensorFlow documentation. Valid values: string, any of the following: (&quot;bilinear&quot;, &quot;nearest&quot;, &quot;bicubic&quot;, &quot;area&quot;, &quot;lanczos3&quot;, &quot;lanczos5&quot;, &quot;gaussian&quot;, or &quot;mitchellcubic&quot;). Default value: &quot;bilinear&quot;.</td>
</tr>
<tr>
<td>initial_accumulator_value</td>
<td>The starting value for the accumulators, or the per-parameter momentum values, for the &quot;adagrad&quot; optimizer. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.0001.</td>
</tr>
<tr>
<td>label_smoothing</td>
<td>Indicates how much to relax the confidence on label values. For example, if label_smoothing is 0.1, then non-target labels are 0.1/num_classes and target labels are 0.9+0.1/num_classes. Valid values: float, range: [0.0, 1.0]. Default value: 0.1.</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The optimizer learning rate. Valid values: float, range: [0.0, 1.0]. Default value: 0.001.</td>
</tr>
<tr>
<td>momentum</td>
<td>The momentum for &quot;sgd&quot;, &quot;nesterov&quot;, and &quot;rmsprop&quot; optimizers. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.9.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>optimizer</td>
<td>The optimizer type. For more information, see Optimizers in the TensorFlow documentation. Valid values: string, any of the following: (&quot;adam&quot;, &quot;sgd&quot;, &quot;nesterov&quot;, &quot;rmsprop&quot;, &quot;adagrad&quot;, &quot;adadelta&quot;). Default value: &quot;adam&quot;.</td>
</tr>
<tr>
<td>regularizers_l2</td>
<td>The L2 regularization factor for the dense layer in the classification layer. Valid values: float, range: [0.0, 1.0]. Default value: .0001.</td>
</tr>
<tr>
<td>reinitialize_top_layer</td>
<td>If set to &quot;Auto&quot;, the top classification layer parameters are re-initialized during fine-tuning. For incremental training, top classification layer parameters are not re-initialized unless set to &quot;True&quot;. Valid values: string, any of the following: (&quot;Auto&quot;, &quot;True&quot; or &quot;False&quot;). Default value: &quot;Auto&quot;.</td>
</tr>
<tr>
<td>rho</td>
<td>The discounting factor for the gradient of the &quot;adadelta&quot; and &quot;rmsprop&quot; optimizers. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.95.</td>
</tr>
<tr>
<td>train_only_on_top_layer</td>
<td>If &quot;True&quot;, only the top classification layer parameters are fine-tuned. If &quot;False&quot;, all model parameters are fine-tuned. Valid values: string, either: (&quot;True&quot; or &quot;False&quot;). Default value: &quot;False&quot;.</td>
</tr>
</tbody>
</table>

**Tune an Image Classification - TensorFlow model**

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

**Metrics computed by the Image Classification - TensorFlow algorithm**

The image classification algorithm is a supervised algorithm. It reports an accuracy metric that is computed during training. When tuning the model, choose this metric as the objective metric.
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>validation:accuracy</td>
<td>The ratio of the number of correct predictions to the total number of predictions made.</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

**Tunable Image Classification - TensorFlow hyperparameters**

Tune an image classification model with the following hyperparameters. The hyperparameters that have the greatest impact on image classification objective metrics are: batch_size, learning_rate, and optimizer. Tune the optimizer-related hyperparameters, such as momentum, regularizers_l2, beta_1, beta_2, and eps based on the selected optimizer. For example, use beta_1 and beta_2 only when adam is the optimizer.

For more information about which hyperparameters are used for each optimizer, see Image Classification - TensorFlow Hyperparameters (p. 2192).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 8, MaxValue: 512</td>
</tr>
<tr>
<td>beta_1</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.999</td>
</tr>
<tr>
<td>beta_2</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.999</td>
</tr>
<tr>
<td>eps</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-8, MaxValue: 1.0</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.5</td>
</tr>
<tr>
<td>momentum</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
<tr>
<td>optimizer</td>
<td>CategoricalParameterRanges</td>
<td>['sgd', 'adam', 'rmsprop', 'nesterov', 'adagrad', 'adadelta']</td>
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<tr>
<td>regularizers_l2</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
<tr>
<td>train_only_on_top_layer</td>
<td>ContinuousParameterRanges</td>
<td>['True', 'False']</td>
</tr>
</tbody>
</table>

**Object Detection - MXNet**

The Amazon SageMaker Object Detection - MXNet algorithm detects and classifies objects in images using a single deep neural network. It is a supervised learning algorithm that takes images as input and identifies all instances of objects within the image scene. The object is categorized into one of the classes in a specified collection with a confidence score that it belongs to the class. Its location and scale in the image are indicated by a rectangular bounding box. It uses the Single Shot multibox Detector (SSD) framework and supports two base networks: VGG and ResNet. The network can be trained from scratch, or trained with models that have been pre-trained on the ImageNet dataset.

**Topics**
Input/Output Interface for the Object Detection Algorithm

The SageMaker Object Detection algorithm supports both RecordIO (application/x-recordio) and image (image/png, image/jpeg, and application/x-image) content types for training in file mode and supports RecordIO (application/x-recordio) for training in pipe mode. However, you can also train in pipe mode using the image files (image/png, image/jpeg, and application/x-image), without creating RecordIO files, by using the augmented manifest format. The recommended input format for the Amazon SageMaker object detection algorithms is Apache MXNet RecordIO. However, you can also use raw images in .jpg or .png format. The algorithm supports only application/x-image for inference.

Note
To maintain better interoperability with existing deep learning frameworks, this differs from the protobuf data formats commonly used by other Amazon SageMaker algorithms.

See the Object Detection Sample Notebooks for more details on data formats.

Train with the RecordIO Format

If you use the RecordIO format for training, specify both train and validation channels as values for the InputDataConfig parameter of the CreateTrainingJob request. Specify one RecordIO (.rec) file in the train channel and one RecordIO file in the validation channel. Set the content type for both channels to application/x-recordio. An example of how to generate RecordIO file can be found in the object detection sample notebook. You can also use tools from the MXNet's GluonCV to generate RecordIO files for popular datasets like the PASCAL Visual Object Classes and Common Objects in Context (COCO).

Train with the Image Format

If you use the image format for training, specify train, validation, train_annotation, and validation_annotation channels as values for the InputDataConfig parameter of CreateTrainingJob request. Specify the individual image data (.jpg or .png) files for the train and validation channels. For annotation data, you can use the JSON format. Specify the corresponding .json files in the train_annotation and validation_annotation channels. Set the content type for all four channels to image/png or image/jpeg based on the image type. You can also use the content type application/x-image when your dataset contains both .jpg and .png images. The following is an example of a .json file.

```json
{
    "file": "your_image_directory/sample_image1.jpg",
    "image_size": [
        {
            "width": 500,
            "height": 400,
            "depth": 3
        }
    ],
    "annotations": [
        {
            "class_id": 0,
            "left": 111,
```
Each image needs a .json file for annotation, and the .json file should have the same name as the corresponding image. The name of above .json file should be "sample_image1.json". There are four properties in the annotation .json file. The property "file" specifies the relative path of the image file. For example, if your training images and corresponding .json files are stored in s3://your_bucket/train/sample_image and s3://your_bucket/train_annotation, specify the path for your train and train_annotation channels as s3://your_bucket/train and s3://your_bucket/train_annotation, respectively.

In the .json file, the relative path for an image named sample_image1.jpg should be sample_image/sample_image1.jpg. The "image_size" property specifies the overall image dimensions. The SageMaker object detection algorithm currently only supports 3-channel images. The "annotations" property specifies the categories and bounding boxes for objects within the image. Each object is annotated by a "class_id" index and by four bounding box coordinates ("left", "top", "width", "height"). The "left" (x-coordinate) and "top" (y-coordinate) values represent the upper-left corner of the bounding box. The "width" (x-coordinate) and "height" (y-coordinate) values represent the dimensions of the bounding box. The origin (0, 0) is the upper-left corner of the entire image. If you have multiple objects within one image, all the annotations should be included in a single .json file. The "categories" property stores the mapping between the class index and class name. The class indices should be numbered successively and the numbering should start with 0. The "categories" property is optional for the annotation .json file.

Train with Augmented Manifest Image Format

The augmented manifest format enables you to do training in pipe mode using image files without needing to create RecordIO files. You need to specify both train and validation channels as values for the InputDataConfig parameter of the CreateTrainingJob request. While using the format, an S3 manifest file needs to be generated that contains the list of images and their corresponding annotations. The manifest file format should be in JSON Lines format in which each line represents one sample. The images are specified using the 'source-ref' tag that points to the S3 location of the image. The annotations are provided under the "AttributeNames" parameter value as specified in the
CreateTrainingJob request. It can also contain additional metadata under the metadata tag, but these are ignored by the algorithm. In the following example, the "AttributeNames are contained in the list "source-ref", "bounding-box":

```json
{"source-ref": "s3://your_bucket/image1.jpg", "bounding-box":{"image_size": [{ "width": 500, "height": 400, "depth":3}], "annotations": [{"class_id": 0, "left": 111, "top": 154, "width": 61, "height": 128}, {"class_id": 5, "left": 161, "top": 250, "width": 80, "height": 50}], "bounding-box-metadata":{"class-map":{"0": "dog", 5": "horse"}, "type": "groundtruth/object-detection"})
{"source-ref": "s3://your_bucket/image2.jpg", "bounding-box":{"image_size": [{ "width": 400, "height": 300, "depth":3}], "annotations": [{"class_id": 1, "left": 100, "top": 120, "width": 43, "height": 78}], "bounding-box-metadata":{"class-map":{"1": "cat"}, "type": "groundtruth/object-detection"})
```

The order of "AttributeNames" in the input files matters when training the Object Detection algorithm. It accepts piped data in a specific order, with image first, followed by annotations. So the "AttributeNames" in this example are provided with "source-ref" first, followed by "bounding-box". When using Object Detection with Augmented Manifest, the value of parameter RecordWrapperType must be set as "RecordIO".

For more information on augmented manifest files, see Provide Dataset Metadata to Training Jobs with an Augmented Manifest File (p. 2700).

Incremental Training

You can also seed the training of a new model with the artifacts from a model that you trained previously with SageMaker. Incremental training saves training time when you want to train a new model with the same or similar data. SageMaker object detection models can be seeded only with another built-in object detection model trained in SageMaker.

To use a pretrained model, in the CreateTrainingJob request, specify the ChannelName as "model" in the InputDataConfig parameter. Set the ContentType for the model channel to application/x-sagemaker-model. The input hyperparameters of both the new model and the pretrained model that you upload to the model channel must have the same settings for the base_network and num_classes input parameters. These parameters define the network architecture. For the pretrained model file, use the compressed model artifacts (in .tar.gz format) output by SageMaker. You can use either RecordIO or image formats for input data.

For more information on incremental training and for instructions on how to use it, see Incremental Training in Amazon SageMaker (p. 2677).

EC2 Instance Recommendation for the Object Detection Algorithm

The object detection algorithm supports P2, P3, G4dn, and G5 GPU instance families. We recommend using GPU instances with more memory for training with large batch sizes. You can run the object detection algorithm on multi-GPU and multi-machine settings for distributed training.

You can use both CPU (such as C5 and M5) and GPU (such as P3 and G4dn) instances for inference.

Object Detection Sample Notebooks

For a sample notebook that shows how to use the SageMaker Object Detection algorithm to train and host a model on the Caltech Birds (CUB 200 2011) dataset using the Single Shot multibox Detector algorithm, see Amazon SageMaker Object Detection for Bird Species. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. The object detection example notebook using
the Object Detection algorithm is located in the **Introduction to Amazon Algorithms** section. To open a notebook, click on its **Use** tab and select **Create copy**.

### How Object Detection Works

The object detection algorithm identifies and locates all instances of objects in an image from a known collection of object categories. The algorithm takes an image as input and outputs the category that the object belongs to, along with a confidence score that it belongs to the category. The algorithm also predicts the object's location and scale with a rectangular bounding box. Amazon SageMaker Object Detection uses the **Single Shot multibox Detector (SSD)** algorithm that takes a convolutional neural network (CNN) pretrained for classification task as the base network. SSD uses the output of intermediate layers as features for detection.

Various CNNs such as **VGG** and **ResNet** have achieved great performance on the image classification task. Object detection in Amazon SageMaker supports both VGG-16 and ResNet-50 as a base network for SSD. The algorithm can be trained in full training mode or in transfer learning mode. In full training mode, the base network is initialized with random weights and then trained on user data. In transfer learning mode, the base network weights are loaded from pretrained models.

The object detection algorithm uses standard data augmentation operations, such as flip, rescale, and jitter, on the fly internally to help avoid overfitting.

### Object Detection Hyperparameters

In the **CreateTrainingJob** request, you specify the training algorithm that you want to use. You can also specify algorithm-specific hyperparameters that are used to help estimate the parameters of the model from a training dataset. The following table lists the hyperparameters provided by Amazon SageMaker for training the object detection algorithm. For more information about how object training works, see **How Object Detection Works** (p. 2200).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_classes</td>
<td>The number of output classes. This parameter defines the dimensions of the network output and is typically set to the number of classes in the dataset.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td>num_training_samples</td>
<td>The number of training examples in the input dataset.</td>
</tr>
<tr>
<td></td>
<td><strong>Note</strong></td>
</tr>
<tr>
<td></td>
<td>If there is a mismatch between this value and the number of samples in the training set, then the behavior of the lr_scheduler_step parameter will be undefined and distributed training accuracy may be affected.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td>base_network</td>
<td>The base network architecture to use.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: ‘vgg-16’ or ‘resnet-50’</td>
</tr>
<tr>
<td></td>
<td>Default value: ‘vgg-16’</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>early_stopping</td>
<td>True to use early stopping logic during training. False not to use it.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: True or False</td>
</tr>
<tr>
<td></td>
<td>Default value: False</td>
</tr>
<tr>
<td>early_stopping_min_epochs</td>
<td>The minimum number of epochs that must be run before the early stopping logic can be invoked. It is used only when early_stopping = True.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 10</td>
</tr>
<tr>
<td>early_stopping_patience</td>
<td>The number of epochs to wait before ending training if no improvement, as defined by the early_stopping_tolerance hyperparameter, is made in the relevant metric. It is used only when early_stopping = True.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 5</td>
</tr>
<tr>
<td>early_stopping_tolerance</td>
<td>The tolerance value that the relative improvement in validation:mAP, the mean average precision (mAP), is required to exceed to avoid early stopping. If the ratio of the change in the mAP divided by the previous best mAP is smaller than the early_stopping_tolerance value set, early stopping considers that there is no improvement. It is used only when early_stopping = True.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 ≤ float ≤ 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0</td>
</tr>
<tr>
<td>image_shape</td>
<td>The image size for input images. We rescale the input image to a square image with this size. We recommend using 300 and 512 for better performance.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer ≥300</td>
</tr>
<tr>
<td></td>
<td>Default: 300</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>epochs</td>
<td>The number of training epochs.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default: 30</td>
</tr>
<tr>
<td>freeze_layer_pattern</td>
<td>The regular expression (regex) for freezing layers in the base network. For example, if we set `freeze_layer_pattern = &quot;^(conv1_</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: string</td>
</tr>
<tr>
<td></td>
<td>Default: No layers frozen.</td>
</tr>
<tr>
<td>kv_store</td>
<td>The weight update synchronization mode used for distributed training. The weights can be updated either synchronously or asynchronously across machines. Synchronous updates typically provide better accuracy than asynchronous updates but can be slower. See the Distributed Training MXNet tutorial for details.</td>
</tr>
<tr>
<td></td>
<td><strong>Note</strong></td>
</tr>
<tr>
<td></td>
<td>This parameter is not applicable to single machine training.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 'dist_sync' or 'dist_async'</td>
</tr>
<tr>
<td></td>
<td>• 'dist_sync': The gradients are synchronized after every batch with all the workers. With 'dist_sync', batch-size now means the batch size used on each machine. So if there are n machines and we use batch size b, then dist_sync behaves like a single machine with batch size n*b.</td>
</tr>
<tr>
<td></td>
<td>• 'dist_async': Performs asynchronous updates. The weights are updated whenever gradients are received from any machine and the weight updates are atomic. However, the order is not guaranteed.</td>
</tr>
<tr>
<td></td>
<td>Default: -</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>label_width</td>
<td>The force padding label width used to sync across training and validation data. For example, if one image in the data contains at most 10 objects, and each object's annotation is specified with 5 numbers, [class_id, left, top, width, height], then the label_width should be no smaller than ((10 \times 5 + \text{header information length})). The header information length is usually 2. We recommend using a slightly larger label_width for the training, such as 60 for this example. Optional Valid values: Positive integer large enough to accommodate the largest annotation information length in the data. Default: 350</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The initial learning rate. Optional Valid values: float in ((0, 1]) Default: 0.001</td>
</tr>
<tr>
<td>lr_scheduler_factor</td>
<td>The ratio to reduce learning rate. Used in conjunction with the lr_scheduler_step parameter defined as (\text{lr_new} = \text{lr_old} \times \text{lr_scheduler_factor}). Optional Valid values: float in ((0, 1)) Default: 0.1</td>
</tr>
<tr>
<td>lr_scheduler_step</td>
<td>The epochs at which to reduce the learning rate. The learning rate is reduced by (\text{lr_scheduler_factor}) at epochs listed in a comma-delimited string: &quot;epoch1, epoch2, ...&quot;. For example, if the value is set to &quot;10, 20&quot; and the lr_scheduler_factor is set to 1/2, then the learning rate is halved after 10th epoch and then halved again after 20th epoch. Optional Valid values: string Default: empty string</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>The batch size for training. In a single-machine multi-gpu setting, each GPU handles mini_batch_size/num_gpu training samples. For the multi-machine training in dist_sync mode, the actual batch size is mini_batch_size*number of machines. A large mini_batch_size usually leads to faster training, but it may cause out of memory problem. The memory usage is related to mini_batch_size, image_shape, and base_network architecture. For example, on a single p3.2xlarge instance, the largest mini_batch_size without an out of memory error is 32 with the base_network set to &quot;resnet-50&quot; and an image_shape of 300. With the same instance, you can use 64 as the mini_batch_size with the base network vgg-16 and an image_shape of 300.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default: 32</td>
</tr>
<tr>
<td>momentum</td>
<td>The momentum for sgd. Ignored for other optimizers.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float in (0, 1)</td>
</tr>
<tr>
<td></td>
<td>Default: 0.9</td>
</tr>
<tr>
<td>nms_threshold</td>
<td>The non-maximum suppression threshold.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float in (0, 1)</td>
</tr>
<tr>
<td></td>
<td>Default: 0.45</td>
</tr>
<tr>
<td>optimizer</td>
<td>The optimizer types. For details on optimizer values, see MXNet's API.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: ['sgd', 'adam', 'rmsprop', 'adadelta']</td>
</tr>
<tr>
<td></td>
<td>Default: 'sgd'</td>
</tr>
<tr>
<td>overlap_threshold</td>
<td>The evaluation overlap threshold.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: float in (0, 1)</td>
</tr>
<tr>
<td></td>
<td>Default: 0.5</td>
</tr>
</tbody>
</table>
**Parameter Name** | **Description**
--- | ---
use_pretrained_model | Indicates whether to use a pre-trained model for training. If set to 1, then the pre-trained model with corresponding architecture is loaded and used for training. Otherwise, the network is trained from scratch.
  **Optional**
  Valid values: 0 or 1
  Default: 1

weight_decay | The weight decay coefficient for sgd and rmsprop. Ignored for other optimizers.
  **Optional**
  Valid values: float in (0, 1)
  Default: 0.0005

**Tune an Object Detection Model**

*Automatic model tuning*, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see [Perform Automatic Model Tuning with SageMaker](#).

**Metrics Computed by the Object Detection Algorithm**

The object detection algorithm reports on a single metric during training: validation:mAP. When tuning a model, choose this metric as the objective metric.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>validation:mAP</td>
<td>Mean Average Precision (mAP) computed on the validation set.</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

**Tunable Object Detection Hyperparameters**

Tune the Amazon SageMaker object detection model with the following hyperparameters. The hyperparameters that have the greatest impact on the object detection objective metric are: mini_batch_size, learning_rate, and optimizer.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-6, MaxValue: 0.5</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 8, MaxValue: 64</td>
</tr>
</tbody>
</table>
### Parameter Table

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>momentum</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
<tr>
<td>optimizer</td>
<td>CategoricalParameterRanges</td>
<td>['sgd', 'adam', 'rmsprop', 'adadelta']</td>
</tr>
<tr>
<td>weight_decay</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
</tbody>
</table>

### Object Detection Request and Response Formats

#### Request Format

Query a trained model by using the model's endpoint. The endpoint takes .jpg and .png image formats with `image/jpeg` and `image/png` content-types.

#### Response Formats

The response is the class index with a confidence score and bounding box coordinates for all objects within the image encoded in JSON format. The following is an example of response .json file:

```json
"prediction": [
    [4.0, 0.86419455409409988, 0.3088374733924866, 0.07030484080314636, 0.7110607028007507, 0.9345266819000244],
    [0.0, 0.73376223592105108, 0.5714187026023865, 0.40427327156066895, 0.827075183391571, 0.9712159633636475],
    [4.0, 0.32643985450267792, 0.3677481412887573, 0.03488320331573486, 0.6318609714508057, 0.5967587828636169],
    [8.0, 0.22552496790885925, 0.6152569651603699, 0.5722782611846924, 0.882301390171051, 0.8985623121261597],
    [3.0, 0.42260299175977707, 0.019305512309074402, 0.08386176824569702, 0.39093565940856934, 0.9574796557426453]
]
```

Each row in this .json file contains an array that represents a detected object. Each of these object arrays consists of a list of six numbers. The first number is the predicted class label. The second number is the associated confidence score for the detection. The last four numbers represent the bounding box coordinates [xmin, ymin, xmax, ymax]. These output bounding box corner indices are normalized by the overall image size. Note that this encoding is different than that use by the input .json format. For example, in the first entry of the detection result, 0.3088374733924866 is the left coordinate (x-coordinate of upper-left corner) of the bounding box as a ratio of the overall image width, 0.07030484080314636 is the top coordinate (y-coordinate of upper-left corner) of the bounding box as a ratio of the overall image height, 0.7110607028007507 is the right coordinate (x-coordinate of lower-right corner) of the bounding box as a ratio of the overall image width, and 0.9345266819000244 is the bottom coordinate (y-coordinate of lower-right corner) of the bounding box as a ratio of the overall image height.

To avoid unreliable detection results, you might want to filter out the detection results with low confidence scores. In the object detection sample notebook, we provide examples of scripts that use a threshold to remove low confidence detections and to plot bounding boxes on the original images.

For batch transform, the response is in JSON format, where the format is identical to the JSON format described above. The detection results of each image is represented as a JSON file. For example:

```json
{"prediction": [[label_id, confidence_score, xmin, ymin, xmax, ymax], [label_id, confidence_score, xmin, ymin, xmax, ymax]]}
```

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For more details on training and inference, see the Object Detection Sample Notebooks (p. 2199).

**OUTPUT: JSON Response Format**

```json
{
   "image_size": [
      {
         "width": 500,
         "height": 400,
         "depth": 3
      }
   ],
   "annotations": [
      {
         "class_id": 0,
         "score": 0.943,
         "left": 111,
         "top": 134,
         "width": 61,
         "height": 128
      },
      {
         "class_id": 0,
         "score": 0.0013,
         "left": 161,
         "top": 250,
         "width": 79,
         "height": 143
      },
      {
         "class_id": 1,
         "score": 0.0133,
         "left": 101,
         "top": 185,
         "width": 42,
         "height": 130
      }
   ]
}
```

**Object Detection - TensorFlow**

The Amazon SageMaker Object Detection - TensorFlow algorithm is a supervised learning algorithm that supports transfer learning with many pretrained models from the TensorFlow Model Garden. Use transfer learning to fine-tune one of the available pretrained models on your own dataset, even if a large amount of image data is not available. The object detection algorithm takes an image as input and outputs a list of bounding boxes. Training datasets must consist of images in .jpg, .jpeg, or .png format.

**Topics**
- How to use the SageMaker Object Detection - TensorFlow algorithm (p. 2208)
- Input and output interface for the Object Detection - TensorFlow algorithm (p. 2209)
- Amazon EC2 instance recommendation for the Object Detection - TensorFlow algorithm (p. 2210)
- Object Detection - TensorFlow sample notebooks (p. 2210)
- How Object Detection - TensorFlow Works (p. 2210)
- TensorFlow Models (p. 2211)
- Object Detection - TensorFlow Hyperparameters (p. 2212)
- Tune an Object Detection - TensorFlow model (p. 2214)
How to use the SageMaker Object Detection - TensorFlow algorithm

You can use Object Detection - TensorFlow as an Amazon SageMaker built-in algorithm. The following section describes how to use Object Detection - TensorFlow with the SageMaker Python SDK. For information on how to use Object Detection - TensorFlow from the Amazon SageMaker Studio UI, see SageMaker JumpStart (p. 45).

The Object Detection - TensorFlow algorithm supports transfer learning using any of the compatible pretrained TensorFlow models. For a list of all available pretrained models, see TensorFlow Models (p. 2211). Every pretrained model has a unique model_id. The following example uses ResNet50 (model_id: tensorflow-od1-ssd-resnet50-v1-fpn-640x640-coco17-tpu-8) to fine-tune on a custom dataset. The pretrained models are all pre-downloaded from the TensorFlow Hub and stored in Amazon S3 buckets so that training jobs can run in network isolation. Use these pre-generated model training artifacts to construct a SageMaker Estimator.

First, retrieve the Docker image URI, training script URI, and pretrained model URI. Then, change the hyperparameters as you see fit. You can see a Python dictionary of all available hyperparameters and their default values with hyperparameters.retrieve_default. For more information, see Object Detection - TensorFlow Hyperparameters (p. 2212). Use these values to construct a SageMaker Estimator.

Note
Default hyperparameter values are different for different models. For example, for larger models, the default number of epochs is smaller.

This example uses the PennFudanPed dataset, which contains images of pedestrians in the street. We pre-downloaded the dataset and made it available with Amazon S3. To fine-tune your model, call .fit using the Amazon S3 location of your training dataset.

```python
from sagemaker import image_uris, model_uris, script_uris, hyperparameters
from sagemaker.estimator import Estimator

model_id, model_version = "tensorflow-od1-ssd-resnet50-v1-fpn-640x640-coco17-tpu-8", "*
training_instance_type = "ml.p3.2xlarge"

# Retrieve the Docker image
train_image_uri =
image_uris.retrieve(model_id=model_id, model_version=model_version, image_scope="training", instance_type=training_instance_type)

# Retrieve the training script
train_source_uri = script_uris.retrieve(model_id=model_id, model_version=model_version, script_scope="training")

# Retrieve the pretrained model tarball for transfer learning
train_model_uri = model_uris.retrieve(model_id=model_id, model_version=model_version, model_scope="training")

# Retrieve the default hyperparameters for fine-tuning the model
hyperparameters = hyperparameters.retrieve_default(model_id=model_id, model_version=model_version)

# [Optional] Override default hyperparameters with custom values
hyperparameters["epochs"] = "5"

# Sample training data is available in this bucket
training_data_bucket = f"jumpstart-cache-prod-{aws_region}"
training_data_prefix = "training-datasets/PennFudanPed_COCO_format/"

training_dataset_s3_path = f"s3://{training_data_bucket}/{training_data_prefix}"

output_bucket = sess.default_bucket()
output_prefix = "jumpstart-example-od-training"
s3_output_location = f"s3://{output_bucket}/{output_prefix}/output"
```
# Create an Estimator instance

tf_od_estimator = Estimator(  
    role=aws_role,  
    image_uri=train_image_uri,  
    source_dir=train_source_uri,  
    model_uri=train_model_uri,  
    entry_point="transfer_learning.py",  
    instance_count=1,  
    instance_type=training_instance_type,  
    max_run=360000,  
    hyperparameters=hyperparameters,  
    output_path=s3_output_location,  
)

# Launch a training job

tf_od_estimator.fit(  
    {"training": training_dataset_s3_path},  
    logs=True
)

For more information about how to use the SageMaker Object Detection - TensorFlow algorithm for transfer learning on a custom dataset, see the [Introduction to SageMaker TensorFlow - Object Detection notebook](#).

### Input and output interface for the Object Detection - TensorFlow algorithm

Each of the pretrained models listed in TensorFlow Models can be fine-tuned to any dataset with any number of image classes. Be mindful of how to format your training data for input to the Object Detection - TensorFlow model.

- **Training data input format**: Your training data should be a directory with an `images` subdirectory and an `annotations.json` file.

The following is an example of an input directory structure. The input directory should be hosted in an Amazon S3 bucket with a path similar to the following: `s3://bucket_name/input_directory/`. Note that the trailing `/` is required.

```
input_directory  
    |--images  
    |   |--abc.png  
    |   |--def.png  
    |   |--annotations.json
```

The `annotations.json` file should contain information for bounding boxes and their class labels in the form of a dictionary "images" and "annotations" keys. The value for the "images" key should be a list of dictionaries. There should be one dictionary for each image with the following information:

- "file_name": `image_name`, "height": `height`, "width": `width`, "id": `image_id`

The value for the "annotations" key should also be a list of dictionaries. There should be one dictionary for each bounding box with the following information:

- "image_id": `image_id`, "bbox": `[xmin, ymin, xmax, ymax]`, "category_id": `bbox_label`

After training, a label mapping file and trained model are saved to your Amazon S3 bucket.

### Incremental training

You can seed the training of a new model with artifacts from a model that you trained previously with SageMaker. Incremental training saves training time when you want to train a new model with the same or similar data.

**Note**

You can use any dataset for incremental training, as long as the set of classes remains the same. The incremental training step is similar to the fine-tuning step, but instead of starting with a pretrained model, you start with an existing fine-tuned model. For more information about how to use incremental training with the SageMaker Object Detection - TensorFlow, see the Introduction to SageMaker TensorFlow - Object Detection notebook.

Inference with the Object Detection - TensorFlow algorithm

You can host the fine-tuned model that results from your TensorFlow Object Detection training for inference. Any input image for inference must be in .jpg, .jpeg, or .png format and be content type application/x-image. The Object Detection - TensorFlow algorithm resizes input images automatically.

Running inference results in bounding boxes, predicted classes, and the scores of each prediction encoded in JSON format. The Object Detection - TensorFlow model processes a single image per request and outputs only one line. The following is an example of a JSON format response:

```
accept: application/json;verbose
{"normalized_boxes":[[xmin1, xmax1, ymin1, ymax1],...],
 "classes":[classidx1, class_idx2,...],
 "scores":[score_1, score_2,...],
 "labels": [label1, label2, ...],
 "tensorflow_model_output":<original output of the model>}
```

If accept is set to application/json, then the model only outputs normalized boxes, classes, and scores.

Amazon EC2 instance recommendation for the Object Detection - TensorFlow algorithm

The Object Detection - TensorFlow algorithm supports all GPU instances for training, including:

- ml.p2.xlarge
- ml.p2.16xlarge
- ml.p3.2xlarge
- ml.p3.16xlarge

We recommend GPU instances with more memory for training with large batch sizes. Both CPU (such as M5) and GPU (P2 or P3) instances can be used for inference. For a comprehensive list of SageMaker training and inference instances across AWS Regions, see Amazon SageMaker Pricing.

Object Detection - TensorFlow sample notebooks

For more information about how to use the SageMaker Object Detection - TensorFlow algorithm for transfer learning on a custom dataset, see the Introduction to SageMaker TensorFlow - Object Detection notebook.

For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. To open a notebook, choose its Use tab and choose Create copy.

How Object Detection - TensorFlow Works

The Object Detection - TensorFlow algorithm takes an image as input and predicts bounding boxes and object labels. Various deep learning networks such as MobileNet, ResNet, Inception, and EfficientNet are highly accurate for object detection. There are also deep learning networks that are trained on large
image datasets, such as Common Objects in Context (COCO), which has 328,000 images. After a network is trained with COCO data, you can then fine-tune the network on a dataset with a particular focus to perform more specific object detection tasks. The Amazon SageMaker Object Detection - TensorFlow algorithm supports transfer learning on many pretrained models that are available in the TensorFlow Model Garden.

According to the number of class labels in your training data, an object detection layer is attached to the pretrained TensorFlow model of your choice. You can then fine-tune either the entire network (including the pretrained model) or only the top classification layer on new training data. With this method of transfer learning, training with smaller datasets is possible.

**TensorFlow Models**

The following pretrained models are available to use for transfer learning with the Object Detection - TensorFlow algorithm.

The following models vary significantly in size, number of model parameters, training time, and inference latency for any given dataset. The best model for your use case depends on the complexity of your fine-tuning dataset and any requirements that you have on training time, inference latency, or model accuracy.

<table>
<thead>
<tr>
<th>Model Name</th>
<th>model_id</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet50 V1 FPN 640</td>
<td>tensorflow-od1-ssd-resnet50-v1-fpn-640x640-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>EfficientDet D0 512</td>
<td>tensorflow-od1-ssd-efficientdet-d0-512x512-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>EfficientDet D1 640</td>
<td>tensorflow-od1-ssd-efficientdet-d1-640x640-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>EfficientDet D2 768</td>
<td>tensorflow-od1-ssd-efficientdet-d2-768x768-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>EfficientDet D3 896</td>
<td>tensorflow-od1-ssd-efficientdet-d3-896x896-coco17-tpu-32</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>MobileNet V1 FPN 640</td>
<td>tensorflow-od1-ssd-mobilenet-v1-fpn-640x640-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>MobileNet V2 FPNLite 320</td>
<td>tensorflow-od1-ssd-mobilenet-v2-fpnlite-320x320-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>MobileNet V2 FPNLite 640</td>
<td>tensorflow-od1-ssd-mobilenet-v2-fpnlite-640x640-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>ResNet50 V1 FPN 1024</td>
<td>tensorflow-od1-ssd-resnet50-v1-</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>Model Name</td>
<td>model_id</td>
<td>Source</td>
</tr>
<tr>
<td>-----------------------</td>
<td>----------------------------------------------</td>
<td>---------------------------------------------</td>
</tr>
<tr>
<td>ResNet101 V1 FPN 1024</td>
<td>tensorflow-od1-ssd-resnet101-v1-fpn-1024x1024-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>ResNet152 V1 FPN 640</td>
<td>tensorflow-od1-ssd-resnet152-v1-fpn-640x640-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
<tr>
<td>ResNet152 V1 FPN 1024</td>
<td>tensorflow-od1-ssd-resnet152-v1-fpn-1024x1024-coco17-tpu-8</td>
<td>TensorFlow Model Garden link</td>
</tr>
</tbody>
</table>

**Object Detection - TensorFlow Hyperparameters**

Hyperparameters are parameters that are set before a machine learning model begins learning. The following hyperparameters are supported by the Amazon SageMaker built-in Object Detection - TensorFlow algorithm. See [Tune an Object Detection - TensorFlow model](p. 2214) for information on hyperparameter tuning.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch_size</td>
<td>The batch size for training. Valid values: positive integer. Default value: 3.</td>
</tr>
<tr>
<td>beta_1</td>
<td>The beta1 for the &quot;adam&quot; optimizer. Represents the exponential decay rate for the first moment estimates. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.9.</td>
</tr>
<tr>
<td>beta_2</td>
<td>The beta2 for the &quot;adam&quot; optimizer. Represents the exponential decay rate for the second moment estimates. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.999.</td>
</tr>
<tr>
<td>early_stopping</td>
<td>Set to &quot;True&quot; to use early stopping logic during training. If &quot;False&quot;, early stopping is not used. Valid values: string, either: (&quot;True&quot; or &quot;False&quot;).</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;False&quot;.</td>
</tr>
<tr>
<td>early_stopping_min_delta</td>
<td>The minimum change needed to qualify as an improvement. An absolute change less than the value of early_stopping_min_delta does not qualify as improvement. Used only when early_stopping is set to &quot;True&quot;. Valid values: float, range: [0.0, 1.0]. Default value: 0.0.</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>early_stopping_patience</td>
<td>The number of epochs to continue training with no improvement. Used only when early_stopping is set to &quot;True&quot;. Valid values: positive integer. Default value: 5.</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>epochs</td>
<td>The number of training epochs. Valid values: positive integer. Default value: 5 for smaller models, 1 for larger models.</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>epsilon</td>
<td>The epsilon for &quot;adam&quot;, &quot;rmsprop&quot;, &quot;adadelta&quot;, and &quot;adagrad&quot; optimizers. Usually set to a small value to avoid division by 0. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 1e-7.</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>initial_accumulator_value</td>
<td>The starting value for the accumulators, or the per-parameter momentum values, for the &quot;adagrad&quot; optimizer. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.1.</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>learning_rate</td>
<td>The optimizer learning rate. Valid values: float, range: [0.0, 1.0]. Default value: 0.001.</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>momentum</td>
<td>The momentum for the &quot;sgd&quot; and &quot;nesterov&quot; optimizers. Ignored for other optimizers. Valid values: float, range: [0.0, 1.0]. Default value: 0.9.</td>
</tr>
</tbody>
</table>
### Parameter Name  | Description
---|---
optimizer | The optimizer type. For more information, see Optimizers in the TensorFlow documentation. 
Valid values: string, any of the following: ("adam", "sgd", "nesterov", "rmsprop", "adagrad", "adadelta"). 
Default value: "adam".
reinitialize_top_layer | If set to "Auto", the top classification layer parameters are re-initialized during fine-tuning. For incremental training, top classification layer parameters are not re-initialized unless set to "True". 
Valid values: string, any of the following: ("Auto", "True" or "False"). 
Default value: "Auto".
\(\rho\) | The discounting factor for the gradient of the "adadelta" and "rmsprop" optimizers. Ignored for other optimizers. 
Valid values: float, range: \([0.0, 1.0]\). 
Default value: 0.95.
train_only_on_top_layer | If "True", only the top classification layer parameters are fine-tuned. If "False", all model parameters are fine-tuned. 
Valid values: string, either: ("True" or "False"). 
Default value: "False".

### Tune an Object Detection - TensorFlow model

**Automatic model tuning**, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

### Metrics computed by the Object Detection - TensorFlow algorithm

Refer to the following chart to find which metrics are computed by the Object Detection - TensorFlow algorithm.

### Tune an Object Detection - TensorFlow model

**Automatic model tuning**, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

For more information about model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

### Metrics computed by the Object Detection - TensorFlow algorithm

Refer to the following chart to find which metrics are computed by the Object Detection - TensorFlow algorithm.
Tunable Object Detection - TensorFlow hyperparameters

Tune an object detection model with the following hyperparameters. The hyperparameters that have the greatest impact on object detection objective metrics are: batch_size, learning_rate, and optimizer. Tune the optimizer-related hyperparameters, such as momentum, regularizers_l2, beta_1, beta_2, and eps based on the selected optimizer. For example, use beta_1 and beta_2 only when adam is the optimizer.

For more information about which hyperparameters are used for each optimizer, see Object Detection - TensorFlow Hyperparameters (p. 2212).

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 8, MaxValue: 512</td>
</tr>
<tr>
<td>beta_1</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.999</td>
</tr>
<tr>
<td>beta_2</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.999</td>
</tr>
<tr>
<td>eps</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-8, MaxValue: 1.0</td>
</tr>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 1e-6, MaxValue: 0.5</td>
</tr>
<tr>
<td>momentum</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
<tr>
<td>optimizer</td>
<td>CategoricalParameterRanges</td>
<td>['sgd', 'adam', 'rmsprop', 'nesterov', 'adagrad', 'adadelta']</td>
</tr>
<tr>
<td>regularizers_l2</td>
<td>ContinuousParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
<tr>
<td>train_only_on_top_layer</td>
<td>CategoricalParameterRanges</td>
<td>['True', 'False']</td>
</tr>
<tr>
<td>initial_accumulator</td>
<td>CategoricalParameterRanges</td>
<td>MinValue: 0.0, MaxValue: 0.999</td>
</tr>
</tbody>
</table>

Semantic Segmentation Algorithm

The SageMaker semantic segmentation algorithm provides a fine-grained, pixel-level approach to developing computer vision applications. It tags every pixel in an image with a class label from a predefined set of classes. Tagging is fundamental for understanding scenes, which is critical to an increasing number of computer vision applications, such as self-driving vehicles, medical imaging diagnostics, and robot sensing.

For comparison, the SageMaker Image Classification - MXNet (p. 2172) is a supervised learning algorithm that analyzes only whole images, classifying them into one of multiple output categories. The Object Detection - MXNet (p. 2196) is a supervised learning algorithm that detects and classifies all instances of an object in an image. It indicates the location and scale of each object in the image with a rectangular bounding box.

Because the semantic segmentation algorithm classifies every pixel in an image, it also provides information about the shapes of the objects contained in the image. The segmentation output is
represented as a grayscale image, called a segmentation mask. A segmentation mask is a grayscale image with the same shape as the input image.

The SageMaker semantic segmentation algorithm is built using the MXNet Gluon framework and the Gluon CV toolkit. It provides you with a choice of three built-in algorithms to train a deep neural network. You can use the Fully-Convolutional Network (FCN) algorithm, Pyramid Scene Parsing (PSP) algorithm, or DeepLabV3.

Each of the three algorithms has two distinct components:

- The backbone (or encoder)—A network that produces reliable activation maps of features.
- The decoder—A network that constructs the segmentation mask from the encoded activation maps.

You also have a choice of backbones for the FCN, PSP, and DeepLabV3 algorithms: ResNet50 or ResNet101. These backbones include pretrained artifacts that were originally trained on the ImageNet classification task. You can fine-tune these backbones for segmentation using your own data. Or, you can initialize and train these networks from scratch using only your own data. The decoders are never pretrained.

To deploy the trained model for inference, use the SageMaker hosting service. During inference, you can request the segmentation mask either as a PNG image or as a set of probabilities for each class for each pixel. You can use these masks as part of a larger pipeline that includes additional downstream image processing or other applications.

Topics
- Semantic Segmentation Sample Notebooks (p. 2216)
- Input/Output Interface for the Semantic Segmentation Algorithm (p. 2216)
- EC2 Instance Recommendation for the Semantic Segmentation Algorithm (p. 2219)
- Semantic Segmentation Hyperparameters (p. 2219)
- Tuning a Semantic Segmentation Model (p. 2224)

Semantic Segmentation Sample Notebooks

For a sample Jupyter notebook that uses the SageMaker semantic segmentation algorithm to train a model and deploy it to perform inferences, see the Semantic Segmentation Example. For instructions on how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291).

To see a list of all of the SageMaker samples, create and open a notebook instance, and choose the SageMaker Examples tab. The example semantic segmentation notebooks are located under Introduction to Amazon algorithms. To open a notebook, choose its Use tab, and choose Create copy.

Input/Output Interface for the Semantic Segmentation Algorithm

SageMaker semantic segmentation expects the customer's training dataset to be on Amazon Simple Storage Service (Amazon S3). Once trained, it produces the resulting model artifacts on Amazon S3. The input interface format for the SageMaker semantic segmentation is similar to that of most standardized semantic segmentation benchmarking datasets. The dataset in Amazon S3 is expected to be presented in two channels, one for train and one for validation using four directories, two for images and two for annotations. Annotations are expected to be uncompressed PNG images. The dataset might also have a label map that describes how the annotation mappings are established. If not, the algorithm uses a default. It also supports the augmented manifest image format (application/x-image) for training in Pipe input mode straight from Amazon S3. For inference, an endpoint accepts images with an image/jpeg content type.
How Training Works

The training data is split into four directories: train, train_annotation, validation, and validation_annotation. There is a channel for each of these directories. The dataset also expected to have one label_map.json file per channel for train_annotation and validation_annotation respectively. If you don't provide these JSON files, SageMaker provides the default set label map.

The dataset specifying these files should look similar to the following example:

```
s3://bucket_name
  |- train
  |   |- 0000.jpg
  |   |- coffee.jpg
  |- validation
  |   |- 00a0.jpg
  |   |- banana.jpg
  |- train_annotation
  |   |- 0000.png
  |   |- coffee.png
  |- validation_annotation
  |   |- 00a0.png
  |   |- banana.png
  |- label_map
    |- train_label_map.json
    |- validation_label_map.json
```

Every JPG image in the train and validation directories has a corresponding PNG label image with the same name in the train_annotation and validation_annotation directories. This naming convention helps the algorithm to associate a label with its corresponding image during training. The train, train_annotation, validation, and validation_annotation channels are mandatory. The annotations are single-channel PNG images. The format works as long as the metadata (modes) in the image helps the algorithm read the annotation images into a single-channel 8-bit unsigned integer. For more information on our support for modes, see the Python Image Library documentation. We recommend using the 8-bit pixel, true color P mode.

The image that is encoded is a simple 8-bit integer when using modes. To get from this mapping to a map of a label, the algorithm uses one mapping file per channel, called the label map. The label map is used to map the values in the image with actual label indices. In the default label map, which is provided by default if you don't provide one, the pixel value in an annotation matrix (image) directly index the label. These images can be grayscale PNG files or 8-bit indexed PNG files. The label map file for the unscaled default case is the following:

```
{
   "scale": "1"
}
```

To provide some contrast for viewing, some annotation software scales the label images by a constant amount. To support this, the SageMaker semantic segmentation algorithm provides a rescaling option to scale down the values to actual label values. When scaling down doesn't convert the value to an appropriate integer, the algorithm defaults to the greatest integer less than or equal to the scale value. The following code shows how to set the scale value to rescale the label values:

```
{
   "scale": "3"
}
```
The following example shows how this "scale" value is used to rescale the encoded_label values of the input annotation image when they are mapped to the mapped_label values to be used in training. The label values in the input annotation image are 0, 3, 6, with scale 3, so they are mapped to 0, 1, 2 for training:

```
encoded_label = [0, 3, 6]
mapped_label = [0, 1, 2]
```

In some cases, you might need to specify a particular color mapping for each class. Use the map option in the label mapping as shown in the following example of a label_map file:

```
{
    "map": {
        "0": 5,
        "1": 0,
        "2": 2
    }
}
```

This label mapping for this example is:

```
encoded_label = [0, 5, 2]
mapped_label = [1, 0, 2]
```

With label mappings, you can use different annotation systems and annotation software to obtain data without a lot of preprocessing. You can provide one label map per channel. The files for a label map in the label_map channel must follow the naming conventions for the four directory structure. If you don't provide a label map, the algorithm assumes a scale of 1 (the default).

**Training with the Augmented Manifest Format**

The augmented manifest format enables you to do training in Pipe mode using image files without needing to create RecordIO files. The augmented manifest file contains data objects and should be in JSON Lines format, as described in the **CreateTrainingJob** request. Each line in the manifest is an entry containing the Amazon S3 URI for the image and the URI for the annotation image.

Each JSON object in the manifest file must contain a source-ref key. The source-ref key should contain the value of the Amazon S3 URI to the image. The labels are provided under the AttributeNames parameter value as specified in the **CreateTrainingJob** request. It can also contain additional metadata under the metadata tag, but these are ignored by the algorithm. In the example below, the AttributeNames are contained in the list of image and annotation references ["source-ref", "city-streets-ref"]. These names must have -ref appended to them. When using the Semantic Segmentation algorithm with Augmented Manifest, the value of the RecordWrapperType parameter must be "RecordIO" and value of the ContentType parameter must be application/x-recordio.

```
{"source-ref": "S3 bucket location", "city-streets-ref": "S3 bucket location", "city-streets-metadata": {"job-name": "label-city-streets", }}
```

For more information on augmented manifest files, see **Provide Dataset Metadata to Training Jobs with an Augmented Manifest File** (p. 2700).

**Incremental Training**

You can also seed the training of a new model with a model that you trained previously using SageMaker. This incremental training saves training time when you want to train a new model with the same or similar data. Currently, incremental training is supported only for models trained with the built-in SageMaker Semantic Segmentation.
To use your own pre-trained model, specify the ChannelName as "model" in the InputDataConfig for the `CreateTrainingJob` request. Set the ContentType for the model channel to application/x-sagemaker-model. The backbone, algorithm, crop_size, and num_classes input parameters that define the network architecture must be consistently specified in the input hyperparameters of the new model and the pre-trained model that you upload to the model channel. For the pretrained model file, you can use the compressed (.tar.gz) artifacts from SageMaker outputs. You can only use Image formats for input data. For more information on incremental training and for instructions on how to use it, see Incremental Training in Amazon SageMaker (p. 2677).

**Produce Inferences**

To query a trained model that is deployed to an endpoint, you need to provide an image and an AcceptType that denotes the type of output required. The endpoint takes JPEG images with an image/jpeg content type. If you request an AcceptType of image/png, the algorithm outputs a PNG file with a segmentation mask in the same format as the labels themselves. If you request an accept type of application/x-recordio-protobuf, the algorithm returns class probabilities encoded in recordio-protobuf format. The latter format outputs a 3D tensor where the third dimension is the same size as the number of classes. This component denotes the probability of each class label for each pixel.

**EC2 Instance Recommendation for the Semantic Segmentation Algorithm**

The SageMaker semantic segmentation algorithm only supports GPU instances for training, and we recommend using GPU instances with more memory for training with large batch sizes. The algorithm can be trained using P2, P3, G4dn, or G5 instances in single machine configurations.

For inference, you can use either CPU instances (such as C5 and M5) and GPU instances (such as P3 and G4dn) or both. For information about the instance types that provide varying combinations of CPU, GPU, memory, and networking capacity for inference, see Amazon SageMaker ML Instance Types.

**Semantic Segmentation Hyperparameters**

The following tables list the hyperparameters supported by the Amazon SageMaker semantic segmentation algorithm for network architecture, data inputs, and training. You specify Semantic Segmentation for training in the `AlgorithmName` of the `CreateTrainingJob` request.

**Network Architecture Hyperparameters**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>backbone</td>
<td>The backbone to use for the algorithm's encoder component.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: resnet-50, resnet-101</td>
</tr>
<tr>
<td></td>
<td>Default value: resnet-50</td>
</tr>
<tr>
<td>use_pretrained_model</td>
<td>Whether a pretrained model is to be used for the backbone.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: True, False</td>
</tr>
<tr>
<td></td>
<td>Default value: True</td>
</tr>
<tr>
<td>algorithm</td>
<td>The algorithm to use for semantic segmentation.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values:</td>
</tr>
</tbody>
</table>
### Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>fcn</td>
<td>Fully-Convolutional Network (FCN) algorithm</td>
</tr>
<tr>
<td>psp</td>
<td>Pyramid Scene Parsing (PSP) algorithm</td>
</tr>
<tr>
<td>deeplab</td>
<td>DeepLab V3 algorithm</td>
</tr>
</tbody>
</table>

Default value: fcn

### Data Hyperparameters

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_classes</td>
<td>The number of classes to segment.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 2 ≤ positive integer ≤ 254</td>
</tr>
<tr>
<td>num_training_samples</td>
<td>The number of samples in the training data. The algorithm uses this value</td>
</tr>
<tr>
<td></td>
<td>to set up the learning rate scheduler.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td>base_size</td>
<td>Defines how images are rescaled before cropping. Images are rescaled such</td>
</tr>
<tr>
<td></td>
<td>that the long size length is set to base_size multiplied by a random number</td>
</tr>
<tr>
<td></td>
<td>from 0.5 to 2.0, and the short size is computed to preserve the aspect ratio.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer &gt; 16</td>
</tr>
<tr>
<td></td>
<td>Default value: 520</td>
</tr>
<tr>
<td>crop_size</td>
<td>The image size for input during training. We randomly rescale the input</td>
</tr>
<tr>
<td></td>
<td>image based on base_size, and then take a random square crop with side</td>
</tr>
<tr>
<td></td>
<td>length equal to crop_size. The crop_size will be automatically rounded up</td>
</tr>
<tr>
<td></td>
<td>to multiples of 8.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer &gt; 16</td>
</tr>
<tr>
<td></td>
<td>Default value: 240</td>
</tr>
</tbody>
</table>

### Training Hyperparameters

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>early_stopping</td>
<td>Whether to use early stopping logic during training.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: True, False</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td><strong>early_stopping_min_epochs</strong></td>
<td>The minimum number of epochs that must be run.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 5</td>
</tr>
<tr>
<td><strong>early_stopping_patience</strong></td>
<td>The number of epochs that meet the tolerance for lower performance</td>
</tr>
<tr>
<td></td>
<td>before the algorithm enforces an early stop.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 4</td>
</tr>
<tr>
<td><strong>early_stopping_tolerance</strong></td>
<td>If the relative improvement of the score of the training job, the mIOU,</td>
</tr>
<tr>
<td></td>
<td>is smaller than this value, early stopping considers the epoch as not</td>
</tr>
<tr>
<td></td>
<td>improved. This is used only when <code>early_stopping</code> = True.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 ≤ float ≤ 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0</td>
</tr>
<tr>
<td><strong>epochs</strong></td>
<td>The number of epochs with which to train.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: positive integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 10</td>
</tr>
<tr>
<td><strong>gamma1</strong></td>
<td>The decay factor for the moving average of the squared gradient for</td>
</tr>
<tr>
<td></td>
<td><code>rmsprop</code>. Used only for <code>rmsprop</code>.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 ≤ float ≤ 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.9</td>
</tr>
<tr>
<td><strong>gamma2</strong></td>
<td>The momentum factor for <code>rmsprop</code>.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 ≤ float ≤ 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.9</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>learning_rate</td>
<td>The initial learning rate.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: $0 &lt; \text{float} \leq 1$</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.001</td>
</tr>
<tr>
<td>lr_scheduler</td>
<td>The shape of the learning rate schedule that controls its decrease over time.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
</tbody>
</table>
|                   | Valid values:  
  - **step**: A stepwise decay, where the learning rate is reduced (multiplied) by the $\text{lr}_\text{scheduler}_\text{factor}$ after epochs specified by $\text{lr}_\text{scheduler}_\text{step}$.  
  - **poly**: A smooth decay using a polynomial function.  
  - **cosine**: A smooth decay using a cosine function.  

<p>|                   | Default value: poly                                                                                                                             |
| lr_scheduler_factor| If $\text{lr}<em>\text{scheduler}$ is set to <strong>step</strong>, the ratio by which to reduce (multiply) the learning_rate after each of the epochs specified by the $\text{lr}</em>\text{scheduler}<em>\text{step}$. Otherwise, ignored. |
|                   | <strong>Optional</strong>                                                                                                                                                                                                |
|                   | Valid values: $0 \leq \text{float} \leq 1$                                                                                                     |
|                   | Default value: 0.1                                                                                                                            |
| lr_scheduler_step | A comma delimited list of the epochs after which the learning_rate is reduced (multiplied) by an $\text{lr}</em>\text{scheduler}<em>\text{factor}$. For example, if the value is set to “10, 20”, then the learning-rate is reduced by $\text{lr}</em>\text{scheduler}<em>\text{factor}$ after the 10th epoch and again by this factor after 20th epoch. |
|                   | <strong>Conditionally Required</strong> if $\text{lr}</em>\text{scheduler}$ is set to <strong>step</strong>. Otherwise, ignored.                                               |
|                   | Valid values: string                                                                                                                          |
|                   | Default value: (No default, as the value is required when used.)                                                                               |
| mini_batch_size   | The batch size for training. Using a large $\text{mini}<em>\text{batch}</em>\text{size}$ usually results in faster training, but it might cause you to run out of memory. Memory usage is affected by the values of the $\text{mini}<em>\text{batch}</em>\text{size}$ and $\text{image}_\text{shape}$ parameters, and the backbone architecture. |
|                   | <strong>Optional</strong>                                                                                                                                                                                                |
|                   | Valid values: positive integer                                                                                                                   |
|                   | Default value: 16                                                                                                                             |</p>
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| momentum       | The momentum for the sgd optimizer. When you use other optimizers, the semantic segmentation algorithm ignores this parameter.  
Optional  
Valid values: $0 < \text{float} \leq 1$  
Default value: 0.9 |
| optimizer      | The type of optimizer. For more information about an optimizer, choose the appropriate link:  
• adam: Adaptive momentum estimation  
• adagrad: Adaptive gradient descent  
• nag: Nesterov accelerated gradient  
• rmsprop: Root mean square propagation  
• sgd: Stochastic gradient descent  
Optional  
Valid values: adam, adagrad, nag, rmsprop, sgd  
Default value: sgd |
| syncbn         | If set to True, the batch normalization mean and variance are computed over all the samples processed across the GPUs.  
Optional  
Valid values: True, False  
Default value: False |
| validation_mini_batch_size | Batch size for validation. A large mini_batch_size usually results in faster training, but it might cause you to run out of memory. Memory usage is affected by the values of the mini_batch_size and image_shape parameters, and the backbone architecture.  
- To score the validation on the entire image without cropping the images, set this parameter to 1. Use this option if you want to measure performance on the entire image as a whole.  
  Note  
  Setting the validation_mini_batch_size parameter to 1 causes the algorithm to create a new network model for every image. This might slow validation and training.  
- To crop images to the size specified in the crop_size parameter, even during evaluation, set this parameter to a value greater than 1.  
Optional  
Valid values: positive integer  
Default value: 16 |
Use Built-in Algorithms

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>weight_decay</td>
<td>The weight decay coefficient for the sgd optimizer. When you use other optimizers, the algorithm ignores this parameter.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 &lt; float &lt; 1</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.0001</td>
</tr>
</tbody>
</table>

### Tuning a Semantic Segmentation Model

**Automatic model tuning**, also known as hyperparameter tuning, finds the best version of a model by running many jobs that test a range of hyperparameters on your dataset. You choose the tunable hyperparameters, a range of values for each, and an objective metric. You choose the objective metric from the metrics that the algorithm computes. Automatic model tuning searches the hyperparameters chosen to find the combination of values that result in the model that optimizes the objective metric.

### Metrics Computed by the Semantic Segmentation Algorithm

The semantic segmentation algorithm reports two validation metrics. When tuning hyperparameter values, choose one of these metrics as the objective.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Optimization Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>validation:mIoU</td>
<td>The area of the intersection of the predicted segmentation and the ground truth divided by the area of union between them for images in the validation set. Also known as the Jaccard Index.</td>
<td>Maximize</td>
</tr>
<tr>
<td>validation:pixel_accuracy</td>
<td>The percentage of pixels that are correctly classified in images from the validation set.</td>
<td>Maximize</td>
</tr>
</tbody>
</table>

### Tunable Semantic Segmentation Hyperparameters

You can tune the following hyperparameters for the semantic segmentation algorithm.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Parameter Type</th>
<th>Recommended Ranges</th>
</tr>
</thead>
<tbody>
<tr>
<td>learning_rate</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-4, MaxValue: 1e-1</td>
</tr>
<tr>
<td>mini_batch_size</td>
<td>IntegerParameterRanges</td>
<td>MinValue: 1, MaxValue: 128</td>
</tr>
<tr>
<td>momentum</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 0.9, MaxValue: 0.999</td>
</tr>
<tr>
<td>optimizer</td>
<td>CategoricalParameterRanges</td>
<td>['sgd', 'adam', 'adadelta']</td>
</tr>
<tr>
<td>weight_decay</td>
<td>ContinuousParameterRange</td>
<td>MinValue: 1e-5, MaxValue: 1e-3</td>
</tr>
</tbody>
</table>
Use Reinforcement Learning with Amazon SageMaker

Reinforcement learning (RL) combines fields such as computer science, neuroscience, and psychology to determine how to map situations to actions to maximize a numerical reward signal. This notion of a reward signal in RL stems from neuroscience research into how the human brain makes decisions about which actions maximize reward and minimize punishment. In most situations, humans are not given explicit instructions on which actions to take, but instead must learn both which actions yield the most immediate rewards, and how those actions influence future situations and consequences.

The problem of RL is formalized using Markov decision processes (MDPs) that originate from dynamical systems theory. MDPs aim to capture high-level details of a real problem that a learning agent encounters over some period of time in attempting to achieve some ultimate goal. The learning agent should be able to determine the current state of its environment and identify possible actions that affect the learning agent's current state. Furthermore, the learning agent's goals should correlate strongly to the state of the environment. A solution to a problem formulated in this way is known as a reinforcement learning method.

What are the differences between reinforcement, supervised, and unsupervised learning paradigms?

Machine learning can be divided into three distinct learning paradigms: supervised, unsupervised, and reinforcement.

In supervised learning, an external supervisor provides a training set of labeled examples. Each example contains information about a situation, belongs to a category, and has a label identifying the category to which it belongs. The goal of supervised learning is to generalize in order to predict correctly in situations that are not present in the training data.

In contrast, RL deals with interactive problems, making it infeasible to gather all possible examples of situations with correct labels that an agent might encounter. This type of learning is most promising when an agent is able to accurately learn from its own experience and adjust accordingly.

In unsupervised learning, an agent learns by uncovering structure within unlabeled data. While a RL agent might benefit from uncovering structure based on its experiences, the sole purpose of RL is to maximize a reward signal.

Topics
- Why is Reinforcement Learning Important? (p. 2225)
- Markov Decision Process (MDP) (p. 2226)
- Key Features of Amazon SageMaker RL (p. 2226)
- Reinforcement Learning Sample Notebooks (p. 2228)
- Sample RL Workflow Using Amazon SageMaker RL (p. 2228)
- RL Environments in Amazon SageMaker (p. 2229)
- Distributed Training with Amazon SageMaker RL (p. 2231)
- Hyperparameter Tuning with Amazon SageMaker RL (p. 2231)

Why is Reinforcement Learning Important?

RL is well-suited for solving large, complex problems, such as supply chain management, HVAC systems, industrial robotics, game artificial intelligence, dialog systems, and autonomous vehicles. Because RL models learn by a continuous process of receiving rewards and punishments for every action taken by the agent, it is possible to train systems to make decisions under uncertainty and in dynamic environments.
Markov Decision Process (MDP)

RL is based on models called Markov Decision Processes (MDPs). An MDP consists of a series of time steps. Each time step consists of the following:

Environment

Defines the space in which the RL model operates. This can be either a real-world environment or a simulator. For example, if you train a physical autonomous vehicle on a physical road, that would be a real-world environment. If you train a computer program that models an autonomous vehicle driving on a road, that would be a simulator.

State

Specifies all information about the environment and past steps that is relevant to the future. For example, in an RL model in which a robot can move in any direction at any time step, the position of the robot at the current time step is the state, because if we know where the robot is, it isn't necessary to know the steps it took to get there.

Action

What the agent does. For example, the robot takes a step forward.

Reward

A number that represents the value of the state that resulted from the last action that the agent took. For example, if the goal is for a robot to find treasure, the reward for finding treasure might be 5, and the reward for not finding treasure might be 0. The RL model attempts to find a strategy that optimizes the cumulative reward over the long term. This strategy is called a policy.

Observation

Information about the state of the environment that is available to the agent at each step. This might be the entire state, or it might be just a part of the state. For example, the agent in a chess-playing model would be able to observe the entire state of the board at any step, but a robot in a maze might only be able to observe a small portion of the maze that it currently occupies.

Typically, training in RL consists of many episodes. An episode consists of all of the time steps in an MDP from the initial state until the environment reaches the terminal state.

Key Features of Amazon SageMaker RL

To train RL models in SageMaker RL, use the following components:

- An RL environment. You can use custom environments, open-source environments, or commercial environments. For information, see RL Environments in Amazon SageMaker (p. 2229).

The following diagram shows the RL components that are supported in SageMaker RL.
Reinforcement Learning Sample Notebooks

The following table outlines a variety of sample notebooks that address different use cases of Amazon SageMaker reinforcement learning.

<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>How to Train Batch RL Policies?</td>
<td>This notebook shows how to use batch RL to train a new policy from an offline dataset.</td>
</tr>
<tr>
<td>How to Solve the Cart-pole Balancing Problem?</td>
<td>This notebook shows how to solve the cart-pole balancing problem with RL.</td>
</tr>
<tr>
<td>How to Solve the Knapsack Problem?</td>
<td>This notebook shows how to use RL to solve the knapsack problem, and how SageMaker Managed Spot Training can be used to run training at a lower cost.</td>
</tr>
<tr>
<td>How to Solve the Mountain Car Problem?</td>
<td>This notebook shows how to solve the mountain car control problem with RL.</td>
</tr>
</tbody>
</table>

Sample RL Workflow Using Amazon SageMaker RL

The following example describes the steps for developing RL models using Amazon SageMaker RL.

For complete code examples, see the sample notebooks at https://github.com/awslabs/amazon-sagemaker-examples/tree/master/reinforcement-learning.

1. **Formulate the RL problem**—First, formulate the business problem into an RL problem. For example, auto scaling enables services to dynamically increase or decrease capacity depending on conditions that you define. Currently, this requires setting up alarms, scaling policies, thresholds, and other manual steps. To solve this with RL, we define the components of the Markov Decision Process:
   a. **Objective**—Scale instance capacity so that it matches the desired load profile.
   b. **Environment**—A custom environment that includes the load profile. It generates a simulated load with daily and weekly variations and occasional spikes. The simulated system has a delay between when new resources are requested and when they become available for serving requests.
   c. **State**—The current load, number of failed jobs, and number of active machines.
   d. **Action**—Remove, add, or keep the same number of instances.
   e. **Reward**—A positive reward for successful transactions and a high penalty for failing transactions beyond a specified threshold.

2. **Define the RL environment**—The RL environment can be the real world where the RL agent interacts or a simulation of the real world. You can connect open source and custom environments developed using Gym interfaces and commercial simulation environments such as MATLAB and Simulink.

3. **Define the presets**—The presets configure the RL training jobs and define the hyperparameters for the RL algorithms.

4. **Write the training code**—Write training code as a Python script and pass the script to a SageMaker training job. In your training code, import the environment files and the preset files, and then define the main() function.

5. **Train the RL Model**—Use the SageMaker RLEstimato r in the Amazon SageMaker Python SDK to start an RL training job. If you are using local mode, the training job runs on the notebook instance.
When you use SageMaker for training, you can select GPU or CPU instances. Store the output from the training job in a local directory if you train in local mode, or on Amazon S3 if you use SageMaker training.

The **RLEstimator** requires the following information as parameters.

a. The source directory where the environment, presets, and training code are uploaded.

b. The path to the training script.

c. The RL toolkit and deep learning framework you want to use. This automatically resolves to the Amazon ECR path for the RL container.

d. The training parameters, such as the instance count, job name, and S3 path for output.

e. Metric definitions that you want to capture in your logs. These can also be visualized in CloudWatch and in SageMaker notebooks.

6. **Visualize training metrics and output**—After a training job that uses an RL model completes, you can view the metrics you defined in the training jobs in CloudWatch. You can also plot the metrics in a notebook by using the Amazon SageMaker Python SDK analytics library. Visualizing metrics helps you understand how the performance of the model as measured by the reward improves over time.

   **Note**
   If you train in local mode, you can't visualize metrics in CloudWatch.

7. **Evaluate the model**—Checkpointed data from the previously trained models can be passed on for evaluation and inference in the checkpoint channel. In local mode, use the local directory. In SageMaker training mode, you need to upload the data to S3 first.

8. **Deploy RL models**—Finally, deploy the trained model on an endpoint hosted on SageMaker containers or on an edge device by using AWS IoT Greengrass.

For more information on RL with SageMaker, see [Using RL with the SageMaker Python SDK](#).

**RL Environments in Amazon SageMaker**

Amazon SageMaker RL uses environments to mimic real-world scenarios. Given the current state of the environment and an action taken by the agent or agents, the simulator processes the impact of the action, and returns the next state and a reward. Simulators are useful in cases where it is not safe to train an agent in the real world (for example, flying a drone) or if the RL algorithm takes a long time to converge (for example, when playing chess).

The following diagram shows an example of the interactions with a simulator for a car racing game.
The simulation environment consists of an agent and a simulator. Here, a convolutional neural network (CNN) consumes images from the simulator and generates actions to control the game controller. With multiple simulations, this environment generates training data of the form $state_t$, $action$, $state_{t+1}$, and $reward_{t+1}$. Defining the reward is not trivial and impacts the RL model quality. We want to provide a few examples of reward functions, but would like to make it user-configurable.

**Topics**
- Use OpenAI Gym Interface for Environments in SageMaker RL (p. 2230)
- Use Open-Source Environments (p. 2231)
- Use Commercial Environments (p. 2231)

**Use OpenAI Gym Interface for Environments in SageMaker RL**

To use OpenAI Gym environments in SageMaker RL, use the following API elements. For more information about OpenAI Gym, see [https://gym.openai.com/docs/](https://gym.openai.com/docs/).

- `env.action_space`—Defines the actions the agent can take, specifies whether each action is continuous or discrete, and specifies the minimum and maximum if the action is continuous.
- `env.observation_space`—Defines the observations the agent receives from the environment, as well as minimum and maximum for continuous observations.
- `env.reset()`—Initializes a training episode. The `reset()` function returns the initial state of the environment, and the agent uses the initial state to take its first action. The action is then sent to `step()` repeatedly until the episode reaches a terminal state. When `step()` returns `done = True`, the episode ends. The RL toolkit re-initializes the environment by calling `reset()`.
- `step()`—Takes the agent action as input and outputs the next state of the environment, the reward, whether the episode has terminated, and an `info` dictionary to communicate debugging information. It is the responsibility of the environment to validate the inputs.
- `env.render()`—Used for environments that have visualization. The RL toolkit calls this function to capture visualizations of the environment after each call to the `step()` function.
Use Open-Source Environments

You can use open-source environments, such as EnergyPlus and RoboSchool, in SageMaker RL by building your own container. For more information about EnergyPlus, see https://energyplus.net/. For more information about RoboSchool, see https://github.com/openai/roboschool. The HVAC and RoboSchool examples in the SageMaker examples repository show how to build a custom container to use with SageMaker RL:

Use Commercial Environments

You can use commercial environments, such as MATLAB and Simulink, in SageMaker RL by building your own container. You need to manage your own licenses.

Distributed Training with Amazon SageMaker RL

Amazon SageMaker RL supports multi-core and multi-instance distributed training. Depending on your use case, training and/or environment rollout can be distributed. For example, SageMaker RL works for the following distributed scenarios:

- Single training instance and multiple rollout instances of the same instance type. For an example, see the Neural Network Compression example in the SageMaker examples repository.
- Single trainer instance and multiple rollout instances, where different instance types for training and rollouts. For an example, see the AWS DeepRacer / AWS RoboMaker example in the SageMaker examples repository.
- Single trainer instance that uses multiple cores for rollout. For an example, see the Roboschool example in the SageMaker examples repository. This is useful if the simulation environment is lightweight and can run on a single thread.
- Multiple instances for training and rollouts. For an example, see the Roboschool example in the SageMaker examples repository.

Hyperparameter Tuning with Amazon SageMaker RL

You can run a hyperparameter tuning job to optimize hyperparameters for Amazon SageMaker RL. The Roboschool example in the sample notebooks in the SageMaker examples repository shows how you can do this with RL Coach. The launcher script shows how you can abstract parameters from the Coach preset file and optimize them.

Manage Machine Learning with Amazon SageMaker Experiments

Amazon SageMaker Experiments is a capability of Amazon SageMaker that lets you organize, track, compare, and evaluate your machine learning experiments.

Machine learning is an iterative process. You need to experiment with multiple combinations of data, algorithm and parameters, all the while observing the impact of incremental changes on model accuracy. Over time this iterative experimentation can result in thousands of model training runs and model versions. This makes it hard to track the best performing models and their input configurations. It’s also difficult to compare active experiments with past experiments to identify opportunities for further incremental improvements.

SageMaker Experiments automatically tracks the inputs, parameters, configurations, and results of your iterations as trials. You can assign, group, and organize these trials into experiments. SageMaker
SageMaker Experiments Features

The following sections provide a brief overview of the features provided by SageMaker Experiments.

Topics
- Organize Experiments (p. 2232)
- Track Experiments (p. 2232)
- Compare and Evaluate Experiments (p. 2233)
- Amazon SageMaker Autopilot (p. 2233)

Organize Experiments

Amazon SageMaker Experiments offers a structured organization scheme to help users group and organize their machine learning iterations. The top level entity, an experiment, is a collection of trials that are observed, compared, and evaluated as a group. A trial is a set of steps called trial components. Each trial component can include a combination of inputs such as datasets, algorithms, and parameters, and produce specific outputs such as models, metrics, datasets, and checkpoints. Examples of trial components are data pre-processing jobs, training jobs, and batch transform jobs.

The goal of an experiment is to determine the trial that produces the best model. Multiple trials are performed, each one isolating and measuring the impact of a change to one or more inputs, while keeping the remaining inputs constant. By analyzing the trials, you can determine which features have the most effect on the model.

Track Experiments

Amazon SageMaker Experiments enables tracking of experiments.

Automated Tracking

SageMaker Experiments automatically tracks Amazon SageMaker Autopilot jobs as experiments with their underlying training jobs tracked as trials. SageMaker Experiments also automatically tracks...
SageMaker independently executed training, batch transform, and processing jobs as trial components, whether assigned to a trial or left unassigned. Unassigned trial components can be associated with a trial at a later time. All experiment artifacts including datasets, algorithms, hyperparameters, and model metrics are tracked and recorded. This data allows customers to trace the complete lineage of a model which helps with model governance, auditing, and compliance verifications.

**Manual Tracking**

SageMaker Experiments provides tracking APIs for recording and tracking machine learning workflows running locally on SageMaker Studio notebooks, including classic SageMaker notebooks. These experiments must be part of a SageMaker training, batch transform, or processing job.

**Compare and Evaluate Experiments**

Amazon SageMaker Experiments is integrated with Amazon SageMaker Studio. When you use SageMaker Studio, SageMaker Experiments automatically tracks your experiments and trials, and presents visualizations of the tracked data and an interface to search the data.

SageMaker Experiments automatically organizes, ranks, and sorts trials based on a chosen metric using the concept of a trial leaderboard. SageMaker Studio produces real-time data visualizations, such as metric charts and graphs, to quickly compare and identify the best performing models. These are updated in real-time as the experiment progresses.

**Amazon SageMaker Autopilot**

Amazon SageMaker Experiments is integrated with Amazon SageMaker Autopilot. When you perform an Autopilot job, SageMaker Experiments creates an experiment for the job, and trials for each of the different combinations of the available trial components, parameters, and artifacts. You can visually drill into all trials and components using SageMaker Studio.

**Create an Amazon SageMaker Experiment**

Create an Amazon SageMaker experiment to track your SageMaker training, processing, and transform jobs.

The following procedure shows you how to create a SageMaker experiment for a SageMaker training, processing, or transform job. Steps labeled as (Studio) describe how to view the experiment in Amazon SageMaker Studio. You don't have to run the experiment in Studio to view the experiment in Studio.

For a tutorial that shows this functionality in an existing SageMaker Studio notebook, see Track and Compare Tutorial (p. 2240).

1. Import the sys module to install the SDKs.

   ```python
   import sys
   ```

2. (Optional) The Amazon SageMaker Python SDK, comes preinstalled in SageMaker Studio. If you plan to run your code outside Studio, install the SageMaker Python SDK.

   ```bash
   !{sys.executable} -m pip install sagemaker
   ```

3. Install the SageMaker Experiments Python SDK.

   ```bash
   !{sys.executable} -m pip install sagemaker-experiments
   ```

4. Import modules.
import time
from time import strftime
import sagemaker
from smexperiments.experiment import Experiment
from smexperiments.trial import Trial
from smexperiments.trial_component import TrialComponent
from smexperiments.tracker import Tracker

5. Get the execution role and create the SageMaker session.

role = sagemaker.get_execution_role()
sm_sess = sagemaker.Session()

6. Create a SageMaker experiment. The experiment name must be unique in your account.

   Note
   The tags parameter is optional. You can search for the tag using Studio, the SageMaker
   console, and the SDK. Tags can also be applied to trials and trial components. For
   information on how to search tags using Studio, see Search by Tag (p. 2250).

   create_date = strftime("%Y-%m-%d-%H-%M-%S")
demo_experiment = Experiment.create(experiment_name = "DEMO-{}".format(create_date),
                                           description = "Demo experiment",
                                           tags = 
                                           ["Key": 'demo-experiments', 'Value':
                                            'demo1'])

7. (Studio) To view the experiment in SageMaker Studio, in the left sidebar, choose the SageMaker
resources icon ( ). In the drop-down menu, select Experiments and trials to display the
experiments browser.

After the code runs, the experiment list contains the new experiment. It might take a moment for
the list to refresh and display the experiment. The filter on the experiment tag is also displayed.
Only experiments that have a matching tag are displayed. Your list should look similar to the
following:
8. Create a trial for the experiment. The trial name must be unique in your account.

```python
demo_trial = Trial.create(trial_name = "DEMO-{}'.format(create_date),
experiment_name = demo_experiment.experiment_name,
tags = [{'Key': 'demo-trials', 'Value': 'demo1'}])
```

9. (Studio) In the experiment list, double-click the experiment to display a list of the trials in the experiment (this example has one trial). Your list should look similar to the following:
10. Create a trial component as part of the trial. The trial component is the SageMaker job.

Add the `ExperimentConfig` parameter to the appropriate method. The SageMaker jobs listed in the following table are supported.

<table>
<thead>
<tr>
<th>Job</th>
<th>SageMaker Python SDK method</th>
<th>Boto3 method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td><code>Estimator.fit</code></td>
<td><code>CreateTrainingJob</code></td>
</tr>
<tr>
<td>Processing</td>
<td><code>Processor.run</code></td>
<td><code>CreateProcessingJob</code></td>
</tr>
<tr>
<td>Transform</td>
<td><code>Transformer.transform</code></td>
<td><code>CreateTransformJob</code></td>
</tr>
</tbody>
</table>

The following examples are for a training job. The `Tags` parameter adds a tag to the trial component. `ExperimentName` isn't specified because the trial was associated with the experiment when the trial was created in an earlier step.

**Using the SageMaker Python SDK**

```python
sagemaker.estimator.Estimator(
    ...
    sagemaker_session = sm_sess,
    tags = [{'Key': 'demo-jobs', 'Value': 'demo2'}])

estimator.fit(
    ...
    experiment_config = {
        # "ExperimentName"
        "TrialName" : demo_trial.trial_name,
        "TrialComponentDisplayName" : "TrainingJob",
    })
```

**Using Boto3**
View and Compare Amazon SageMaker Experiments, Trials, and Trial Components

An Amazon SageMaker experiment consists of multiple trials with a related objective. A trial consists of one or more trial components, such as a data preprocessing job and a training job.

You use the experiments browser to display a list of these entities. You can filter the list by entity name, type, and tags. The entities are presented in a hierarchical view (that is, experiments > trials > trial components). Double-click an entity to see other entities that are at a lower level in the hierarchy. Use the breadcrumbs above the list to move to a higher level in the hierarchy.

For a tutorial using a SageMaker example notebook, see Track and Compare Tutorial (p. 2240). For an overview of the Studio user interface, see Amazon SageMaker Studio UI Overview (p. 118).

Topics

- View Experiments, Trials, and Trial Components (p. 2238)
- Compare Experiments, Trials, and Trial Components (p. 2239)
View Experiments, Trials, and Trial Components

Amazon SageMaker Studio provides an experiments browser that you can use to view lists of experiments, trials, and trial components. You can choose one of these entities to view detailed information about the entity or choose multiple entities for comparison.

**To view experiments, trials, and trial components**

1. In the left sidebar of Studio, choose the **SageMaker resources** icon (\(\text{📍}\)). In the drop-down menu, select **Experiments and trials** to display the experiments browser.

   A list of experiments and their properties is displayed. The list includes all the SageMaker experiments in your account, including experiments created outside of SageMaker Studio.

   **Note**
   To view all the properties, you might have to expand the width of the experiments browser by dragging the right border.

2. In the experiments list, double-click an experiment to display a list of the trials in the experiment.

3. Double-click a trial to display a list of the components in the trial.
4. Double-click one of the components to open the Describe Trial Component tab.

5. On the Describe Trial Component tab, choose any of the following column headings to see available information about each trial component:
   - **Charts** – Build your own charts.
   - **Metrics** – Metrics that are logged by a Tracker during a trial run.
   - **Parameters** – Hyperparameter values and instance information.
   - **Artifacts** – Amazon S3 bucket storage locations for the input dataset and the output model.
   - **AWS Settings** – Job name, ARN, status, creation time, training time, billable time, instance information, and others.
   - **Debugger** – A list of debugger rules and any issues found.
   - **Trial Mappings**

For information about comparing Experiments entities, see View and Compare Amazon SageMaker Experiments, Trials, and Trial Components (p. 2237).

**Compare Experiments, Trials, and Trial Components**

You can compare experiments, trials, and trial components by selecting the entities and opening them in the trial components list. The trial components list is referred to as the Studio Leaderboard. In the Leaderboard you can do the following:

- View detailed information about the entities
- Compare entities
• Stop a training job
• Deploy a model

To compare experiments, trials, and trial components

1. In the left sidebar of SageMaker Studio, choose the SageMaker Experiment List icon ( ).
2. In the Experiments browser, choose either the experiment or trial list. For more information, see View Experiments, Trials, and Trial Components (p. 2238).
3. Choose the experiments or trials that you want to compare, right-click the selection, and then choose Open in trial component list. The Leaderboard opens and lists the associated Experiments entities as shown in the following screenshot.

The Leaderboard has a TABLE PROPERTIES pane on the right side. Use the Settings icon ( ) to open and close the pane. You can hide or display properties by category or by individual columns. When you display a chart, the pane changes to display chart properties.

For information on searching the Experiments entities, see Search Experiments Using Amazon SageMaker Studio (p. 2246).

Track and Compare Tutorial

This tutorial demonstrates how to visually track and compare trials in a model training experiment using Amazon SageMaker Studio. The basis of the tutorial is the MNIST Handwritten Digits Classification Experiment notebook.

It is intended that this topic be viewed alongside Studio with the MNIST notebook open. As you run through the cells, the sections in this document highlight the relevant code and show you how to observe the results in Studio. Some of the code snippets have been edited for brevity.

To clean up the resources created by the notebook, see Clean Up Amazon SageMaker Experiment Resources (p. 2251).

For a tutorial that showcases additional features of Studio, see Amazon SageMaker Studio Tour (p. 132).

Prerequisites
• A local copy of the MNIST example notebook and the companion mnist.py file. Both files are available from the sagemaker_experiments/mnist-handwritten-digits-classification-experiment folder in the aws/amazon-sagemaker-examples repository. To download the files, choose each link, right-click on the Raw button, and then choose Save as.

• An IAM Identity Center or IAM account to sign-on to SageMaker Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).

Topics

• Open the Notebook in Studio (p. 2241)
• Install the Experiments SDK and Import Modules (p. 2241)
• Transform and Track the Input Data (p. 2242)
• Create and Track an Experiment (p. 2242)
• Compare and Analyze Trials (p. 2244)

Open the Notebook in Studio

To open the notebook

1. Sign-on to Studio.
2. In the left sidebar, choose the File Browser icon ( ).
3. At the top of the file browser pane, choose the Up arrow icon and then a File Upload dialog opens. Browse to and choose your local versions of the mnist-handwritten-digits-classification-experiment.ipynb and mnist.py files, and then choose Open.
4. The two files are listed in the file browser. Double-click the uploaded notebook file to open the notebook in a new tab.
5. At the top right of the notebook, make sure the kernel is Python 3 (Data Science). If not, choose the current kernel name to open the Select Kernel dropdown. Choose Python 3 (Data Science) and then choose Select.

Install the Experiments SDK and Import Modules

The Amazon SageMaker Experiments Python SDK is separate from the Amazon SageMaker Python SDK, which comes preinstalled in SageMaker Studio. Run the first few cells in the notebook to install the Experiments SDK and import the Experiments modules. The relevant sections of the notebook cells are displayed below.

```python
import sys
!{sys.executable} -m pip install sagemaker-experiments

import sagemaker
from sagemaker import get_execution_role
from sagemaker.session import Session
from sagemaker.analytics import ExperimentAnalytics
from smexperiments.experiment import Experiment
from smexperiments.trial import Trial
from smexperiments.trial_component import TrialComponent
from smexperiments.tracker import Tracker
```
Transform and Track the Input Data

The next few cells create an Amazon S3 bucket and a folder in the bucket named `mnist`. In Studio, the file browser displays the `mnist` folder. The input data is downloaded to the `mnist/MNIST/raw` folder, normalized, and then the transformed data is uploaded to the `mnist/MNIST/processed` folder. You can drill down into the `mnist` folder to display, but not open, the data files.

Your screen should look similar to the following:

The last cell in the Dataset section creates a Tracker for the transform job. The tracker logs the normalization parameters and the URI of the Amazon S3 bucket where the transformed dataset is stored. In a later section, we show how to find this information in Studio. In the next section, the tracker is used to track the experiment and trial runs.

```
with Tracker.create(display_name="Preprocessing", sagemaker_boto_client=sm) as tracker:
    tracker.log_parameters({
        "normalization_mean": 0.1307,
        "normalization_std": 0.3081,
    })
    tracker.log_input(name="mnist-dataset", media_type="s3/uri", value=inputs)
```

Create and Track an Experiment

The following procedure creates and tracks an experiment to determine the effect of the model's `num_hidden_channel` hyperparameter. As part of the experiment, five trials are created inside a loop, one for each value of the `num_hidden_channel` hyperparameter. Later in the notebook, you'll compare the results of these five trials.

1. In the left sidebar of Studio, choose the SageMaker resources icon (🔍). In the dropdown menu, choose Experiments and trials to display the list of experiments in your account.
2. Run the following cell.

```
mnist_experiment = Experiment.create(
    experiment_name=f"mnist-hand-written-digits-classification-{int(time.time())}",
    description="Classification of mnist hand-written digits",
    sagemaker_boto_client=sm)
print(mnist_experiment)
```

Output:

```
Experiment(sagemaker_boto_client=<botocore.client.SageMaker object at 0x7f7152b326d8>,
    experiment_name='mnist-hand-written-digits-classification-1575947870',
    description='Classification of mnist hand-written digits',
    experiment_arn='arn:aws:sagemaker:us-east-2:acct-id:experiment/mnist-hand-
    written-digits-classification-1575947870')
```

After the code runs, the experiments list contains an entry for the experiment. It might take a moment to display and you might have to refresh the experiments list. Your screen should look similar to the following:
3. Run the following cell.

```python
preprocessing_trial_component = tracker.trial_component
```

After the code runs, the experiments list contains an entry labeled **Unassigned trial components**. The trial component entry is the data preprocessing step previously created. Double-click the trial component for verification. The trial component isn't associated with an experiment at this time. Your screen should look similar to the following:

4. Choose the Home icon in the navigation breadcrumb at the top on the experiments browser. From there, double-click on your experiment to display a list of the trials in the experiment.

5. The following code create trials for the experiment. Each trial trains a model using a different number for the `num_hidden_channel` hyperparameter. The preprocessing trial component is added to each trial for complete tracking (for example, for auditing purposes). The code also specifies definitions for the following metrics:

- Train loss
- Test loss
- Test accuracy

The definitions tell SageMaker to capture those metrics from the algorithm's log output. The metrics are used later to evaluate and compare the models.

```python
preprocessing_trial_component = tracker.trial_component
for i, num_hidden_channel in enumerate([2, 5, 10, 20, 32]):
    trial_name = f"cnn-training-job-{num_hidden_channel}-hidden-channels-{int(time.time())}"
    cnn_trial = Trial.create(
        trial_name=trial_name,
        experiment_name=mnist_experiment.experiment_name,
        sagemaker_boto_client=sm,
    )
    hidden_channel_trial_name_map[num_hidden_channel] = trial_name
    cnn_trial.add_trial_component(preprocessing_trial_component)
```
estimator = PyTorch(
    py_version='py3',
    framework_version='1.1.0',
    ...
    hyperparameters={
        'hidden_channels': num_hidden_channel,
    ...
    },
    metric_definitions=[
        {'Name':'train:loss', 'Regex':'Train Loss: (.*?);'},
        {'Name':'test:loss', 'Regex':'Test Average loss: (.*)?;'},
        {'Name':'test:accuracy', 'Regex':'Test Accuracy: (.*)%;'}
    ],
    enable_sagemaker_metrics=True,
)

estimator = PyTorch(
    py_version='py3',
    framework_version='1.1.0',
    ...
    hyperparameters={
        'hidden_channels': num_hidden_channel,
    ...
    },
    metric_definitions=[
        {'Name':'train:loss', 'Regex':'Train Loss: (.*?);'},
        {'Name':'test:loss', 'Regex':'Test Average loss: (.*)?;'},
        {'Name':'test:accuracy', 'Regex':'Test Accuracy: (.*)%;'}
    ],
    enable_sagemaker_metrics=True,
)

cnn_training_job_name = "cnn-training-job-{}".format(int(time.time()))
estimator.fit(
    inputs={'training': inputs},
    job_name=cnn_training_job_name,
    experiment_config={
        "TrialName": cnn_trial.trial_name,
        "TrialComponentDisplayName": "Training",
    },
)

The trial list automatically updates as each training job runs. It takes a few minutes for each trial to be displayed. Your screen should look similar to the following:

![Trial list in SageMaker Studio](image)

**Compare and Analyze Trials**

This section deviates from the notebook and shows you how to compare and analyze the trained models using the SageMaker Studio UI.

**To view the details of a trial**

1. Double-click one of the trials to display a list of the trial components associated with the trial. There's a preprocessing job and training job for each trial. Double-click one of the components to open a new tab that displays information about each component.

2. Under **Trial stages**, choose **Preprocessing**. On the **Describe Trial Component** menu, choose **Parameters** to display the normalization parameters that were previously logged. Next, choose **Artifacts** to display the URI of the Amazon S3 bucket where the transformed dataset was stored.

3. Under **Trial stages**, choose **Training**. On the **Describe Trial Component** menu, choose the following items to display information about the training job trial component.
• **Metrics** – test:loss, test:accuracy, and train:loss
• **Parameters** – hyperparameter values and instance information
• **Artifacts** – Amazon S3 storage for the input dataset and the output model
• **AWS Settings** – job name, ARN, status, creation time, training time, billable time, instance information, and others

To view a list of trials ordered by test:accuracy

1. Choose the experiment name on the navigation breadcrumb above **TRIAL COMPONENTS** to display the trial list.
2. Choose all five trials. Hold down the CTRL/CMD key and select each trial. Right-click the selection and then choose **Open in trial component list**. A new tab opens that displays each trial and trial component.
3. If the **TABLE PROPERTIES** pane isn't open, choose the **Settings** icon (⤢) in the upper right corner to open it. Deselect everything except **Trial**, **Metrics**, and **Training job**. Choose the **Settings** icon to close the pane.
4. Choose the **test:accuracy** column header to sort the list by decreasing maximum test accuracy. Your screen should look similar to the following:

![Table with sorted trials](image)

To view a chart of test:loss versus num_hidden_channel

1. In the **TRIAL COMPONENTS** pane, choose all five trials and then choose **Add chart**. Select inside the chart area to open the preferences pane for **CHART PROPERTIES**.
2. In **CHART PROPERTIES**, choose the following:
   • **Data type** - Summary statistics
   • **Chart type** - Line
   • **X-axis** - hidden-channels
   • **Y-axis** - test:loss_last
Search Experiments Using Amazon SageMaker Studio

You can search your experiments, trials, and trial components using the experiments browser. After choosing the entities, you can search on properties of these entities on the Amazon SageMaker Leaderboard.

Topics

- Search Experiments, Trials, and Trial Components (p. 2246)
- Search the SageMaker Studio Leaderboard (p. 2247)
- Search by Tag (p. 2250)

Search Experiments, Trials, and Trial Components

You can search and create multiple filters to display a subset of experiments, trials, and trial components in the experiments browser. After you search and filter your list, you can open the entities in the Leaderboard and search on additional properties.

To search for experiments, trials, and trial components, and apply filters

For more information about the following steps, along with screenshots, see Search the SageMaker Studio Leaderboard (p. 2247).

1. In the experiments browser, navigate to the entity type you want to search for: experiment, trial, or trial component.
2. Place your cursor in the search box to display the list of column that are searchable.
3. Choose the column that you want to search on and one of the following dialog boxes opens that's specific to the column you chose:
• **String** – Enter a text string in the search dialog box that opens. Enter a string of at least three characters that’s part of the component’s property value. This filter limits the list to those components with a property value that contains the text string.

• **Discrete values** – Choose one or more property values from the list. This filter limits the list to those components with a property value that matches at least one of the chosen values.

• **Date** – Enter a date in **From Date** and **To Date**, or select the dates from the calendar. This filter limits the list to those components that were created or last modified in the specified date range.

• **Tag** – In **Search tag key**, start entering the tag’s key. A list of tag keys is filtered to only those keys with a name that starts with the text string that you enter. Choose the tag key that you want to search on from the list. In **Search tag value**, enter the complete tag value, and then choose **Apply**.

4. To create the filter, choose **Apply**.

5. To apply additional filters, repeat the preceding steps. You can have a maximum of 20 filters. An entity must match all filters to be displayed.

**Search the SageMaker Studio Leaderboard**

The Amazon SageMaker Studio trial components list is referred to as the Leaderboard. You can use the Leaderboard to compare your trials and experiments. The Leaderboard lists properties of the trials, such as the trial status, debugger status, tags, metrics, hyperparameters, and input and output artifacts.

You can search the Leaderboard to find specific trial components. You apply the results of a search to create a filter that displays only those components that satisfy the filter. You can apply up to 20 filters. A component is displayed only if it matches all filters. To remove a filter, choose the X that displays to the right of the filter.

**To search the Leaderboard and apply filters**

1. If the **TABLE PROPERTIES** pane isn’t open in SageMaker Studio, choose the **Settings** icon (⚙️) in the upper-right corner to open it.

2. In the **Settings** pane, select the check boxes for the columns that you want to view, and then choose the **Settings** icon to close the pane.

3. Place your cursor in the **Search column name** box to display the following list of **TABLE PROPERTIES** column names that are searchable:

   **Summary section**
   - Trial component name
   - Trial component type
   - Created
   - Last modified
   - Created by
   - Tags

   **Detail sections** (all columns)
   - Metrics
   - Parameters
   - Input artifacts
   - Output artifacts
4. To limit the column names when you search the detail sections, start typing the column name. The list displays only those columns with a name that starts with the text string that you enter.

5. Choose the column that you want to search on. This opens a dialog that's specific to the type of data in that column.

6. Enter your search criteria in the dialog for the appropriate data type:

   - **String** – Enter a text string in the search dialog box that opens. Enter a string of at least three characters that's part of the component's property value. This filter limits the list to those components with a property value that contains the text string.

   - **Discrete values** – Choose one or more of the property values from the list. This filter limits the list to those components with a property value that matches at least one of the chosen values. For the **Trial component type** column, **Others** matches components with no value in the column.
• **Date** – Enter a date in **From Date** and **To Date** or select the dates from the calendar. This filter limits the list to those components that were created or last modified in the specified data range.

• **Created by** – Select **Me** or **Everyone else**. This filter limits the list to those components that were created by the currently signed-in user or everyone but the currently signed-in user.

• **Tag** – Choose the tag to search. For more information, see Search by Tag (p. 2250).

• **Detail columns** – Specify the conditions that the component's property value must satisfy.
7. To create the filter, choose **Apply**.
8. To apply additional filters, repeat the preceding steps. A component must match all filters to be displayed. You can have a maximum of 20 filters.

### Search by Tag

You can add searchable tags to experiments, trials, and trial components when the entities are created or afterwards using the *AddTags* API. A tag consists of a unique case-sensitive key and an optional value. Multiple tags can be added to an entity. You can add the same tag to multiple entities.

#### To search by tag and apply filters

1. If the **TABLE PROPERTIES** pane isn't open in SageMaker Studio, choose the **Settings** icon (⚙️) in the upper-right corner to open it.
2. In the **Settings** pane, select **Tags** if it isn't selected, and then choose the **Settings** icon to close the pane.
3. Place your cursor in the **Search column name** box and then choose **Tags**.
4. In **Search tag key**, start entering the tag's key. A list of tag keys displays only those keys with a name that starts with the text string that you enter.
5. Choose the tag key that you want to search on from the list.
6. In **Search tag value**, enter the complete tag value, and then choose **Apply**.

7. The trial component list displays only those components that have tags that match the key-value pair you chose.

8. To add more tag filters, repeat the previous steps. A tag must match all filters for the component to be displayed.

---

**Clean Up Amazon SageMaker Experiment Resources**

To avoid incurring unnecessary charges, delete the Amazon SageMaker Experiment resources you no longer need. You can't delete Experiment resources through the SageMaker Management Console or the Amazon SageMaker Studio UI. This topic shows you how to clean up these resources using Boto3 and the Experiments SDK. For more information about the Experiments SDK, see [sagemaker-experiments](#).

To delete the experiment, you must delete all trials in the experiment. To delete a trial, you must remove all trial components from the trial. To delete a trial component, you must remove the component from all trials.

**Note**

Trial components can exist independent of trials and experiments. You do not have to delete them. If you want to reuse them, comment out `tc.delete()` in the code.
**Clean Up Using the Experiments SDK**

To clean up using the Experiments SDK

```python
import sys
!{sys.executable} -m pip install sagemaker-experiments

import time
from smexperiments.experiment import Experiment
from smexperiments.trial import Trial
from smexperiments.trial_component import TrialComponent

def cleanup_sme_sdk(experiment):
    for trial_summary in experiment.list_trials():
        trial = Trial.load(trial_name=trial_summary.trial_name)
        for trial_component_summary in trial.list_trial_components():
            tc = TrialComponent.load(
                trial_component_name=trial_component_summary.trial_component_name)
            trial.remove_trial_component(tc)
            try:
                # comment out to keep trial components
                tc.delete()
            except:
                # tc is associated with another trial
                continue
            # to prevent throttling
            time.sleep(.5)
        trial.delete()
    experiment_name = experiment.experiment_name
    experiment.delete()
    print(f"\nExperiment {experiment_name} deleted")

Call cleanup_sme_sdk

experiment_to_cleanup = Experiment.load(
    # Use experiment name not display name
    experiment_name="experiment-name")
cleanup_sme_sdk(experiment_to_cleanup)
```

**Clean Up Using the Python SDK (Boto3)**

To clean up using Boto 3

```python
import boto3
sm = boto3.Session().client('sagemaker')

Define cleanup_boto3
```
Search Using the Amazon SageMaker Console and API

Developing a machine learning model typically requires extensive experimenting with different datasets, algorithms, and hyperparameter values. To manage up to thousands of machine learning model experiments, use the search capabilities in SageMaker.

You can use SageMaker search to:

- Organize, find, and evaluate training jobs using properties, hyperparameters, performance metrics, or any metadata.
- Find the best performing model by reviewing training job and model metrics, such as training loss or validation accuracy.
- Trace a model’s lineage to the training job and its related resources, such as the training datasets.

This topic covers searching from the SageMaker console and the SageMaker API. For information on searching in Amazon SageMaker Studio, see Search Experiments Using Studio (p. 2246).

Topics

- Sample Notebooks for Managing ML Experiments (p. 2254)
- Organize, Find, and Evaluate Training Jobs (Console) (p. 2254)
- Find and Evaluate Training Jobs (API) (p. 2256)
- Verify the Datasets Used by Your Training Jobs (p. 2257)
Sample Notebooks for Managing ML Experiments

For a sample notebook that uses Amazon SageMaker model tracking capability to manage ML experiments, see Managing ML Experimentation using Amazon SageMaker Model Tracking Capability.

For instructions on how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After you have created a notebook instance and opened it, choose the SageMaker Examples tab to see a list of all of the SageMaker samples. The notebook for managing ML experiments is located in the Advanced Functionality section. To open a notebook, choose its Use tab, and choose Create copy. If you have questions, post them on the Amazon Machine Learning Developer Forum.

Organize, Find, and Evaluate Training Jobs (Console)

To organize training jobs, assign one or more tags to them.

To find a specific training job, model, or resource, use model tracking to search on keywords assigned to any searchable items. Searchable items include training jobs, models, hyperparameters, metadata, tags, and URLs. To refine your tracking results, you can search using multiple criteria.

To choose the best model for deployment, evaluate how all models performed against one or more metrics. You can use model tracking results to list, sort, and evaluate the performance of the models in your experiments.

Topics

- Use Tags to Track Training Jobs (Console) (p. 2254)
- Find Training Jobs (Console) (p. 2255)
- Evaluate Models (Console) (p. 2255)

Use Tags to Track Training Jobs (Console)

To group training jobs, create tags with descriptive keys and a value. For example, create tag keys for: project, owner, customer, and industry.

Add tags to training jobs (console)

1. Open the Amazon SageMaker console.
2. In the navigation pane, choose Training jobs and Create training job.
3. Scroll to the bottom of the page and enter a key and value for the tag.
4. To add another tag, choose Add tag, and add another key-value pair.
Find Training Jobs (Console)

You can search for training jobs using a variety of job attributes. Note that some search parameters appear only if you have created a training job with that attribute. For example, Tags appears only if you have added a tag for a training job.

To find training jobs (console)

1. Open the Amazon SageMaker console.
2. In the navigation pane, choose Search.
3. Add Parameters.
   a. In the search box, enter a parameter and choose a parameter type, for example TrainingJobName.
   b. Choose a conditional operation. For numeric values, use operators such as is equals to, lesser than, or or greater than. For text-based values, use operators such as equals to or contains.
   c. Enter a value for the parameter.
4. (Optional) To refine your search, add additional search criteria. Choose Add row and enter the parameter values.
5. Choose Search.

Evaluate Models (Console)

To evaluate a model's performance, review its metadata, hyperparameters, and metrics. To highlight metrics, adjust the view to show only metrics and important hyperparameters.

To evaluate a model (console)

1. Open the Amazon SageMaker console.
2. In the navigation pane, choose Search and search for training jobs by specifying relevant parameters. The results are displayed in a table.

3. Open the preferences window by choosing the settings icon in the search results table.
4. To show or hide a hyperparameter or metric, turn it on or off by choosing **Hyperparameter** or **Metric**.

5. Make necessary changes, then choose **Update view**.

6. After viewing metrics and important hyperparameters, you can compare and contrast the result. Then, you can choose the best model to host or investigate the models that are performing poorly.

### Find and Evaluate Training Jobs (API)

To find and evaluate training jobs or to get suggestions for items used in experiments that are searchable, you can use the **Search** API.

**Topics**
- Find Training Jobs (API) (p. 2256)
- Evaluate Models (API) (p. 2256)
- Get Suggestions for a Search (API) (p. 2257)

#### Find Training Jobs (API)

To find training jobs, create a search parameter using the `search_params` parameter. Then use the `search` function in the `smclient` subprocess in the AWS SDK for Python (Boto3).

The following example shows how to use the **Search** API to find training jobs.

```python
import boto3

search_params={
    "MaxResults": 10,
    "Resource": "TrainingJob",
    "SearchExpression": {
        "Filters": [
            {"Name": "Tags.Project", "Operator": "Equals", "Value": "Project_Binary_Classifier"}
        ],
        "SortBy": "Metrics.train:binary_classification_accuracy",
        "SortOrder": "Descending"
    }
}

smclient = boto3.client(service_name='sagemaker')
results = smclient.search(**search_params)
```

#### Evaluate Models (API)

To evaluate models, run a search as described in Find Training Jobs (API) (p. 2256), review model metrics, then, use the AWS SDK for Python (Boto3) to create a table and plot it.

The following example shows how to evaluate models and to display the results in a table.

```python
import pandas

headers=["Training Job Name", "Training Job Status", "Batch Size", "Binary Classification Accuracy"]
rows=[]
for result in results['Results']:
    trainingJob = result['TrainingJob']
    metrics = trainingJob['FinalMetricDataList']
    result_row = [trainingJob['Name'], trainingJob['Status'], trainingJob['BatchSize'], metrics['binary_classification_accuracy']]
    rows.append(result_row)

df = pandas.DataFrame(rows, columns=headers)
```
rows.append([trainingJob['TrainingJobName'],
    trainingJob['TrainingJobStatus'],
    trainingJob['HyperParameters']['mini_batch_size'],
    metrics[[x['MetricName'] for x in
    metrics].index('train:binary_classification_accuracy')]['Value']]])

df = pandas.DataFrame(data=rows,columns=headers)
from IPython.display import display, HTML
display(HTML(df.to_html()))

Get Suggestions for a Search (API)

To get suggestions for a search, use the GetSearchSuggestions API.

The following example for AWS SDK for Python (Boto3) is a get_search_suggestions request for items containing linear.

```python
search_suggestion_params={
    "Resource": "TrainingJob",
    "SuggestionQuery": {
        "PropertyNameQuery": {
            "PropertyNameHint": "linear"
        }
    }
}
```

The following is an example response for a get_search_suggestions request.

```
{
    'PropertyNameSuggestions': [
        {'PropertyName': 'hyperparameters.linear_init_method'},
        {'PropertyName': 'hyperparameters.linear_init_value'},
        {'PropertyName': 'hyperparameters.linear_init_sigma'},
        {'PropertyName': 'hyperparameters.linear_lr'},
        {'PropertyName': 'hyperparameters.linear_wd'}
    ]
}
```

After getting search suggestions, you can use one of the property names in a search.

Verify the Datasets Used by Your Training Jobs

You can use model tracking capability to verify which datasets were used in training, where holdout datasets were used, and other details about training jobs. For example, use model tracking capability to verify that a specific dataset was used in a training job for an audit or to verify compliance.

To check whether a specific dataset was used in a training job, you search for the URL to its location in Amazon Simple Storage Service (Amazon S3). Model tracking capability returns the training jobs that used the dataset that you specify. If your search doesn't return the dataset (the result is empty), the dataset wasn't used in a training job. An empty result confirms, for example, that a holdout dataset wasn't used.

Trace Model Lineage

You can use model tracking capability to get information about the lineage of training jobs and the model resources that were used for them, including the dataset, algorithm, hyperparameters, and metrics. For example, if you find that the performance of a hosted model has declined, you can review its training job and the resources it used to determine what's causing the problem.
Topics

- Trace Model Lineage (Console) (p. 2258)
- Trace Model Lineage (API) (p. 2258)

Trace Model Lineage (Console)

To trace a model's lineage (console)

1. Open the Amazon SageMaker console.
2. In the navigation pane, choose Endpoints, and choose the relevant endpoint.
3. Scroll to the Endpoint configuration settings section. This section lists all of the model versions deployed at the endpoint, with a hyperlink to the training job that created each.

Trace Model Lineage (API)

To trace a model's lineage, get the model's name, then use it to search for training jobs.

The following example shows how to trace a model's lineage using the API.

```python
# Get the name of model deployed at endpoint
endpoint_config = smclient.describe_endpoint_config(EndpointConfigName=endpointName)
model_name = endpoint_config['ProductionVariants'][0]['ModelName']

# Get the model's name
model = smclient.describe_model(ModelName=model_name)

# Search the training job by the location of model artifacts in Amazon S3
search_params={
    "MaxResults": 1,
    "Resource": "TrainingJob",
    "SearchExpression": {
        "Filters": [
            {
                "Name": "ModelArtifacts.S3ModelArtifacts",
                "Operator": "Equals",
                "Value": model['PrimaryContainer']['ModelDataUrl']
            }
        ]
    }
}
results = smclient.search(**search_params)
```

After finding the training job, you can review the resources used to train the model.

Debug and Profile Training Jobs Using Amazon SageMaker Debugger

Debug, profile, and monitor training jobs in real time to detect non-converging conditions, optimize resource utilization by eliminating bottlenecks, improve training time, and reduce costs of your machine learning models using Amazon SageMaker Debugger.

Amazon SageMaker Debugger Features

A machine learning (ML) training job can have problems such as system bottlenecks, overfitting, saturated activation functions, and vanishing gradients, which can compromise model performance.
SageMaker Debugger profiles and debugs training jobs to help resolve such problems and improve your ML model's compute resource utilization and performance. Debugger offers tools to send alerts when training anomalies are found, take actions against the problems, and identify the root cause of them by visualizing collected metrics and tensors.

SageMaker Debugger supports the Apache MXNet, PyTorch, TensorFlow, and XGBoost frameworks. For more information about available frameworks and versions supported by SageMaker Debugger, see Supported Frameworks and Algorithms (p. 2260).

The high-level Debugger workflow is as follows:

1. Modify your training script with the sagemaker-debugger Python SDK if needed.
2. Configure a SageMaker training job with SageMaker Debugger.
   - Configure using the SageMaker Estimator API (for Python SDK).
   - Configure using the SageMaker CreateTrainingJob request (for Boto3 or CLI).
   - Configure custom training containers (p. 2412) with SageMaker Debugger.
3. Start a training job and monitor training issues in real time.
   - SageMaker Studio Debugger dashboards in Studio Experiments and trials (p. 2317).
   - List of Debugger Built-in Rules (p. 2365).
4. Get alerts and take prompt actions against the training issues.
   - Receive texts and emails and stop training jobs when training issues are found using Debugger Built-in Actions for Rules (p. 2294).
   - Set up your own actions using Amazon CloudWatch Events and AWS Lambda (p. 2298).
5. Receive training reports, suggestions to fix the issues, and insights into your training jobs.
   - Studio Debugger Insights dashboard for deep learning frameworks
   - Deep learning framework profiling report
   - SageMaker XGBoost training report
6. Explore deep analysis of the training issues and bottlenecks.
   - For profiling training jobs, see Analyze Data Using the SMDebug Client Library (p. 2357).
   - For debugging model output tensors, see Visualize Debugger Output Tensors in TensorBoard (p. 2293).
7. Fix the issues, considering the suggestions provided by Debugger, and repeat steps 1–5 until you optimize your model and achieve target accuracy.

The SageMaker Debugger developer guide walks you through the following topics.

**Topics**
Supported Frameworks and Algorithms

The following table shows SageMaker machine learning frameworks and algorithms supported by Debugger.

<table>
<thead>
<tr>
<th>SageMaker-supported frameworks and algorithms</th>
<th>Monitoring system bottlenecks</th>
<th>Profiling deep learning framework operations</th>
<th>Debugging output tensors</th>
</tr>
</thead>
<tbody>
<tr>
<td>TensorFlow</td>
<td>All AWS Deep learning containers</td>
<td>AWS TensorFlow deep learning containers 2.3.1 or later</td>
<td>AWS TensorFlow deep learning containers 1.15.4 or later</td>
</tr>
<tr>
<td>PyTorch</td>
<td>AWS PyTorch deep learning containers 1.6.0 or later</td>
<td>AWS PyTorch deep learning containers 1.5.0 or later</td>
<td></td>
</tr>
<tr>
<td>MXNet</td>
<td>-</td>
<td>-</td>
<td>AWS MXNet deep learning containers 1.6.0 or later</td>
</tr>
<tr>
<td>XGBoost</td>
<td>1.0-1, 1.2-1, 1.3-1</td>
<td>-</td>
<td>1.0-1, 1.2-1, 1.3-1</td>
</tr>
<tr>
<td>SageMaker generic estimator</td>
<td>SageMaker built-in algorithms using image URIs</td>
<td>-</td>
<td>Custom training containers (p. 2412) (available for TensorFlow, PyTorch, MXNet, and XGBoost with manual hook registration)</td>
</tr>
<tr>
<td></td>
<td>Custom training containers (p. 2412) (with the AWS deep learning container images, public Docker images, or your own Docker images)</td>
<td>-</td>
<td></td>
</tr>
</tbody>
</table>

- **Monitoring system bottlenecks** – Monitor the system utilization rate for resources such as CPU, GPU, memories, network, and data I/O metrics. This is a framework and model agnostic feature and available for any training jobs in SageMaker.
- **Profiling deep learning framework operations** – Profile the deep learning operations of the TensorFlow and PyTorch frameworks, such as step durations, data loaders, forward and backward operations, Python profiling metrics, and framework-specific metrics.
• **Debugging output tensors** – Track and debug model parameters, such as weights, gradients, biases, and scalar values of your training job. Available deep learning frameworks are Apache MXNet, TensorFlow, PyTorch, and XGBoost.

  **Important**
  For the TensorFlow framework with Keras, SageMaker Debugger deprecates the zero code change support for debugging models built using the `tf.keras` modules of TensorFlow 2.6 and later. This is due to breaking changes announced in the TensorFlow 2.6.0 release note. For instructions on how to update your training script, see the section called “TensorFlow” (p. 2276).

  **Important**
  Since PyTorch v1.12.0 and later, SageMaker Debugger deprecates the zero code change support for debugging models. This is due to breaking changes that cause SageMaker Debugger to interfere with the `torch.jit` functionality. For instructions on how to update your training script, see the section called “PyTorch” (p. 2274).

If the framework or algorithm that you want to train and debug is not listed in the table, go to the AWS Discussion Forum and leave feedback on SageMaker Debugger.

**AWS Regions**

Amazon SageMaker Debugger is available in all regions where Amazon SageMaker is in service except the following region.

- Asia Pacific (Jakarta): `ap-southeast-3`

To find if Amazon SageMaker is in service in your AWS Region, see AWS Regional Services.

**Use Debugger with Custom Training Containers**

Bring your training containers to SageMaker and gain insights into your training jobs using Debugger. Maximize your work efficiency by optimizing your model on Amazon EC2 instances using the monitoring and debugging features.

For more information about how to build your training container with the `sagemaker-debugger` client library, push it to the Amazon Elastic Container Registry (Amazon ECR), and monitor and debug, see Use Debugger with Custom Training Containers (p. 2412).

**Debugger Open-Source GitHub Repositories**

Debugger APIs are provided through the SageMaker Python SDK and designed to construct Debugger hook and rule configurations for the SageMaker `CreateTrainingJob` and `DescribeTrainingJob` API operations. The `sagemaker-debugger` client library provides tools to register hooks and access the training data through its `trial` feature, all through its flexible and powerful API operations. It supports the machine learning frameworks TensorFlow, PyTorch, MXNet, and XGBoost on Python 3.6 and later.

For direct resources about the Debugger and `sagemaker-debugger` API operations, see the following links:

- The Amazon SageMaker Python SDK documentation
- The Amazon SageMaker Python SDK - Debugger APIs
- The `sagemaker-debugger` Python SDK documentation for the Amazon SageMaker Debugger open source client library
• The sagemaker-debugger PyPI

If you use the SDK for Java to conduct SageMaker training jobs and want to configure Debugger APIs, see the following references:

• Amazon SageMaker Debugger API Operations (p. 2429)
• Configure Debugger Using Amazon SageMaker API (p. 2415)

Amazon SageMaker Debugger Architecture

This topic walks you through a high-level overview of the Amazon SageMaker Debugger workflow.

Debugger supports profiling functionality for performance optimization to identify computation issues, such as system bottlenecks and underutilization, and to help optimize hardware resource utilization at scale.

Debugger's debugging functionality for model optimization is about analyzing non-converging training issues that can arise while minimizing the loss functions using optimization algorithms, such as gradient descent and its variations.

The following diagram shows the architecture of SageMaker Debugger. The blocks with bold boundary lines are what Debugger manages to analyze your training job.
Debugger stores the following data from your training jobs in your secured Amazon S3 bucket:

- **System metrics** – Hardware resource utilization data, such as CPU, GPU, CPU and GPU memory, network, and data input and output (I/O) metrics.
- **Framework metrics** – Metrics to track each framework operation per call or sampling, such as convolutional layer operations in the forward pass, batch normalization operations in the backward pass, data loader processes between steps, and gradient descent algorithm operations to calculate and update the loss function.
- **Output tensors** – Collections of scalars and model parameters that are continuously updated during the forward and backward passes while training ML models. The output tensors include scalar values (accuracy and loss) and matrices (weights, gradients, input layers, and output layers).

**Note**  
By default, Debugger monitors and debugs SageMaker training jobs without any Debugger-specific parameters configured in SageMaker estimators. Debugger collects system metrics.
every 500 milliseconds and basic output tensors (scalar outputs such as loss and accuracy) every 500 steps. It also runs the ProfilerReport rule to analyze the system metrics and aggregate the Studio Debugger insights dashboard and a profiling report. Debugger saves the output data in your secured Amazon S3 bucket.

The Debugger built-in rules run on processing containers, which are designed to evaluate machine learning models by processing the training data collected in your S3 bucket (see Process Data and Evaluate Models). The built-in rules are fully managed by Debugger. You can also create your own rules customized to your model to watch for any issues you want to monitor.

Get Started with Debugger Tutorials

The following topics walk you through tutorials from the basics to advanced use cases of monitoring, profiling, and debugging SageMaker training jobs using Debugger. Explore the Debugger features and learn how you can debug and improve your machine learning models efficiently by using Debugger.

Topics

- Debugger Tutorial Videos (p. 2264)
- Debugger Example Notebooks (p. 2265)
- Debugger Advanced Demos and Visualization (p. 2267)

Debugger Tutorial Videos

The following videos provide a tour of Amazon SageMaker Debugger capabilities using SageMaker Studio and SageMaker notebook instances.

Topics

- Analyze, Detect, and Get Alerted on Problems with Training Runs Using Amazon SageMaker Debugger (p. 2264)
- Debug Models with Amazon SageMaker Debugger in Studio (p. 2264)
- Deep Dive on Amazon SageMaker Debugger and SageMaker Model Monitor (p. 2265)

Analyze, Detect, and Get Alerted on Problems with Training Runs Using Amazon SageMaker Debugger

*Emily Webber, AWS Machine Learning Specialist / Length: 13 minutes 54 seconds*

This tutorial video gives you a tour of Amazon SageMaker Debugger to capture, debug, and visualize model output data from a training model with MXNet. Learn how Amazon SageMaker Debugger makes the training process transparent by automatically capturing metrics, analyzing training runs, and detecting problems.

Analyze, Detect, and Get Alerted on Problems with Training Runs Using Amazon SageMaker Debugger

You can find the example notebook in this video at Visualizing Debugging Tensors of MXNet training in the Amazon SageMaker Examples GitHub repository.

Debug Models with Amazon SageMaker Debugger in Studio

*Julien Simon, AWS Technical Evangelist / Length: 14 minutes 17 seconds*

This tutorial video demonstrates how to use Amazon SageMaker Debugger to capture and inspect debugging information from a training model. The example training model used in this video is a simple
convolutional neural network (CNN) based on Keras with the TensorFlow backend. SageMaker in a TensorFlow framework and Debugger enable you to build an estimator directly using the training script and debug the training job.

**Debug Models with Amazon SageMaker Debugger (part 1)**

You can find the example notebook in the video in this Studio Demo repository provided by the author. You need to clone the debugger.ipynb notebook file and the mnist_keras_tf.py training script to your SageMaker Studio or a SageMaker notebook instance. After you clone the two files, specify the path keras_script_path to the mnist_keras_tf.py file inside the debugger.ipynb notebook. For example, if you cloned the two files in the same directory, set it as keras_script_path = "mnist_keras_tf.py".

**Deep Dive on Amazon SageMaker Debugger and SageMaker Model Monitor**

*Julien Simon, AWS Technical Evangelist | Length: 44 minutes 34 seconds*

This video session explores advanced features of Debugger and SageMaker Model Monitor that help boost productivity and the quality of your models. First, this video shows how to detect and fix training issues, visualize tensors, and improve models with Debugger. Next, at 22:41, the video shows how to monitor models in production and identify prediction issues such as missing features or data drift using SageMaker Model Monitor. Finally, it offers cost optimization tips to help you make the most of your machine learning budget.

**Debug Models with Debugger (part 2)**

You can find the example notebook in the video in this AWS Dev Days 2020 repository offered by the author.

**Debugger Example Notebooks**

*SageMaker Debugger example notebooks* are provided in the aws/amazon-sagemaker-examples repository. The Debugger example notebooks walk you through basic to advanced use cases of debugging and profiling training jobs.

We recommend that you run the example notebooks on SageMaker Studio or a SageMaker Notebook instance because most of the examples are designed for training jobs in the SageMaker ecosystem, including Amazon EC2, Amazon S3, and Amazon SageMaker Python SDK.

To clone the example repository to SageMaker Studio, follow the instructions at Amazon SageMaker Studio Tour.

To find the examples in a SageMaker Notebook instance, follow the instructions at SageMaker Notebook Instance Example Notebooks.

**Important**

To use the new Debugger features, you need to upgrade the SageMaker Python SDK and the SMDebug client library. In your iPython kernel, Jupyter Notebook, or JupyterLab environment, run the following code to install the latest versions of the libraries and restart the kernel.

```
import sys
import IPython
!{sys.executable} -m pip install -U sagemaker smdebug
IPython.Application.instance().kernel.do_shutdown(True)
```

**Debugger Example Notebooks for Profiling Training Jobs**

The following list shows Debugger example notebooks introducing Debugger's adaptability to monitor and profile training jobs for various machine learning models, datasets, and frameworks.
<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Framework</th>
<th>Model</th>
<th>Dataset</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon SageMaker Debugger Profiling Data Analysis</td>
<td>TensorFlow</td>
<td>Keras ResNet50</td>
<td>Cifar-10</td>
<td>This notebook provides an introduction to interactive analysis of profiled data captured by SageMaker Debugger. Explore the full functionality of the SMDebug interactive analysis tools.</td>
</tr>
<tr>
<td>Profile machine learning training with Amazon SageMaker Debugger</td>
<td>TensorFlow</td>
<td>1-D Convolutional Neural Network</td>
<td>IMDB dataset</td>
<td>Profile a TensorFlow 1-D CNN for sentiment analysis of IMDB data that consists of movie reviews labeled as having positive or negative sentiment. Explore the Studio Debugger insights and Debugger profiling report.</td>
</tr>
<tr>
<td>Profiling PyTorch ResNet model training with various distributed training settings</td>
<td>PyTorch</td>
<td>ResNet50</td>
<td>Cifar-10</td>
<td>Run PyTorch training jobs with various distributed training settings, monitor system resource utilization, and profile model performance using Debugger.</td>
</tr>
</tbody>
</table>

**Debugger Example Notebooks for Analyzing Model Parameters**

The following list shows Debugger example notebooks introducing Debugger's adaptability to debug training jobs for various machine learning models, datasets, and frameworks.

<table>
<thead>
<tr>
<th>Notebook Title</th>
<th>Framework</th>
<th>Model</th>
<th>Dataset</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amazon SageMaker Debugger - Use built-in rule</td>
<td>TensorFlow</td>
<td>Convolutional Neural Network</td>
<td>MNIST</td>
<td>Use the Amazon SageMaker Debugger built-in rules for debugging a TensorFlow model.</td>
</tr>
<tr>
<td>Amazon SageMaker Debugger - Tensorflow 2.1</td>
<td>TensorFlow</td>
<td>ResNet50</td>
<td>Cifar-10</td>
<td>Use the Amazon SageMaker Debugger hook configuration and built-in rules for debugging</td>
</tr>
<tr>
<td>Notebook</td>
<td>Framework</td>
<td>Model</td>
<td>Dataset</td>
<td>Description</td>
</tr>
<tr>
<td>----------</td>
<td>-----------</td>
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<td>-------------</td>
</tr>
<tr>
<td>Visualizing Debugging Tensors of MXNet training</td>
<td>MXNet</td>
<td>Gluon Convolutional Neural Network</td>
<td>Fashion MNIST</td>
<td>Run a training job and configure SageMaker Debugger to store all tensors from this job, then visualize those tensors in a notebook.</td>
</tr>
<tr>
<td>Enable Spot Training with Amazon SageMaker Debugger</td>
<td>MXNet</td>
<td>Gluon Convolutional Neural Network</td>
<td>Fashion MNIST</td>
<td>Learn how Debugger collects tensor data from a training job on a spot instance, and how to use the Debugger built-in rules with managed spot training.</td>
</tr>
<tr>
<td>Explain an XGBoost model that predicts an individual’s income with Amazon SageMaker Debugger</td>
<td>XGBoost</td>
<td>XGBoost Regression</td>
<td>Adult Census dataset</td>
<td>Learn how to use the Debugger hook and built-in rules for collecting and visualizing tensor data from an XGBoost regression model, such as loss values, features, and SHAP values.</td>
</tr>
</tbody>
</table>

To find advanced visualizations of model parameters and use cases, see the next topic at Debugger Advanced Demos and Visualization (p. 2267).

**Debugger Advanced Demos and Visualization**

The following demos walk you through advanced use cases and visualization scripts using Debugger.

**Topics**

- Train and Tune Your Models with Amazon SageMaker Experiments and Debugger (p. 2267)
- Using SageMaker Debugger to Monitor a Convolutional Autoencoder Model Training (p. 2270)
- Using SageMaker Debugger to Monitor Attentions in BERT Model Training (p. 2270)
- Using SageMaker Debugger to Visualize Class Activation Maps in Convolutional Neural Networks (CNNs) (p. 2273)

**Train and Tune Your Models with Amazon SageMaker Experiments and Debugger**

*Dr. Nathalie Rauschmayr, AWS Applied Scientist | Length: 49 minutes 26 seconds*

**Train and Prune Models with SageMaker Experiments and Debugger**

Find out how Amazon SageMaker Experiments and Debugger can simplify the management of your training jobs. Amazon SageMaker Debugger provides transparent visibility into training jobs and saves training metrics into your Amazon S3 bucket. SageMaker Experiments enables you to call the training information as trials through SageMaker Studio and supports visualization of the training job. This helps you keep model quality high while reducing less important parameters based on importance rank.

This video demonstrates a *model pruning* technique that makes pre-trained ResNet50 and AlexNet models lighter and affordable while keeping high standards for model accuracy.
Amazon SageMaker Developer Guide
Tutorials

SageMaker Estimator trains those algorithms supplied from the PyTorch model zoo in an AWS Deep Learning Containers with PyTorch framework, and Debugger extracts training metrics from the training process.

The video also demonstrates how to set up a Debugger custom rule to watch the accuracy of a pruned model, to trigger an Amazon CloudWatch event and an AWS Lambda function when the accuracy hits a threshold, and to automatically stop the pruning process to avoid redundant iterations.

Learning objectives are as follows:

• Learn how to use SageMaker to accelerate ML model training and improve model quality.
• Understand how to manage training iterations with SageMaker Experiments by automatically capturing input parameters, configurations, and results.
• Discover how Debugger makes the training process transparent by automatically capturing real-time tensor data from metrics such as weights, gradients, and activation outputs of convolutional neural networks.
• Use CloudWatch to trigger Lambda when Debugger catches issues.
• Master the SageMaker training process using SageMaker Experiments and Debugger.

You can find the notebooks and training scripts used in this video from SageMaker Debugger PyTorch Iterative Model Pruning.

The following image shows how the iterative model pruning process reduces the size of AlexNet by cutting out the 100 least significant filters based on importance rank evaluated by activation outputs and gradients.

The pruning process reduced the initial 50 million parameters to 18 million. It also reduced the estimated model size from 201 MB to 73 MB.

Pruning iteration: 0

<table>
<thead>
<tr>
<th>Layer (type)</th>
<th>Output Shape</th>
<th>Param #</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conv2d-1</td>
<td>[-1, 58, 55, 55]</td>
<td>21,112</td>
</tr>
<tr>
<td>ReLU-2</td>
<td>[-1, 58, 55, 55]</td>
<td>0</td>
</tr>
<tr>
<td>MaxPool2d-3</td>
<td>[-1, 58, 27, 27]</td>
<td>0</td>
</tr>
<tr>
<td>Conv2d-4</td>
<td>[-1, 166, 27, 27]</td>
<td>240,866</td>
</tr>
<tr>
<td>ReLU-5</td>
<td>[-1, 166, 27, 27]</td>
<td>0</td>
</tr>
<tr>
<td>MaxPool2d-6</td>
<td>[-1, 166, 13, 13]</td>
<td>0</td>
</tr>
<tr>
<td>Conv2d-7</td>
<td>[-1, 305, 13, 13]</td>
<td>455,975</td>
</tr>
<tr>
<td>ReLU-8</td>
<td>[-1, 305, 13, 13]</td>
<td>0</td>
</tr>
<tr>
<td>Conv2d-9</td>
<td>[-1, 206, 13, 13]</td>
<td>565,676</td>
</tr>
<tr>
<td>ReLU-10</td>
<td>[-1, 206, 13, 13]</td>
<td>0</td>
</tr>
<tr>
<td>Conv2d-11</td>
<td>[-1, 217, 13, 13]</td>
<td>402,535</td>
</tr>
<tr>
<td>ReLU-12</td>
<td>[-1, 217, 13, 13]</td>
<td>0</td>
</tr>
<tr>
<td>MaxPool2d-13</td>
<td>[-1, 217, 6, 6]</td>
<td>0</td>
</tr>
<tr>
<td>AdaptiveAvgPool2d-14</td>
<td>[-1, 217, 6, 6]</td>
<td>0</td>
</tr>
<tr>
<td>Dropout-15</td>
<td>[-1, 7812]</td>
<td>0</td>
</tr>
<tr>
<td>Linear-16</td>
<td>[-1, 4096]</td>
<td>32,002,048</td>
</tr>
<tr>
<td>ReLU-17</td>
<td>[-1, 4096]</td>
<td>0</td>
</tr>
<tr>
<td>Dropout-18</td>
<td>[-1, 4096]</td>
<td>0</td>
</tr>
<tr>
<td>Linear-19</td>
<td>[-1, 4096]</td>
<td>16,781,312</td>
</tr>
<tr>
<td>ReLU-20</td>
<td>[-1, 4096]</td>
<td>0</td>
</tr>
<tr>
<td>Linear-21</td>
<td>[-1, 101]</td>
<td>413,797</td>
</tr>
</tbody>
</table>

Total params: 58,883,321
Trainable params: 58,883,321
Non-trainable params: 0

Input size (MB): 0.57
Forward/backward pass size (MB): 7.27
Params size (MB): 194.18
Estimated Total Size (MB): 201.95
You also need to track model accuracy, and the following image shows how you can plot the model pruning process to visualize changes in model accuracy based on the number of parameters in SageMaker Studio.

In SageMaker Studio, choose the Experiments tab, select a list of tensors saved by Debugger from the pruning process, and then compose a Trial Component List panel. Select all ten iterations and then choose Add chart to create a Trial Component Chart. After you decide on a model to deploy, choose the trial component and choose a menu to perform an action or choose Deploy model.

Note
To deploy a model through SageMaker Studio using the following notebook example, add a line at the end of the train function in the train.py script.

# In the train.py script, look for the train function in line 58.
def train(epochs, batch_size, learning_rate):
    ...
    print('acc:{:.4f}'.format(correct/total))
    hook.save_scalar("accuracy", correct/total, sm_metric=True)

    # Add the following code to line 128 of the train.py script to save the pruned models
    # under the current SageMaker Studio model directory
    torch.save(model.state_dict(), os.environ['SM_MODEL_DIR'] + '/model.pt')
Using SageMaker Debugger to Monitor a Convolutional Autoencoder Model Training

This notebook demonstrates how SageMaker Debugger visualizes tensors from an unsupervised (or self-supervised) learning process on a MNIST image dataset of handwritten numbers.

The training model in this notebook is a convolutional autoencoder with the MXNet framework. The convolutional autoencoder has a bottleneck-shaped convolutional neural network that consists of an encoder part and a decoder part.

The encoder in this example has two convolution layers to produce compressed representation (latent variables) of the input images. In this case, the encoder produces a latent variable of size (1, 20) from an original input image of size (28, 28) and significantly reduces the size of data for training by 40 times.

The decoder has two deconvolutional layers and ensures that the latent variables preserve key information by reconstructing output images.

The convolutional encoder powers clustering algorithms with smaller input data size and the performance of clustering algorithms such as k-means, k-NN, and t-Distributed Stochastic Neighbor Embedding (t-SNE).

This notebook example demonstrates how to visualize the latent variables using Debugger, as shown in the following animation. It also demonstrates how the t-SNE algorithm classifies the latent variables into ten clusters and projects them into a two-dimensional space. The scatter plot color scheme on the right side of the image reflects the true values to show how well the BERT model and t-SNE algorithm organize the latent variables into the clusters.

Using SageMaker Debugger to Monitor Attentions in BERT Model Training

Bidirectional Encode Representations from Transformers (BERT) is a language representation model. As the name of model reflects, the BERT model builds on transfer learning and the Transformer model for natural language processing (NLP).

The BERT model is pre-trained on unsupervised tasks such as predicting missing words in a sentence or predicting the next sentence that naturally follows a previous sentence. The training data contains 3.3 billion words (tokens) of English text, from sources such as Wikipedia and electronic books. For a simple
example, the BERT model can give a high *attention* to appropriate verb tokens or pronoun tokens from a subject token.

The pre-trained BERT model can be fine-tuned with an additional output layer to achieve state-of-the-art model training in NLP tasks, such as automated responses to questions, text classification, and many others.

Debugger collects tensors from the fine-tuning process. In the context of NLP, the weight of neurons is called *attention*.

This notebook demonstrates how to use the pre-trained BERT model from the GluonNLP model zoo on the Stanford Question and Answering dataset and how to set up SageMaker Debugger to monitor the training job.

Plotting *attention scores* and individual neurons in the query and key vectors can help to identify causes of incorrect model predictions. With SageMaker Debugger, you can retrieve the tensors and plot the *attention-head view* in real time as training progresses and understand what the model is learning.

The following animation shows the attention scores of the first 20 input tokens for ten iterations in the training job provided in the notebook example.
Using SageMaker Debugger to Visualize Class Activation Maps in Convolutional Neural Networks (CNNs)

This notebook demonstrates how to use SageMaker Debugger to plot class activation maps for image detection and classification in convolutional neural networks (CNNs). In deep learning, a convolutional neural network (CNN or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. One of the applications that adopts the class activation maps is self-driving cars, which require instantaneous detection and classification of images such as traffic signs, roads, and obstacles.

In this notebook, the PyTorch ResNet model is trained on the German Traffic Sign Dataset, which contains more than 40 classes of traffic-related objects and more than 50,000 images in total.

During the training process, SageMaker Debugger collects tensors to plot the class activation maps in real time. As shown in the animated image, the class activation map (also called as a saliency map) highlights regions with high activation in red color.

Using tensors captured by Debugger, you can visualize how the activation map evolves during the model training. The model starts by detecting the edge on the lower-left corner at the beginning of the training job. As the training progresses, the focus shifts to the center and detects the speed limit sign, and the model successfully predicts the input image as Class 3, which is a class of speed limit 60km/h signs, with a 97% confidence level.

Debug Training Jobs Using Amazon SageMaker Debugger

To prepare your training script and run training jobs with SageMaker Debugger to debug model training progress, you follow the typical two-step process: modify your training script using the sagemaker-debugger Python SDK, and construct a SageMaker estimator using the SageMaker Python SDK. Go through the following topics to learn how to use SageMaker Debugger's debugging functionality.

Topics

- Step 1: Adapt Your Training Script to Register a Hook (p. 2274)
- Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK (p. 2278)
- Action on Amazon SageMaker Debugger Rules (p. 2293)
- Visualize Amazon SageMaker Debugger Output Tensors in TensorBoard (p. 2303)
Step 1: Adapt Your Training Script to Register a Hook

Amazon SageMaker Debugger comes with a client library called the `sagemaker-debugger Python SDK`. The `sagemaker-debugger` Python SDK provides tools for adapting your training script before training and analysis tools after training. In this page, you'll learn how to adapt your training script using the client library.

The `sagemaker-debugger` Python SDK provides wrapper functions that help register a hook to extract model tensors, without altering your training script. To get started with collecting model output tensors and debug them to find training issues, make the following modifications in your training script.

**Tip**
While you're following this page, use the `sagemaker-debugger open source SDK documentation` for API references.

Topics
- Adapt Your PyTorch Training Script (p. 2274)
- Adapt Your TensorFlow Training Script (p. 2276)

Adapt Your PyTorch Training Script

To start collecting model output tensors and debug training issues, make the following modifications to your PyTorch training script.

**For PyTorch 1.12.0**

If you bring a PyTorch training script, you can run the training job and extract model output tensors with a few additional code lines in your training script. You need to use the `hook APIs` in the `sagemaker-debugger` client library. Walk through the following instructions that break down the steps with code examples.

1. Create a hook.

   **(Recommended) For training jobs within SageMaker**

   ```python
   import smdebug.pytorch as smd
   hook=smd.get_hook(create_if_not_exists=True)
   ```

   When you launch a training job in the section called “Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK” (p. 2278) with any of the DebuggerHookConfig, TensorBoardConfig, or Rules in your estimator, SageMaker adds a JSON configuration file to your training instance that is picked up by the `get_hook` function. Note that if you do not include any of the configuration APIs in your estimator, there will be no configuration file for the hook to find, and the function returns None.

   **(Optional) For training jobs outside SageMaker**

   If you run training jobs in local mode, directly on SageMaker Notebook instances, Amazon EC2 instances, or your own local devices, use `smd.Hook` class to create a hook. However, this approach can only store the tensor collections and usable for TensorBoard visualization. SageMaker Debugger's built-in Rules don't work with the local mode because the Rules require SageMaker ML training instances and S3 to store outputs from the remote instances in real time. The `smd.get_hook` API returns None in this case.

   If you want to create a manual hook to save tensors in local mode, use the following code snippet with the logic to check if the `smd.get_hook` API returns None and create a manual hook using the `smd.Hook` class. Note that you can specify any output directory in your local machine.
import smdebug.pytorch as smd
hook = smd.get_hook(create_if_not_exists=True)

if hook is None:
    hook = smd.Hook(
        out_dir='./path/to/your/local/output/',
        export_tensorboard=True
    )

2. Wrap your model with the hook's class methods.

   The hook.register_module() method takes your model and iterates through each layer, looking for any tensors that match with regular expressions that you'll provide through the configuration in the section called “Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK” (p. 2278). The collectable tensors through this hook method are weights, biases, activations, gradients, inputs, and outputs.

   hook.register_module(model)

   **Tip**
   
   If you collect the entire output tensors from a large deep learning model, the total size of those collections can exponentially grow and might cause bottlenecks. If you want to save specific tensors, you can also use the hook.save_tensor() method. This method helps you pick the variable for the specific tensor and save to a custom collection named as you want. For more information, see step 7 (p. 2276) of this instruction.

3. Warp the loss function with the hook's class methods.

   The hook.register_loss method is to wrap the loss function. It extracts loss values every save_interval that you'll set during configuration in the section called “Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK” (p. 2278), and saves them to the "losses" collection.

   hook.register_loss(loss_function)

4. Add hook.set_mode(ModeKeys.TRAIN) in the train block. This indicates the tensor collection is extracted during the training phase.

   def train():
       ...
       hook.set_mode(ModeKeys.TRAIN)

5. Add hook.set_mode(ModeKeys.EVAL) in the validation block. This indicates the tensor collection is extracted during the validation phase.

   def validation():
       ...
       hook.set_mode(ModeKeys.EVAL)

6. Use hook.save_scalar() to save custom scalars. You can save scalar values that aren't in your model. For example, if you want to record the accuracy values computed during evaluation, add the following line of code below the line where you calculate accuracy.

   hook.save_scalar("accuracy", accuracy)

   Note that you need to provide a string as the first argument to name the custom scalar collection. This is the name that'll be used for visualizing the scalar values in TensorBoard, and can be any string you want.
7. Use `hook.save_tensor()` to save custom tensors. Similarly to `hook.save_scalar()`, you can save additional tensors, defining your own tensor collection. For example, you can extract input image data that are passed into the model and save as a custom tensor by adding the following code line, where "images" is an example name of the custom tensor, `image_inputs` is an example variable for the input image data.

```python
hook.save_tensor("images", image_inputs)
```

Note that you must provide a string to the first argument to name the custom tensor. `hook.save_tensor()` has the third argument `collections_to_write` to specify the tensor collection to save the custom tensor. The default is `collections_to_write="default"`. If you don't explicitly specify the third argument, the custom tensor is saved to the "default" tensor collection.

After you have completed adapting your training script, proceed to the section called “Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK” (p. 2278).

**Adapt Your TensorFlow Training Script**

To start collecting model output tensors and debug training issues, make the following modifications to your TensorFlow training script.

**Create a hook for training jobs within SageMaker**

```python
import smdebug.tensorflow as smd
hook=smd.get_hook(hook_type="keras", create_if_not_exists=True)
```

This creates a hook when you start a SageMaker training job. When you launch a training job in the section called “Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK” (p. 2278) with any of the DebuggerHookConfig, TensorBoardConfig, or Rules in your estimator, SageMaker adds a JSON configuration file to your training instance that is picked up by the `smd.get_hook` method. Note that if you do not include any of the configuration APIs in your estimator, there will be no configuration file for the hook to find, and the function returns `None`.

**(Optional) Create a hook for training jobs outside SageMaker**

If you run training jobs in local mode, directly on SageMaker Notebook instances, Amazon EC2 instances, or your own local devices, use `smd.Hook` class to create a hook. However, this approach can only store the tensor collections and usable for TensorBoard visualization. SageMaker Debugger's built-in Rules don't work with the local mode. The `smd.get_hook` method also returns `None` in this case.

If you want to create a manual hook, use the following code snippet with the logic to check if the hook returns `None` and create a manual hook using the `smd.Hook` class.

```python
import smdebug.tensorflow as smd
hook=smd.get_hook(hook_type="keras", create_if_not_exists=True)
if hook is None:
    hook=smd.KerasHook(
        out_dir="/path/to/your/local/output/",
        export_tensorboard=True
    )
```

After adding the hook creation code, proceed to the following topic for TensorFlow Keras.

**Note**

SageMaker Debugger currently supports TensorFlow Keras only.
Register the hook in your TensorFlow Keras training script

The following procedure walks you through how to use the hook and its methods to collect output scalars and tensors from your model and optimizer.

1. Wrap your Keras model and optimizer with the hook’s class methods.

   The `hook.register_model()` method takes your model and iterates through each layer, looking for any tensors that match with regular expressions that you’ll provide through the configuration in the section called “Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK” (p. 2278). The collectable tensors through this hook method are weights, biases, and activations.

   ```python
   model=tf.keras.Model(...) 
   hook.register_model(model)
   ```

2. Wrap the optimizer by the `hook.wrap_optimizer()` method.

   ```python
   optimizer=tf.keras.optimizers.Adam(...) 
   optimizer=hook.wrap_optimizer(optimizer)
   ```


   To collect tensors from the model, such as the input and output tensors of each layer, you must run the training in eager mode. Otherwise, SageMaker Debugger will not be able to collect the tensors. However, other tensors, such as model weights, biases, and the loss, can be collected without explicitly running in eager mode.

   ```python
   model.compile( 
       loss="categorical_crossentropy", 
       optimizer=optimizer, 
       metrics=["accuracy"], 
       # Required for collecting tensors of each layer 
       run_eagerly=True
   )
   ```

4. Register the hook to the `tf.keras.Model.fit()` method.

   To collect the tensors from the hooks that you registered, add `callbacks=[hook]` to the Keras `model.fit()` class method. This will pass the `sagemaker-debugger` hook as a Keras callback.

   ```python
   model.fit( 
       X_train, Y_train, 
       batch_size=batch_size, 
       epochs=epoch, 
       validation_data=(X_valid, Y_valid), 
       shuffle=True, 
       callbacks=[hook]
   )
   ```

5. TensorFlow 2.x provides only symbolic gradient variables that do not provide access to their values. To collect gradients, wrap `tf.GradientTape` by the `hook.wrap_tape()` method, which requires you to write your own training step as follows.

   ```python
   def training_step(model, dataset):
       with hook.wrap_tape(tf.GradientTape()) as tape:
           pred=model(data)
           loss_value=loss_fn(labels, pred)
           grads=tape.gradient(loss_value, model.trainable_variables) 
           optimizer.apply_gradients(zip(grads, model.trainable_variables))
   ```
By wrapping the tape, the \texttt{sagemaker-debugger} hook can identify output tensors such as gradients, parameters, and losses. Wrapping the tape ensures that the \texttt{hook.wrap_tape()} method around functions of the tape object, such as \texttt{push_tape()}, \texttt{pop_tape()}, \texttt{gradient()}, will set up the writers of SageMaker Debugger and save tensors that are provided as input to \texttt{gradient()} (trainable variables and loss) and output of \texttt{gradient()} (gradients).

\textbf{Note}
To collect with a custom training loop, make sure that you use eager mode. Otherwise, SageMaker Debugger is not able to collect any tensors.

For a full list of actions that the \texttt{sagemaker-debugger} hook APIs offer to construct hooks and save tensors, see \texttt{Hook Methods} in the \texttt{sagemaker-debugger Python SDK documentation}.

After you have completed adapting your training script, proceed to the section called “Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK” (p. 2278).

\section*{Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK}

To configure a SageMaker estimator with SageMaker Debugger, use Amazon SageMaker Python SDK and specify Debugger-specific parameters. To fully utilize the debugging functionality, there are three parameters you need to configure: \texttt{debugger_hook_config}, \texttt{tensorboard_output_config}, and \texttt{rules}.

\textbf{Important}
Before constructing and running the estimator \texttt{fit} method to launch a training job, make sure that you adapt your training script following the instructions at the section called “Step 1: Adapt Your Training Script to Register a Hook” (p. 2274).

\section*{Construct a SageMaker Estimator with Debugger-specific parameters}

The code examples in this section show how to construct a SageMaker estimator with the Debugger-specific parameters.

\textbf{Note}
The following code examples are templates for constructing the SageMaker framework estimators and not directly executable. You need to proceed to the next sections and configure the Debugger-specific parameters.

\textbf{PyTorch}

```python
# An example of constructing a SageMaker PyTorch estimator
import boto3
import sagemaker
from sagemaker.pytorch import PyTorch
from sagemaker.debugger import CollectionConfig, DebuggerHookConfig, Rule, rule_configs

session=boto3.session.Session()
region=session.region_name

ddebugger_hook_config=DebuggerHookConfig(...)
rules=[
    Rule.sagemaker(rule_configs.built_in_rule())
]

estimator=PyTorch(entrpoint="directory/to/your_training_script.py",
    role=sagemaker.get_execution_role(),
    debugger_hook_config=debugger_hook_config,
    rules=rules)
```

2278
base_job_name = "debugger-demo",
instance_count = 1,
instance_type = "ml.p3.2xlarge",
framework_version = "1.12.0",
py_version = "py37",

# Debugger-specific parameters
degger_hook_config = debugger_hook_config,
rules = rules
)
estimator.fit(wait = False)

# TensorFlow
import boto3
import sagemaker
from sagemaker.tensorflow import TensorFlow
from sagemaker.debugger import CollectionConfig, DebuggerHookConfig, Rule, rule_configs
session = boto3.session.Session()
region = session.region_name
degger_hook_config = DebuggerHookConfig(...) 
rule =[ 
    Rule.sagemaker(rule_configs.built_in_rule()),
    ProfilerRule.sagemaker(rule_configs.BuiltInRule())
]
estimator = TensorFlow(
    entry_point = "directory/to/your_training_script.py",
    role = sagemaker.get_execution_role(),
    base_job_name = "debugger-demo",
    instance_count = 1,
    instance_type = "ml.p3.2xlarge",
    framework_version = "2.9.0",
    py_version = "py39",
    # Debugger-specific parameters
degger_hook_config = debugger_hook_config,
rules = rules
)
estimator.fit(wait = False)

# MXNet
import sagemaker
from sagemaker.mxnet import MXNet
from sagemaker.debugger import CollectionConfig, DebuggerHookConfig, Rule, rule_configs
degger_hook_config = DebuggerHookConfig(...)
rule = [
    Rule.sagemaker(rule_configs.built_in_rule())
]
estimator = MXNet(
    entry_point = "directory/to/your_training_script.py",
    role = sagemaker.get_execution_role(),
    base_job_name = "debugger-demo",
    instance_count = 1,
    instance_type = "ml.p3.2xlarge",
    framework_version = "1.12.0",
    py_version = "py37",
    # Debugger-specific parameters
degger_hook_config = debugger_hook_config,
rules = rules
)
estimator.fit(wait = False)
# Debugger-specific parameters
default_configs=debugger_hook_config, rules=rules

estimator.fit(wait=False)

### XGBoost

# An example of constructing a SageMaker XGBoost estimator
import sagemakerrom sagemaker.xgboost.estimator import XGBoost
from sagemaker.debugger import CollectionConfig, DebuggerHookConfig, Rule, rule_configs

default_configs=DebuggerHookConfig(...)ules=[
    Rule.sagemaker(rule_configs.built_in_rule())
]
estimator=XGBoost(
estart="directory/to/your_training_script.py",
role=sagemaker.get_execution_role(),
base_job_name="debugger-demo",
instance_count=1,
instance_type="ml.p3.2xlarge",
framework_version="1.5-1",

# Debugger-specific parameters
default_configs=debugger_hook_config, rules=rules

estimator.fit(wait=False)

### Generic estimator

# An example of constructing a SageMaker generic estimator using the XGBoost algorithm
import boto3
import sagemaker
from sagemaker.estimator import Estimator
from sagemaker.image_uris import image_uris
from sagemaker.debugger import CollectionConfig, DebuggerHookConfig, Rule, rule_configs

default_configs=DebuggerHookConfig(...)ules=[
    Rule.sagemaker(rule_configs.built_in_rule())
]

region=boto3.Session().region_name
xgboost_container=sagemaker.image_uris.retrieve("xgboost", region, "1.5-1")
estimator=Estimator(
estart=role=sagemaker.get_execution_role(),
image_url=xgboost_container,
base_job_name="debugger-demo",
instance_count=1,
instance_type="ml.m5.2xlarge",

# Debugger-specific parameters
default_configs=debugger_hook_config,
rules=rules
)
estimator.fit(wait=False)

Configure the following parameters to activate SageMaker Debugger:

- `debugger_hook_config` (an object of `DebuggerHookConfig`) – Required to activate the hook in the adapted training script during the section called “Step 1: Adapt Your Training Script to Register a Hook” (p. 2274), configure the SageMaker training launcher (estimator) to collect output tensors from your training job, and save the tensors into your secured S3 bucket or local machine. To learn how to configure the `debugger_hook_config` parameter, see Configure SageMaker Debugger to Save Tensors (p. 2281).

- `rules` (a list of `Rule` objects) – Configure this parameter to activate SageMaker Debugger built-in rules that you want to run in real time. The built-in rules are logics that automatically debug the training progress of your model and find training issues by analyzing the output tensors saved in your secured S3 bucket. To learn how to configure the `rules` parameter, see Configure Debugger Built-in Rules (p. 2287). To find a complete list of built-in rules for debugging output tensors, see the section called “Debugger Rule” (p. 2366). If you want to create your own logic to detect any training issues, see the section called “Create Custom Rules” (p. 2410).

  **Note**
  The built-in rules are available only through SageMaker training instances. You cannot use them in local mode.

- `tensorboard_output_config` (an object of `TensorBoardOutputConfig`) – Configure SageMaker Debugger to collect output tensors in the TensorBoard-compatible format and save to your S3 output path specified in the `TensorBoardOutputConfig` object. To learn more, see the section called “Visualize Debugger Output Tensors in TensorBoard” (p. 2303).

  **Note**
  The `tensorboard_output_config` must be configured with the `debugger_hook_config` parameter, which also requires you to adapt your training script by adding the `sagemaker-debugger` hook.

  **Note**
  SageMaker Debugger securely saves output tensors in subfolders of your S3 bucket. For example, the format of the default S3 bucket URI in your account is `s3://sagemaker-<region>-<12digit_account_id>/<base-job-name>/<debugger-subfolders>/`. There are two subfolders created by SageMaker Debugger: `debug-output`, and `rule-output`. If you add the `tensorboard_output_config` parameter, you'll also find `tensorboard-output` folder.

See the following topics to find more examples of how to configure the Debugger-specific parameters in detail.

**Topics**
- Configure SageMaker Debugger to Save Tensors (p. 2281)
- Configure Debugger Built-in Rules (p. 2287)
- Turn Off Debugger (p. 2292)
- Useful SageMaker Estimator Classmethods for Debugger (p. 2293)

**Configure SageMaker Debugger to Save Tensors**

Tensors are data collections of updated parameters from the backward and forward pass of each training iteration. SageMaker Debugger collects the output tensors to analyze the state of a training
job. SageMaker Debugger's `CollectionConfig` and `DebuggerHookConfig` API operations provide methods for grouping tensors into collections and saving them to a target S3 bucket.

**Note**
After properly configured and activated, SageMaker Debugger saves the output tensors in a default S3 bucket, unless otherwise specified. The format of the default S3 bucket URI is `s3://sagemaker-<region>-<12digit_account_id>/<training-job-name>/debug-output/`.

While constructing a SageMaker estimator, activate SageMaker Debugger by specifying the `debugger_hook_config` parameter. The following steps include examples of how to set up the `debugger_hook_config` using the `CollectionConfig` and `DebuggerHookConfig` API operations to pull tensors out of your training jobs and save them.

### Configure Tensor Collections Using the `CollectionConfig` API

Use the `CollectionConfig` API operation to configure tensor collections. Debugger provides pre-built tensor collections that cover a variety of regular expressions (regex) of parameters if using Debugger-supported deep learning frameworks and machine learning algorithms. As shown in the following example code, add the built-in tensor collections you want to debug.

```python
from sagemaker.debugger import CollectionConfig
collection_configs=[
    CollectionConfig(name="weights"),
    CollectionConfig(name="gradients")
]
```

The preceding collections set up the Debugger hook to save the tensors every 500 steps based on the default "save_interval" value.

For a full list of available Debugger built-in collections, see [Debugger Built-in Collections](#).

If you want to customize the built-in collections, such as changing the save intervals and tensor regex, use the following `CollectionConfig` template to adjust parameters.

```python
from sagemaker.debugger import CollectionConfig
collection_configs=[
    CollectionConfig(
        name="tensor_collection",
        parameters={
            "key_1": "value_1",
            "key_2": "value_2",
            ...
            "key_n": "value_n"
        }
    )
]
```

For more information about available parameter keys, see `CollectionConfig` in the [Amazon SageMaker Python SDK](#). For example, the following code example shows how you can adjust the save intervals of the "losses" tensor collection at different phases of training: save loss every 100 steps in training phase and validation loss every 10 steps in validation phase.

```python
from sagemaker.debugger import CollectionConfig
collection_configs=[
    CollectionConfig(
        name="losses",
        parameters={
```
Tip
This tensor collection configuration object can be used for both DebuggerHookConfig and Rule API operations.

Configure the DebuggerHookConfig API to Save Tensors

Use the DebuggerHookConfig API to create a debugger_hook_config object using the collection_configs object you created in the previous step.

```python
from sagemaker.debugger import DebuggerHookConfig

ddebugger_hook_config=DebuggerHookConfig(
    collection_configs=collection_configs
)
```

Debugger saves the model training output tensors into the default S3 bucket. The format of the default S3 bucket URI is `s3://sagemaker-<region>-<12digit_account_id>/<training-job-name>/debug-output/`.

If you want to specify an exact S3 bucket URI, use the following code example:

```python
from sagemaker.debugger import DebuggerHookConfig
ddebugger_hook_config=DebuggerHookConfig(
    s3_output_path="specify-your-s3-bucket-uri",
    collection_configs=collection_configs
)
```

For more information, see DebuggerHookConfig in the Amazon SageMaker Python SDK.

Example Notebooks and Code Samples to Configure Debugger Hook

The following sections provide notebooks and code examples of how to use Debugger hook to save, access, and visualize output tensors.

Topics
- Tensor Visualization Example Notebooks (p. 2283)
- Save Tensors Using Debugger Built-in Collections (p. 2285)
- Save Tensors Using Debugger Modified Built-in Collections (p. 2286)
- Save Tensors Using Debugger Custom Collections (p. 2286)

Tensor Visualization Example Notebooks

The following two notebook examples show advanced use of Amazon SageMaker Debugger for visualizing tensors. Debugger provides a transparent view into training deep learning models.

- Interactive Tensor Analysis in SageMaker Studio Notebook with MXNet

  This notebook example shows how to visualize saved tensors using Amazon SageMaker Debugger. By visualizing the tensors, you can see how the tensor values change while training deep learning algorithms. This notebook includes a training job with a poorly configured neural network and uses Amazon SageMaker Debugger to aggregate and analyze tensors, including gradients, activation...
outputs, and weights. For example, the following plot shows the distribution of gradients of a convolutional layer that is suffering from a vanishing gradient problem.

This notebook also illustrates how a good initial hyperparameter setting improves the training process by generating the same tensor distribution plots.

- **Visualizing and Debugging Tensors from MXNet Model Training**

This notebook example shows how to save and visualize tensors from an MXNet Gluon model training job using Amazon SageMaker Debugger. It illustrates that Debugger is set to save all tensors to an Amazon S3 bucket and retrieves ReLu activation outputs for the visualization. The following figure shows a three-dimensional visualization of the ReLu activation outputs. The color scheme is set to blue to indicate values close to 0 and yellow to indicate values close to 1.

In this notebook, the TensorPlot class imported from tensor_plot.py is designed to plot convolutional neural networks (CNNs) that take two-dimensional images for inputs. The
tensor_plot.py script provided with the notebook retrieves tensors using Debugger and visualizes the CNN. You can run this notebook on SageMaker Studio to reproduce the tensor visualization and implement your own convolutional neural network model.

- **Real-time Tensor Analysis in a SageMaker Notebook with MXNet**

This example guides you through installing required components for emitting tensors in an Amazon SageMaker training job and using the Debugger API operations to access those tensors while training is running. A gluon CNN model is trained on the Fashion MNIST dataset. While the job is running, you will see how Debugger retrieves activation outputs of the first convolutional layer from each of 100 batches and visualizes them. Also, this will show you how to visualize weights after the job is done.

**Save Tensors Using Debugger Built-in Collections**

You can use built-in collections of tensors using the CollectionConfig API and save them using the DebuggerHookConfig API. The following example shows how to use the default settings of Debugger hook configurations to construct a SageMaker TensorFlow estimator. You can also utilize this for MXNet, PyTorch, and XGBoost estimators.

**Note**

In the following example code, the s3_output_path parameter for DebuggerHookConfig is optional. If you do not specify it, Debugger saves the tensors at s3://<output_path>/debug-output/, where the <output_path> is the default output path of SageMaker training jobs. For example:

```
"s3://sagemaker-us-east-1-111122223333/sagemaker-debugger-training-YYYY-MM-DD-HH-MM-SS-123/debug-output"
```

```python
import sagemaker
from sagemaker.tensorflow import TensorFlow
from sagemaker.debugger import DebuggerHookConfig, CollectionConfig

# use Debugger CollectionConfig to call built-in collections
collection_configs=[
    CollectionConfig(name="weights"),
    CollectionConfig(name="gradients"),
    CollectionConfig(name="losses"),
    CollectionConfig(name="biases")
]

# configure Debugger hook
# set a target S3 bucket as you want
sagemaker_session=sagemaker.Session()
BUCKET_NAME=sagemaker_session.default_bucket()
LOCATION_IN_BUCKET='debugger-built-in-collections-hook'

hook_config=DebuggerHookConfig(
    s3_output_path='s3://{BUCKET_NAME}/{LOCATION_IN_BUCKET}'.format(BUCKET_NAME=BUCKET_NAME, LOCATION_IN_BUCKET=LOCATION_IN_BUCKET),
    collection_configs=collection_configs
)

# construct a SageMaker TensorFlow estimator
sagemaker_estimator=TensorFlow(
    entry_point='directory/to/your_training_script.py',
    role=sm.get_execution_role(),
    base_job_name='debugger-demo-job',
    instance_count=1,
    instance_type="ml.p3.2xlarge",
    framework_version="2.9.0",
)```
import sagemaker
from sagemaker.tensorflow import TensorFlow
from sagemaker.debugger import DebuggerHookConfig, CollectionConfig

# use Debugger CollectionConfig to call and modify built-in collections
collection_configs=[[CollectionConfig(
    name="losses",
    parameters={"save_interval": "50"})]

# configure Debugger hook
# set a target S3 bucket as you want
sagemaker_session=sagemaker.Session()
BUCKET_NAME=sagemaker_session.default_bucket()
LOCATION_IN_BUCKET='debugger-modified-collections-hook'

hook_config=DebuggerHookConfig(
    s3_output_path='s3://{BUCKET_NAME}/{LOCATION_IN_BUCKET}'.format(BUCKET_NAME=BUCKET_NAME, LOCATION_IN_BUCKET=LOCATION_IN_BUCKET),
    collection_configs=collection_configs)

# construct a SageMaker TensorFlow estimator
sagemaker_estimator=TensorFlow(
    entry_point='directory/to/your_training_script.py',
    role=sm.get_execution_role(),
    base_job_name='debugger-demo-job',
    instance_count=1,
    instance_type="ml.p3.2xlarge",
    framework_version="2.9.0",
    py_version="py39",
    # debugger-specific hook argument below
    debugger_hook_config=hook_config)

sagemaker_estimator.fit()
import sagemaker
from sagemaker.tensorflow import TensorFlow
from sagemaker.debugger import DebuggerHookConfig, CollectionConfig

# use Debugger CollectionConfig to create a custom collection

collection_configs = [
    CollectionConfig(
        name="custom_activations_collection",
        parameters={
            "include_regex": "relu|tanh", # Required
            "reductions": "mean,variance,max,abs_mean,abs_variance,abs_max"
        }
    )
]

# configure Debugger hook
# set a target S3 bucket as you want
sagemaker_session=sagemaker.Session()
BUCKET_NAME=sagemaker_session.default_bucket()
LOCATION_IN_BUCKET='debugger-custom-collections-hook'

hook_config = DebuggerHookConfig(  
    s3_output_path='s3://{BUCKET_NAME}/{LOCATION_IN_BUCKET}'.format(BUCKET_NAME=BUCKET_NAME, LOCATION_IN_BUCKET=LOCATION_IN_BUCKET),  
    collection_configs=collection_configs
)

# construct a SageMaker TensorFlow estimator
sagemaker_estimator=TensorFlow(
    entry_point='directory/to/your_training_script.py',
    role=sm.get_execution_role(),
    base_job_name='debugger-demo-job',
    instance_count=1,
    instance_type="ml.p3.2xlarge",
    framework_version="2.9.0",
    py_version="py39",
    # debugger-specific hook argument below
    debugger_hook_config=hook_config
)

sagemaker_estimator.fit()

For a full list of CollectionConfig parameters, see Debugger CollectionConfig.

Configure Debugger Built-in Rules

Amazon SageMaker Debugger’s built-in rules analyze tensors emitted during the training of a model. SageMaker Debugger offers the Rule API operation that monitors training job progress and errors for the success of training your model. For example, the rules can detect whether gradients are getting too large or too small, whether a model is overfitting or overtraining, and whether a training job does not decrease loss function and improve. To see a full list of available built-in rules, see List of Debugger Built-in Rules (p. 2365).

In the following topics, you’ll learn how to use the SageMaker Debugger built-in rules.

Topics

- Use Debugger Built-in Rules with the Default Parameter Settings (p. 2288)
- Use Debugger Built-in Rules with Custom Parameter Values (p. 2288)
- Example Notebooks and Code Samples to Configure Debugger Rules (p. 2289)
Use Debugger Built-in Rules with the Default Parameter Settings

To specify Debugger built-in rules in an estimator, you need to configure a list object. The following example code shows the basic structure of listing the Debugger built-in rules:

```python
from sagemaker.debugger import Rule, rule_configs
rules=[
    Rule.sagemaker(rule_configs.built_in_rule_name_1()),
    Rule.sagemaker(rule_configs.built_in_rule_name_2()),
    ...
    Rule.sagemaker(rule_configs.built_in_rule_name_n()),
    ... # You can also append more profiler rules in the ProfilerRule.sagemaker(rule_configs.*()) format.
]
```

For more information about default parameter values and descriptions of the built-in rule, see List of Debugger Built-in Rules (p. 2365).

To find the SageMaker Debugger API reference, see sagemaker.debugger.rule_configs and sagemaker.debugger.Rule.

For example, to inspect the overall training performance and progress of your model, construct a SageMaker estimator with the following built-in rule configuration.

```python
from sagemaker.debugger import Rule, rule_configs
rules=[
    Rule.sagemaker(rule_configs.loss_not_decreasing()),
    Rule.sagemaker(rule_configs.overfit()),
    Rule.sagemaker(rule_configs.overtraining()),
    Rule.sagemaker(rule_configs.stalled_training_rule())
]
```

When you start the training job, Debugger collects system resource utilization data every 500 milliseconds and the loss and accuracy values every 500 steps by default. Debugger analyzes the resource utilization to identify if your model is having bottleneck problems. The loss_not_decreasing, overfit, overtraining, and stalled_training_rule monitors if your model is optimizing the loss function without those training issues. If the rules detect training anomalies, the rule evaluation status changes to IssueFound. You can set up automated actions, such as notifying training issues and stopping training jobs using Amazon CloudWatch Events and AWS Lambda. For more information, see Action on Amazon SageMaker Debugger Rules (p. 2293).

Use Debugger Built-in Rules with Custom Parameter Values

If you want to adjust the built-in rule parameter values and customize tensor collection regex, configure the base_config and rule_parameters parameters for the ProfilerRule.sagemaker and Rule.sagemaker class methods. In case of the Rule.sagemaker class methods, you can also customize tensor collections through the collections_to_save parameter. The instruction of how to use the CollectionConfig class is provided at Configure Tensor Collections Using the CollectionConfig API (p. 2282).

Use the following configuration template for built-in rules to customize parameter values. By changing the rule parameters as you want, you can adjust the sensitivity of the rules to be triggered.

- The base_config argument is where you call the built-in rule methods.
- The rule_parameters argument is to adjust the default key values of the built-in rules listed in List of Debugger Built-in Rules (p. 2365).
• The `collections_to_save` argument takes in a tensor configuration through the `CollectionConfig` API, which requires name and parameters arguments.
• To find available tensor collections for name, see Debugger Built-in Tensor Collections.
• For a full list of adjustable parameters, see Debugger CollectionConfig API.

For more information about the Debugger rule class, methods, and parameters, see SageMaker Debugger Rule class in the Amazon SageMaker Python SDK.

```python
from sagemaker.debugger import Rule, ProfilerRule, rule_configs, CollectionConfig
rules=[
    Rule.sagemaker(
        base_config=rule_configs.built_in_rule_name(),
        rule_parameters={
            "key": "value"
        },
        collections_to_save=[
            CollectionConfig(
                name="tensor_collection_name",
                parameters={
                    "key": "value"
                }
            )
        ]
    )
]
```

The parameter descriptions and value customization examples are provided for each rule at List of Debugger Built-in Rules (p. 2365).

Example Notebooks and Code Samples to Configure Debugger Rules

In the following sections, notebooks and code samples of how to use Debugger rules to monitor SageMaker training jobs are provided.

Topics
• Debugger Built-in Rules Example Notebooks (p. 2289)
• Debugger Built-in Rules Example Code (p. 2290)
• Use Debugger Built-in Rules with Parameter Modifications (p. 2291)

Debugger Built-in Rules Example Notebooks

The following example notebooks show how to use Debugger built-in rules when running training jobs with Amazon SageMaker:
• Using a SageMaker Debugger built-in rule with TensorFlow
• Using a SageMaker Debugger built-in rule with Managed Spot Training and MXNet
• Using a SageMaker Debugger built-in rule with XGBoost
• Using a SageMaker Debugger built-in rule with parameter modifications for a real-time training job analysis with XGBoost

While running the example notebooks in SageMaker Studio, you can find the training job trial created on the Studio Experiment List tab. For example, as shown in the following screenshot, you can find and open a Describe Trial Component window of your current training job. On the Debugger tab, you can
check if the Debugger rules, `vanishing_gradient()` and `loss_not_decreasing()`, are monitoring the training session in parallel. For a full instruction of how to find your training job trial components in the Studio UI, see SageMaker Studio - View Experiments, Trials, and Trial Components.

There are two ways of using the Debugger built-in rules in the SageMaker environment: deploy the built-in rules as it is prepared or adjust their parameters as you want. The following topics show you how to use the built-in rules with example codes.

**Debugger Built-in Rules Example Code**

The following code sample shows how to set the Debugger built-in rules using the `Rule.sagemaker` method. To specify built-in rules that you want to run, use the `rules_configs` API operation to call the built-in rules. To find a full list of Debugger built-in rules and default parameter values, see List of Debugger Built-in Rules (p. 2365).

```python
import sagemaker
from sagemaker.tensorflow import TensorFlow
from sagemaker.debugger import Rule, CollectionConfig, rule_configs

# call built-in rules that you want to use.
built_in_rules = [
    Rule.sagemaker(rule_configs.vanishing_gradient()),
    Rule.sagemaker(rule_configs.loss_not_decreasing())
]

# construct a SageMaker estimator with the Debugger built-in rules
```
sagemaker_estimator=TensorFlow(
    entry_point='directory/to/your_training_script.py',
    role=sm.get_execution_role(),
    base_job_name='debugger-built-in-rules-demo',
    instance_count=1,
    instance_type="ml.p3.2xlarge",
    framework_version="2.9.0",
    py_version="py39",

    # debugger-specific arguments below
    rules=built_in_rules
)
sagemaker_estimator.fit()

**Note**
The Debugger built-in rules run in parallel with your training job. The maximum number of built-in rule containers for a training job is 20.

For more information about the Debugger rule class, methods, and parameters, see the SageMaker Debugger Rule class in the Amazon SageMaker Python SDK.

To find an example of how to adjust the Debugger rule parameters, see the following Use Debugger Built-in Rules with Parameter Modifications (p. 2291) section.

**Use Debugger Built-in Rules with Parameter Modifications**
The following code example shows the structure of built-in rules to adjust parameters. In this example, the stalled_training_rule collects the losses tensor collection from a training job at every 50 steps and an evaluation stage at every 10 steps. If the training process starts stalling and not collecting tensor outputs for 120 seconds, the stalled_training_rule stops the training job.

```python
import sagemaker
from sagemaker.tensorflow import TensorFlow
from sagemaker.debugger import Rule, CollectionConfig, rule_configs

# call the built-in rules and modify the CollectionConfig parameters
base_job_name_prefix= 'smdebug-stalled-demo-' + str(int(time.time()))
built_in_rules_modified=[
    Rule.sagemaker(
        base_config=rule_configs.stalled_training_rule(),
        rule_parameters={
            'threshold': '120',
            'training_job_name_prefix': base_job_name_prefix,
            'stop_training_on_fire' : 'True'
        }
    )
    collections_to_save=[
        CollectionConfig(name="losses",
                        parameters={
                            "train.save_interval": "50"
                            "eval.save_interval": "10"
                        }
        )
    ]
]

# construct a SageMaker estimator with the modified Debugger built-in rule
sagemaker_estimator=TensorFlow(
    entry_point='directory/to/your_training_script.py',
    role=sm.get_execution_role(),
    base_job_name='debugger-built-in-rules-demo',
    instance_count=1,
    instance_type="ml.p3.2xlarge",
    framework_version="2.9.0",
    py_version="py39",

    # debugger-specific arguments below
    rules=built_in_rules
)
sagemaker_estimator.fit()
```
base_job_name=base_job_name_prefix,
instance_count=1,
instance_type="ml.p3.2xlarge",
framework_version="2.9.0",
py_version="py39",
    # debugger-specific arguments below
    rules=built_in_rules_modified
)
sagemaker_estimator.fit()

For an advanced configuration of the Debugger built-in rules using the CreateTrainingJob API, see Configure Debugger Using Amazon SageMaker API (p. 2415).

**Turn Off Debugger**

If you want to completely turn off Debugger, do one of the following:

- Before starting a training job, do the following:

  To stop both monitoring and profiling, include the `disable_profiler` parameter to your estimator and set it to `True`.

    **Warning**
    If you disable it, you won't be able to view the comprehensive Studio Debugger insights dashboard and the autogenerated profiling report.

  To stop debugging, set the `debugger_hook_config` parameter to `False`.

    **Warning**
    If you disable it, you won't be able to collect output tensors and cannot debug your model parameters.

    ```python
    estimator=Estimator(
        ...,
        disable_profiler=True
        debugger_hook_config=False
    )
    ```

    For more information about the Debugger-specific parameters, see SageMaker Estimator in the Amazon SageMaker Python SDK.

- While a training job is running, do the following:

  To disable both monitoring and profiling while your training job is running, use the following estimator classmethod:

    ```python
    estimator.disable_profiling()
    ```

  To disable framework profiling only and keep system monitoring, use the `update_profiler` method:

    ```python
    estimator.update_profiler(disable_framework_metrics=True)
    ```

    For more information about the estimator extension methods, see the `estimator.disable_profiling` and `estimator.update_profiler` classmethods in the Amazon SageMaker Python SDK documentation.
Useful SageMaker Estimator Classmethods for Debugger

The following estimator class methods are useful for accessing your SageMaker training job information and retrieving output paths of training data collected by Debugger. The following methods are executable after you initiate a training job with the `estimator.fit()` method.

- To check the base S3 bucket URI of a SageMaker training job:
  ```python
  estimator.output_path
  ```

- To check the base job name of a SageMaker training job:
  ```python
  estimator.latest_training_job.job_name
  ```

- To see a full `CreateTrainingJob` API operation configuration of a SageMaker training job:
  ```python
  estimator.latest_training_job.describe()
  ```

- To check a full list of the Debugger rules while a SageMaker training job is running:
  ```python
  estimator.latest_training_job.rule_job_summary()
  ```

- To check the S3 bucket URI where the model parameter data (output tensors) are saved:
  ```python
  estimator.latest_job_debugger_artifacts_path()
  ```

- To check the S3 bucket URI at where the model performance data (system and framework metrics) are saved:
  ```python
  estimator.latest_job_profiler_artifacts_path()
  ```

- To check the Debugger rule configuration for debugging output tensors:
  ```python
  estimator.debugger_rule_configs
  ```

- To check the list of the Debugger rules for debugging while a SageMaker training job is running:
  ```python
  estimator.debugger_rules
  ```

- To check the Debugger rule configuration for monitoring and profiling system and framework metrics:
  ```python
  estimator.profiler_rule_configs
  ```

- To check the list of the Debugger rules for monitoring and profiling while a SageMaker training job is running:
  ```python
  estimator.profiler_rules
  ```

For more information about the SageMaker estimator class and its methods, see Estimator API in the Amazon SageMaker Python SDK.

Action on Amazon SageMaker Debugger Rules

Based on the Debugger rule evaluation status, you can set up automated actions such as stopping a training job and sending notifications using Amazon Simple Notification Service (Amazon SNS). You can
also create your own actions using Amazon CloudWatch Events and AWS Lambda. To learn how to set up automated actions based on the Debugger rule evaluation status, see the following topics.

**Topics**
- Debugger Built-in Actions for Rules (p. 2294)
- Create Actions on Rules Using Amazon CloudWatch and AWS Lambda (p. 2298)

**Debugger Built-in Actions for Rules**

Use Debugger built-in actions to respond to issues found by Debugger Rule (p. 2366). The Debugger rule_configs class provides tools to configure a list of actions, including automatically stopping training jobs and sending notifications using Amazon Simple Notification Service (Amazon SNS) when the Debugger rules find training issues.

**Step 1: Set Up Amazon SNS, Create an SMDebugRules Topic, and Subscribe to the Topic**

This section walks you through how to set up an Amazon SNS SMDebugRules topic, subscribe to it, and confirm the subscription to receive notifications from the Debugger rules.

*Note*
For more information about billing for Amazon SNS, see Amazon SNS pricing and Amazon SNS FAQs.

**To create a SMDebugRules topic**

2. In the left navigation pane, choose Topics.
3. On the Topics page, choose Create topic.
4. On the Create topic page, in the Details section, do the following:
   a. For Type, choose Standard for topic type.
   b. In Name, enter SMDebugRules.
5. Skip all other optional settings and choose Create topic. If you want to learn more about the optional settings, see Creating an Amazon SNS topic.

**To subscribe to the SMDebugRules topic**

2. In the left navigation pane, choose Subscriptions.
3. On the Subscriptions page, choose Create subscription.
4. On the Create subscription page, in the Details section, do the following:
   b. For Protocol, choose Email or SMS.
   c. For Endpoint, enter the endpoint value, such as an email address or a phone number that you want to receive notifications.

*Note*
Make sure you type the correct email address and phone number. Phone numbers must include +, a country code, and phone number, with no special characters or spaces. For example, the phone number +1 (222) 333-4444 is formatted as +12223334444.
5. Skip all other optional settings and choose Create subscription. If you want to learn more about the optional settings, see Subscribing to an Amazon SNS topic.

After you subscribe to the SMDebugRules topic, you receive the following confirmation message in email or by phone:

**AWS Notification - Subscription Confirmation**

You have chosen to subscribe to the topic: arn:aws:snsus-east-1:11112223333:SMDebugRules

To confirm this subscription, click or visit the link below (If this was in error no action is necessary):

Confirm subscription

Please do not reply directly to this email. If you wish to remove yourself from receiving all future SNS subscription confirmation requests please send an email to sns-opt-out

For more information about Amazon SNS, see Mobile text messaging (SMS) and Email notifications in the Amazon SNS Developer Guide.

**Step 2: Set Up Your IAM Role to Attach Required Policies**

In this step, you add the required policies to your IAM role.

**To add the required policies to your IAM role**

1. Sign in to the AWS Management Console and open the IAM console at https://console.aws.amazon.com/iam/.
2. In the left navigation pane, choose Policies, and choose Create policy.
3. On the Create policy page, do the following to create a new sns-access policy:
   a. Choose the JSON tab.
   b. Paste the JSON strings formatted in bold in the following code into the "Statement", replacing the 12-digit AWS account ID with your AWS account ID.

   ```json
   {
   "Version": "2012-10-17",
   "Statement": [
   {
   "Sid": "VisualEditor0",
   "Effect": "Allow",
   "Action": [
   "sns:Publish",
   "sns:CreateTopic",
   "sns:Subscribe"
   ],
   "Resource": "arn:aws:sns:*:11112223333:SMDebugRules"
   }
   ]
   }
   ```

c. At the bottom of the page, choose Review policy.

d. On the Review page, for Name, enter sns-access.

e. At the bottom of the page, choose Create policy.

4. Go back to the IAM console, and choose Roles in the left navigation pane.
5. Look up the IAM role that you use for SageMaker model training and choose that IAM role.
6. On the Permissions tab of the Summary page, choose Attach policies.
7. Search for the sns-access policy, select the check box next to the policy, and then choose Attach policy.

For more examples of setting up IAM policies for Amazon SNS, see Example cases for Amazon SNS access control.

Step 3: Configure Debugger Rules with the Built-in Actions

After successfully finishing the required settings in the preceding steps, you can configure the Debugger built-in actions for debugging rules as shown in the following example script. You can choose which built-in actions to use while building the actions list object. The rule_configs is a helper module that provides high-level tools to configure Debugger built-in rules and actions. The following built-in actions are available for Debugger:

- `rule_configs.StopTraining()` – Stops a training job when the Debugger rule finds an issue.
- `rule_configs.Email("abc@abc.com")` – Sends a notification via email when the Debugger rule finds an issue. Use the email address that you used when you set up your SNS topic subscription.
- `rule_configs.SMS("+1234567890")` – Sends a notification via text message when the Debugger rule finds an issue. Use the phone number that you used when you set up your SNS topic subscription.

Note
Make sure you type the correct email address and phone number. Phone numbers must include +, a country code, and a phone number, with no special characters or spaces. For example, the phone number +1 (222) 333-4444 is formatted as +12223334444.

You can use all of the built-in actions or a subset of actions by wrapping up using the `rule_configs.ActionList()` method, which takes the built-in actions and configures a list of actions.

To add all of the three built-in actions to a single rule

If you want to assign all of the three built-in actions to a single rule, configure a Debugger built-in action list while constructing an estimator. Use the following template to construct the estimator, and Debugger will stop training jobs and send notifications through email and text for any rules that you use to monitor your training job progress.

```python
from sagemaker.debugger import Rule, rule_configs

# Configure an action list object for Debugger rules
actions = rule_configs.ActionList(  
    rule_configs.StopTraining(),  
    rule_configs.Email("abc@abc.com"),  
    rule_configs.SMS("+1234567890")
)

# Configure rules for debugging with the actions parameter
rules = [
    Rule.sagemaker(  
        base_config=rule_configs.build_in_rule(),  
        rule_parameters={"paramter_key": value },  
        actions=actions  
    )
]

estimator = Estimator(  
    ...
```
To create multiple built-in action objects to assign different actions to a single rule

If you want to assign the built-in actions to be triggered at different threshold values of a single rule, you can create multiple built-in action objects as shown in the following script. To avoid a conflict error by running the same rule, you must submit different rule job names (specify different strings for the rules’ name attribute) as shown in the following example script template. This example shows how to set up StalledTrainingRule (p. 2398) to take two different actions: send an email to abc@abc.com when a training job stalls for 60 seconds, and stop the training job if stalling for 120 seconds.

```python
from sagemaker.debugger import Rule, rule_configs
import time
base_job_name_prefix = 'smdebug-stalled-demo-' + str(int(time.time()))

# Configure an action object for StopTraining
action_stop_training = rule_configs.ActionList(
    rule_configs.StopTraining()
)

# Configure an action object for Email
action_email = rule_configs.ActionList(
    rule_configs.Email("abc@abc.com")
)

# Configure a rule with the Email built-in action to trigger if a training job stalls for 60 seconds
stalled_training_job_rule_email = Rule.sagemaker(
    base_config=rule_configs.stalled_training_rule(),
    rule_parameters={
        "threshold": "60",
        "training_job_name_prefix": base_job_name_prefix
    },
    actions=action_email
)
stalled_training_job_rule_email.name="StalledTrainingJobRuleEmail"

# Configure a rule with the StopTraining built-in action to trigger if a training job stalls for 120 seconds
stalled_training_job_rule = Rule.sagemaker(
    base_config=rule_configs.stalled_training_rule(),
    rule_parameters={
        "threshold": "120",
        "training_job_name_prefix": base_job_name_prefix
    },
    actions=action_stop_training
)
stalled_training_job_rule.name="StalledTrainingJobRuleStopTraining"

estimator = Estimator(
    ...
    rules = [stalled_training_job_rule_email, stalled_training_job_rule]
)
estimator.fit(wait=False)
```

While the training job is running, the Debugger built-in action sends notification emails and text messages whenever the rule finds issues with your training job. The following screenshot shows an example of email notification for a training job that has a stalled training job issue.
The following screenshot shows an example text notification that Debugger sends when the rule finds a StalledTraining issue.

Considerations for Using the Debugger Built-in Actions

- To use the Debugger built-in actions, an internet connection is required. This feature is not supported in the network isolation mode provided by Amazon SageMaker or Amazon VPC.
- The built-in actions cannot be used for Debugger ProfilerRule (p. 2366).
- The built-in actions cannot be used on training jobs with spot training interruptions.
- In email or text notifications, None appears at the end of messages. This does not have any meaning, so you can disregard the text None.

Create Actions on Rules Using Amazon CloudWatch and AWS Lambda

Amazon CloudWatch collects Amazon SageMaker model training job logs and Amazon SageMaker Debugger rule processing job logs. Configure Debugger with Amazon CloudWatch Events and AWS Lambda to take action based on Debugger rule evaluation status.

CloudWatch Logs for Debugger Rules and Training Jobs

To find training job logs and Debugger rule job logs

2. In the left navigation pane under the Log node, choose Log Groups.
3. In the log groups list, do the following:
   - Choose /aws/sagemaker/TrainingJobs for training job logs.
   - Choose /aws/sagemaker/ProcessingJobs for Debugger rule job logs.
You can use the training and Debugger rule job status in the CloudWatch logs to take further actions when there are training issues.

For more information about monitoring training jobs using CloudWatch, see Monitor Amazon SageMaker.

Set Up Debugger for Automated Training Job Termination Using CloudWatch and Lambda

The Debugger rules monitor training job status, and a CloudWatch Events rule watches the Debugger rule training job evaluation status.

Step 1: Create a Lambda Function

To create a Lambda function

1. Open the AWS Lambda console at https://console.aws.amazon.com/lambda/.
2. In the left navigation pane, choose Functions and then choose Create function.
3. On the Create function page, choose Author from scratch option.
4. In the Basic information section, enter a Function name (for example, debugger-rule-stop-training-job).
5. For Runtime, choose Python 3.7.
6. For Permissions, expand the drop down option, and choose Change default execution role.
7. For Execution role, choose Use an existing role and choose the IAM role that you use for training jobs on SageMaker.
   
   **Note**
   
   Make sure you use the execution role with AmazonSageMakerFullAccess and AWSLambdaBasicExecutionRole attached. Otherwise, the Lambda function won't properly react to the Debugger rule status changes of the training job. If you are unsure which execution role is being used, run the following code in a Jupyter notebook cell to retrieve the execution role output:

   ```python
   import sagemaker
   sagemaker.get_execution_role()
   ```

8. At the bottom of the page, choose Create function.

The following figure shows an example of the Create function page with the input fields and selections completed.
Step 2: Configure the Lambda function

To configure the Lambda function

1. In the Function code section of the configuration page, paste the following Python script in the Lambda code editor pane. The `lambda_handler` function monitors the Debugger rule evaluation status collected by CloudWatch and triggers the `StopTrainingJob` API operation. The AWS SDK for Python (Boto3) client for SageMaker provides a high-level method, `stop_training_job`, which triggers the `StopTrainingJob` API operation.

```python
import json
import boto3
import logging

logger = logging.getLogger()
logger.setLevel(logging.INFO)

def lambda_handler(event, context):
    training_job_name = event.get("detail").get("TrainingJobName")
    logging.info(f'Analyzing Debugger rules for training job: {training_job_name}')
```

eval_statuses = event.get("detail").get("DebugRuleEvaluationStatuses", None)
if eval_statuses is None or len(eval_statuses) == 0:
    logging.info("Couldn't find any debug rule statuses, skipping...")
    return {
        'statusCode': 200,
        'body': json.dumps('Nothing to do')
    }

# should only attempt stopping jobs with InProgress status
training_job_status = event.get("detail").get("TrainingJobStatus", None)
if training_job_status != 'InProgress':
    logging.debug(f"Current Training job status({training_job_status}) is not 'InProgress'. Exiting")
    return {
        'statusCode': 200,
        'body': json.dumps('Nothing to do')
    }

client = boto3.client('sagemaker')
for status in eval_statuses:
    logging.info(status.get("RuleEvaluationStatus") + ', RuleEvaluationStatus=' + str(status))
    if status.get("RuleEvaluationStatus") == "IssuesFound":
        secondary_status = event.get("detail").get("SecondaryStatus", None)
        logging.info(f'About to stop training job, since evaluation of rule configuration
                     {status.get("RuleConfigurationName")} resulted in "IssuesFound".
                     training job "{training_job_name}" status is
                     {training_job_status}, secondary status is "{secondary_status}" +
                     Attempting to stop training job "{training_job_name}"' +
        )
        try:
            client.stop_training_job(
                TrainingJobName=training_job_name
            )
        except Exception as e:
            logging.error("Encountered error while trying to "
                          "stop training job {}: {}".format(
                          training_job_name, str(e))
        )
    raise e
return None

For more information about the Lambda code editor interface, see Creating functions using the AWS Lambda console editor.

2. Skip all other settings and choose Save at the top of the configuration page.

Step 3: Create a CloudWatch Events Rule and Link to the Lambda Function for Debugger

To create a CloudWatch Events rule and link to the Lambda function for Debugger

2. In the left navigation pane, choose Rules under the Events node.
3. Choose Create rule.
4. In the Event Source section of the Step 1: Create rule page, choose SageMaker for Service Name, and choose SageMaker Training Job State Change for Event Type. The Event Pattern Preview should look like the following example JSON strings:
5. In the Targets section, choose Add target*, and choose the debugger-rule-stop-training-job Lambda function that you created. This step links the CloudWatch Events rule with the Lambda function.

6. Choose Configure details and go to the Step 2: Configure rule details page.

7. Specify the CloudWatch rule definition name. For example, debugger-cw-event-rule.

8. Choose Create rule to finish.

9. Go back to the Lambda function configuration page and refresh the page. Confirm that it's configured correctly in the Designer panel. The CloudWatch Events rule should be registered as a trigger for the Lambda function. The configuration design should look like the following example:

Run Example Notebooks to Test Automated Training Job Termination

You can run the following example notebooks, which are prepared for experimenting with stopping a training job using Debugger's built-in rules.

- Amazon SageMaker Debugger - Reacting to CloudWatch Events from Rules

This example notebook runs a training job that has a vanishing gradient issue. The Debugger VanishingGradient (p. 2386) built-in rule is used while constructing the SageMaker TensorFlow estimator. When the Debugger rule detects the issue, the training job is terminated.
• **Detect Stalled Training and Invoke Actions Using SageMaker Debugger Rule**

This example notebook runs a training script with a code line that forces it to sleep for 10 minutes. The Debugger StalledTrainingRule (p. 2398) built-in rule invokes issues and stops the training job.

**Disable the CloudWatch Events Rule to Stop Using the Automated Training Job Termination**

If you want to disable the automated training job termination, you need to disable the CloudWatch Events rule. In the Lambda Designer panel, choose the EventBridge (CloudWatch Events) block linked to the Lambda function. This shows an EventBridge panel below the Designer panel (for example, see the previous screen shot). Select the check box next to EventBridge (CloudWatch Events): debugger-cw-event-rule, and then choose Disable. If you want to use the automated termination functionality later, you can enable the CloudWatch Events rule again.

**Visualize Amazon SageMaker Debugger Output Tensors in TensorBoard**

Use SageMaker Debugger to create output tensor files that are compatible with TensorBoard. Load the files to visualize in TensorBoard and analyze your SageMaker training jobs. Debugger automatically generates output tensor files that are compatible with TensorBoard. For any hook configuration you customize for saving output tensors, Debugger has the flexibility to create scalar summaries, distributions, and histograms that you can import to TensorBoard.

You can enable this by passing DebuggerHookConfig and TensorBoardOutputConfig objects to an estimator.

The following procedure explains how to save scalars, weights, and biases as full tensors, histograms, and distributions that can be visualized with TensorBoard. Debugger saves them to the training container's local path (the default path is /opt/ml/output/tensors) and syncs to the Amazon S3 locations passed through the Debugger output configuration objects.

**To save TensorBoard compatible output tensor files using Debugger**

1. Set up a tensorboard_output_config configuration object to save TensorBoard output using the Debugger TensorBoardOutputConfig class. For the s3_output_path parameter, specify the default S3 bucket of the current SageMaker session or a preferred S3 bucket. This example does not add the container_local_output_path parameter; instead, it is set to the default local path /opt/ml/output/tensors.
import sagemaker
from sagemaker.debugger import TensorBoardOutputConfig

bucket = sagemaker.Session().default_bucket()
tensorboard_output_config = TensorBoardOutputConfig(s3_output_path='s3://{}/'.format(bucket))

For additional information, see the Debugger TensorBoardOutputConfig API in the Amazon SageMaker Python SDK.

2. Configure the Debugger hook and customize the hook parameter values. For example, the following code configures a Debugger hook to save all scalar outputs every 100 steps in training phases and 10 steps in validation phases, the weights parameters every 500 steps (the default save_interval value for saving tensor collections is 500), and the bias parameters every 10 global steps until the global step reaches 500.

from sagemaker.debugger import CollectionConfig, DebuggerHookConfig

hook_config = DebuggerHookConfig(hook_parameters={
    "train.save_interval": "100",
    "eval.save_interval": "10"
},
collection_configs=[
    CollectionConfig("weights"),
    CollectionConfig(name="biases",
        parameters={
    "save_interval": "10",
    "end_step": "500",
    "save_histogram": "True"
            }
    )
],
)

For more information about the Debugger configuration APIs, see the Debugger CollectionConfig and DebuggerHookConfig APIs in the Amazon SageMaker Python SDK.

3. Construct a SageMaker estimator with the Debugger parameters passing the configuration objects. The following example template shows how to create a generic SageMaker estimator. You can replace estimator and Estimator with other SageMaker frameworks' estimator parent classes and estimator classes. Available SageMaker framework estimators for this functionality are TensorFlow, PyTorch, and MXNet.

from sagemaker.estimator import Estimator

estimator = Estimator(
    ...
    # Debugger parameters
destructor_hook_config=hook_config,
tensorboard_output_config=tensorboard_output_config
) estimator.fit()

The estimator.fit() method starts a training job, and Debugger writes the output tensor files in real time to the Debugger S3 output path and to the TensorBoard S3 output path. To retrieve the output paths, use the following estimator methods:
• For the Debugger S3 output path, use 
estimator.latest_job_debugger_artifacts_path().
• For the TensorBoard S3 output path, use 
estimator.latest_job_tensorboard_artifacts_path().

4. After the training has completed, check the names of saved output tensors:

from smdebug.trials import create_trial
trial = create_trial(estimator.latest_job_debugger_artifacts_path())
trial.tensor_names()

5. Check the TensorBoard output data in Amazon S3:

tensorboard_output_path=estimator.latest_job_tensorboard_artifacts_path()
print(tensorboard_output_path)
!aws s3 ls {tensorboard_output_path}/

6. Download the TensorBoard output data to your notebook instance. For example, the following AWS CLI command downloads the TensorBoard files to /logs/fit under the current working directory of your notebook instance.

!aws s3 cp --recursive {tensorboard_output_path} ./logs/fit

7. Compress the file directory to a TAR file to download to your local machine.

!tar -cf logs.tar logs

8. Download and extract the Tensorboard TAR file to a directory on your device, launch a Jupyter notebook server, open a new notebook, and run the TensorBoard app.

!tar -xf logs.tar
%load_ext tensorboard
%tensorboard --logdir logs/fit

Profile Training Jobs Using Amazon SageMaker Debugger

To run training jobs with SageMaker Debugger to profile resource utilization status, statistics, and framework operations, add profiler configuration when you construct a SageMaker estimator using the SageMaker Python SDK. Go through the following topics to learn how to use SageMaker Debugger’s profiling functionality.

Topics
• Configure Debugger Using Amazon SageMaker Python SDK (p. 2306)
• Configure Built-in Profiler Rules Managed by Amazon SageMaker Debugger (p. 2315)
• Amazon SageMaker Debugger in Amazon SageMaker Studio (p. 2317)
• SageMaker Debugger Interactive Reports (p. 2333)
• Analyze Data Using the SMDebug Client Library (p. 2357)
Configure Debugger Using Amazon SageMaker Python SDK

To configure Debugger to profile your training job and resource utilization, use Amazon SageMaker Python SDK and specify Debugger-specific parameters while constructing SageMaker estimators. There are two parameters you need to configure: profiler_config and rules.

**Note**
By default, SageMaker Debugger monitors and debugs SageMaker training jobs without any Debugger-specific parameters configured in SageMaker estimators. SageMaker Debugger collects system metrics every 500 milliseconds and basic output tensors (scalar outputs such as loss and accuracy) every 500 steps. It also runs the ProfilerReport rule to analyze the system metrics and aggregate the Studio Debugger insights dashboard and a profiling report. Debugger saves the output data in your secured S3 bucket.

**Important**
To use the new SageMaker Debugger features, you need to upgrade the SageMaker Python SDK and the SMDebug client library. In your iPython kernel, Jupyter Notebook, or JupyterLab environment, run the following code to install the latest versions of the libraries and restart the kernel.

```python
import sys
import IPython
!{sys.executable} -m pip install -U sagemaker smdebug
IPython.Application.instance().kernel.do_shutdown(True)
```

**Construct a SageMaker Estimator with Debugger**

The following example codes show how to construct a SageMaker estimator with the Debugger-specific parameters depending on a framework of your choice. Throughout the documentation in the following topics, you can find more information about how to configure the Debugger-specific parameters that you can mix and match as you want.

**Note**
The following example codes are not directly executable. You need to proceed to the next sections and configure the Debugger-specific parameters.

**PyTorch**

To access the deep profiling feature for PyTorch, currently you need to specify the latest AWS deep learning container images with CUDA 11 and later.

```python
# An example of constructing a SageMaker PyTorch estimator
import boto3
import sagemaker
from sagemaker.pytorch import PyTorch
from sagemaker.debugger import ProfilerConfig, ProfilerRule, rule_configs

session=boto3.session.Session()
region=session.region_name

profiler_config=ProfilerConfig(...)
rules=[
    ProfilerRule.sagemaker(rule_configs.BuiltInRule())
]

estimator=PyTorch(
    entry_point="directory/to/your_training_script.py",
    role=sagemaker.get_execution_role(),
    base_job_name="debugger-profiling-demo",
    )
```
instance_count=1,
instance_type="ml.p3.2xlarge",
framework_version="1.12.0",
py_version="py37",

# SageMaker Debugger parameters
profiler_config=profiler_config,
rules=rules
)

estimator.fit(wait=False)

TensorFlow

To access the deep profiling feature for TensorFlow, currently you need to specify the latest AWS
deep learning container images with CUDA 11 and later.

# An example of constructing a SageMaker TensorFlow estimator
import boto3
import sagemaker
from sagemaker.tensorflow import TensorFlow
from sagemaker.debugger import ProfilerConfig, ProfilerRule, rule_configs

session=boto3.session.Session()
region=session.region_name

profiler_config=ProfilerConfig(...)  
rules=[
    ProfilerRule.sagemaker(rule_configs.BuiltInRule())
]

estimator=TensorFlow(
    entry_point="directory/to/your_training_script.py",
    role=sagemaker.get_execution_role(),
    base_job_name="debugger-profiling-demo",
    instance_count=1,
    instance_type="ml.p3.2xlarge",
    framework_version="2.8.0",
    py_version="py37",

    # SageMaker Debugger parameters
    profiler_config=profiler_config,
    rules=rules
)

estimator.fit(wait=False)

MXNet

# An example of constructing a SageMaker MXNet estimator
import sagemaker
from sagemaker.mxnet import MXNet
from sagemaker.debugger import ProfilerConfig, ProfilerRule, rule_configs

profiler_config=ProfilerConfig(...)  
rules=[
    ProfilerRule.sagemaker(rule_configs.BuiltInRule())
]

estimator=MXNet(
    entry_point="directory/to/your_training_script.py",
    role=sagemaker.get_execution_role(),
    base_job_name="debugger-profiling-demo",

instance_count=1, instance_type="ml.p3.2xlarge", framework_version="1.7.0", py_version="py37",

# SageMaker Debugger parameters
profiler_config=profiler_config, rules=rules
)
estimator.fit(wait=False)

**Note**
For MXNet, when configuring the profiler_config parameter, you can only configure for system monitoring. Profiling framework metrics is not supported for MXNet.

**XGBoost**

# An example of constructing a SageMaker XGBoost estimator
import sagemaker
from sagemaker.xgboost.estimator import XGBoost
from sagemaker.debugger import ProfilerConfig, ProfilerRule, rule_configs
profiler_config=ProfilerConfig(...) rules=[
    ProfilerRule.sagemaker(rule_configs.BuiltInRule())
]
estimator=XGBoost(
    entry_point="directory/to/your_training_script.py", role=sagemaker.get_execution_role(), base_job_name="debugger-profiling-demo", instance_count=1, instance_type="ml.p3.2xlarge", framework_version="1.5-1",

    # Debugger-specific parameters
    profiler_config=profiler_config, rules=rules
)
estimator.fit(wait=False)

**Note**
For XGBoost, when configuring the profiler_config parameter, you can only configure for system monitoring. Profiling framework metrics is not supported for XGBoost.

**Generic estimator**

# An example of constructing a SageMaker generic estimator using the XGBoost algorithm
import boto3
import sagemaker
from sagemaker.estimator import Estimator
from sagemaker import image_uris
from sagemaker.debugger import ProfilerConfig, DebuggerHookConfig, Rule, ProfilerRule, rule_configs
profiler_config=ProfilerConfig(...) rules=[
    ProfilerRule.sagemaker(rule_configs.BuiltInRule())
]
region=boto3.Session().region_name
xgboost_container=sagemaker.image_uris.retrieve("xgboost", region, "1.5-1")

estimator=Estimator(
    role=sagemaker.get_execution_role(),
    image_uri=xgboost_container,
    base_job_name="debugger-demo",
    instance_count=1,
    instance_type="ml.m5.2xlarge",

    # Debugger-specific parameters
    profiler_config=profiler_config,
    rules=rules
)

estimator.fit(wait=False)

Where you configure the following parameters:

- **profiler_config parameter** – Configure Debugger to collect system metrics and framework metrics from your training job and save into your secured S3 bucket URI or local machine. To learn how to configure the profiler_config parameter, see Configure Debugger Monitoring Hardware System Resource Utilization (p. 2309) and Configure Debugger Framework Profiling (p. 2310).

- **rules parameter** – Configure this parameter to enable Debugger built-in rules that you want to run in parallel. The rules automatically analyze your training job and find training issues. The ProfilerReport rule saves the Debugger profiling reports in your secured S3 bucket. To learn how to configure the rules parameter, see Configure Debugger Built-in Rules (p. 2287).

**Note**

Debugger securely saves output data in subfolders of your default S3 bucket. For example, the format of the default S3 bucket URI is s3://sagemaker-<region>-<12digit_account_id>/<base-job-name>/debugger-subfolders/. There are three subfolders created by Debugger: debug-output, profiler-output, and rule-output. You can also retrieve the default S3 bucket URIs using the SageMaker estimator classmethods (p. 2293).

See the following topics to find out how to configure the Debugger-specific parameters in detail.

**Topics**

- Configure Debugger Monitoring Hardware System Resource Utilization (p. 2309)
- Configure Debugger Framework Profiling (p. 2310)
- Updating Debugger System Monitoring and Framework Profiling Configuration while a Training Job is Running (p. 2313)
- Turn Off Debugger (p. 2314)

**Configure Debugger Monitoring Hardware System Resource Utilization**

To adjust Debugger system monitoring time intervals, use the ProfilerConfig API operation to create a parameter object while constructing a SageMaker framework or generic estimator depending on your preference.

**Note**

By default, for all SageMaker training jobs, Debugger collects hardware system utilization data from Amazon EC2 instances every 500 milliseconds for system monitoring, without any Debugger-specific parameters specified in SageMaker estimators.
Debugger saves the system metrics in a default S3 bucket. The format of the default S3 bucket URI is s3://sagemaker-<region>-<12digit_account_id>/<training-job-name>/profiler-output/.

The following example code shows how to set up the profiler_config parameter with a system monitoring time interval of 1000 milliseconds.

```python
from sagemaker.debugger import ProfilerConfig
profiler_config=ProfilerConfig(
    system_monitor_interval_millis=1000
)
```

- `system_monitor_interval_millis` (int) – Specify the monitoring intervals in milliseconds to record system metrics. Available values are 100, 200, 500, 1000 (1 second), 5000 (5 seconds), and 60000 (1 minute) milliseconds. The default value is 500 milliseconds.

To see the progress of system monitoring, see Open the Amazon SageMaker Debugger Insights Dashboard (p. 2317).

### Configure Debugger Framework Profiling

To enable Debugger framework profiling, configure the framework_profile_params parameter when you construct an estimator. Debugger framework profiling collects framework metrics, such as data from initialization stage, data loader processes, Python operators of deep learning frameworks and training scripts, detailed profiling within and between steps, with cProfile or Pyinstrument options. Using the FrameworkProfile class, you can configure custom framework profiling options.

**Note**

Before getting started with Debugger framework profiling, verify that the framework used to build your model is supported by Debugger for framework profiling. For more information, see Supported Frameworks and Algorithms (p. 2260). Debugger saves the framework metrics in a default S3 bucket. The format of the default S3 bucket URI is s3://sagemaker-<region>-<12digit_account_id>/<training-job-name>/profiler-output/.

### Start a Training Job with the Default System Monitoring and Framework Profiling

The following example code is the simplest profiler_config parameter setting to start the default system monitoring and the default framework profiling. The FrameworkProfile class in the following example code initiates the default framework profiling when a training job starts. Debugger framework profiling includes the following options: detailed profiling, data loader profiling, and Python profiling.

```python
from sagemaker.debugger import ProfilerConfig, FrameworkProfile
profiler_config=ProfilerConfig(
    framework_profile_params=FrameworkProfile()
)
```

With this profiler_config parameter configuration, Debugger calls the default settings of monitoring and profiling. Debugger monitors system metrics every 500 milliseconds; profiles the fifth step with the detailed profiling option; the seventh step with the data loader profiling option; and the ninth, tenth, and eleventh steps with the Python profiling option.

To find available profiling configuration options, the default parameter settings, and examples of how to configure them, see Start a Training Job with the Default System Monitoring and Customized Framework Profiling.
If you want to change the system monitoring interval and enable the default framework profiling, you can specify the `system_monitor_interval_millis` parameter explicitly with the `framework_profile_params` parameter. For example, to monitor every 1000 milliseconds and enable the default framework profiling, use the following example code.

```python
from sagemaker.debugger import ProfilerConfig, FrameworkProfile
profiler_config=ProfilerConfig(
    system_monitor_interval_millis=1000,
    framework_profile_params=FrameworkProfile()
)
```

For more information about the `FrameworkProfile` class, see SageMaker Debugger APIs – FrameworkProfile in the Amazon SageMaker Python SDK.

### Start a Training Job with the Default System Monitoring and Customized Framework Profiling for Target Steps or a Target Time Range

If you want to specify target steps or target time intervals to profile your training job, you need to specify parameters for the `FrameworkProfile` class. The following code examples show how to specify the target ranges for profiling along with system monitoring.

- **For a target step range**

  With the following example configuration, Debugger monitors the entire training job every 500 milliseconds (the default monitoring) and profiles a target step range from step 5 to step 15 (for 10 steps).

  ```python
  from sagemaker.debugger import ProfilerConfig, FrameworkProfile
  profiler_config=ProfilerConfig(
      framework_profile_params=FrameworkProfile(start_step=5, num_steps=10)
  )
  ```

  With the following example configuration, Debugger monitors the entire training job every 1000 milliseconds and profiles a target step range from step 5 to step 15 (for 10 steps).

  ```python
  from sagemaker.debugger import ProfilerConfig, FrameworkProfile
  profiler_config=ProfilerConfig(
      system_monitor_interval_millis=1000,
      framework_profile_params=FrameworkProfile(start_step=5, num_steps=10)
  )
  ```

- **For a target time range**

  With the following example configuration, Debugger monitors the entire training job every 500 milliseconds (the default monitoring) and profiles a target time range from the current Unix time for 600 seconds.

  ```python
  import time
  from sagemaker.debugger import ProfilerConfig, FrameworkProfile
  profiler_config=ProfilerConfig(
      framework_profile_params=FrameworkProfile(start_unix_time=int(time.time()),
      duration=600)
  )
  ```
With the following example configuration, Debugger monitors the entire training job every 1000 milliseconds and profiles a target time range from the current Unix time for 600 seconds.

```python
import time
from sagemaker.debugger import ProfilerConfig, FrameworkProfile

profiler_config=ProfilerConfig(
    system_monitor_interval_millis=1000,
    framework_profile_params=FrameworkProfile(start_unix_time=int(time.time()),
                                              duration=600)
)
```

The framework profiling is performed for all of the profiling options at the target step or time range.

To find more information about available profiling options, see SageMaker Debugger APIs – FrameworkProfile in the Amazon SageMaker Python SDK.

The next section shows you how to script the available profiling options.

### Start a Training Job with the Default System Monitoring and Customized Framework Profiling with Different Profiling Options

You can use the following profiling configuration classes to manage the framework profiling options:

- **DetailedProfilingConfig** – Specify a target step or time range to profile framework operations using the native framework profilers (TensorFlow profiler and PyTorch profiler). For example, if using TensorFlow, the Debugger hooks enable the TensorFlow profiler to collect TensorFlow-specific framework metrics. Detailed profiling enables you to profile all framework operators at a pre-step (before the first step), within steps, and between steps of a training job.

  **Note**
  Detailed profiling might significantly increase GPU memory consumption. We do not recommend enabling detailed profiling for more than a couple of steps.

- **DataloaderProfilingConfig** – Specify a target step or time range to profile deep learning framework data loader processes. Debugger collects every data loader event of the frameworks.

  **Note**
  Data loader profiling might lower the training performance while collecting information from data loaders. We don't recommend enabling data loader profiling for more than a couple of steps.
  Debugger is preconfigured to annotate data loader processes only for the AWS deep learning containers. Debugger cannot profile data loader processes from any other custom or external training containers.

- **PythonProfilingConfig** – Specify a target step or time range to profile Python functions. You can also choose between two Python profilers: cProfile and Pyinstrument.

  - **cProfile** – The standard Python profiler. cProfile collects information for every Python operator called during training. With cProfile, Debugger saves cumulative time and annotation for each function call, providing complete detail about Python functions. In deep learning, for example, the most frequently called functions might be the convolutional filters and backward pass operators, and cProfile profiles every single of them. For the cProfile option, you can further select a timer option: total time, CPU time, and off-CPU time. While you can profile every function call executing on processors (both CPU and GPU) in CPU time, you can also identify I/O or network bottlenecks with the off-CPU time option. The default is total time, and Debugger profiles both CPU and off-CPU time. With cProfile, you are able to drill down to every single functions when analyzing the profile data.
• **Pyinstrument** – Pyinstrument is a low-overhead Python profiler that works based on sampling. With the Pyinstrument option, Debugger samples profiling events every millisecond. Because Pyinstrument measures elapsed wall-clock time instead of CPU time, the Pyinstrument option can be a better choice over the cProfile option for reducing profiling noise (filtering out irrelevant function calls that are cumulatively fast) and capturing operators that are actually compute intensive (cumulatively slow) for training your model. With Pyinstrument, you are able to see a tree of function calls and better understand the structure and root cause of the slowness.

**Note**

Enabling Python profiling might slow down the overall training time. cProfile profiles the most frequently called Python operators at every call, so the processing time on profiling increases with respect to the number of calls. For Pyinstrument, the cumulative profiling time increases with respect to time because of its sampling mechanism.

The following example configuration shows the full structure when you use the different profiling options with specified values.

```python
import time
from sagemaker.debugger import (ProfilerConfig,
                               FrameworkProfile,
                               DetailedProfilingConfig,
                               DataloaderProfilingConfig,
                               PythonProfilingConfig,
                               PythonProfiler, cProfileTimer)

profiler_config=ProfilerConfig(
    system_monitor_interval_millis=500,
    framework_profile_params=FrameworkProfile(
        detailed_profiling_config=DetailedProfilingConfig(
            start_step=5,
            num_steps=1
        ),
        dataloader_profiling_config=DataloaderProfilingConfig(
            start_step=7,
            num_steps=1
        ),
        python_profiling_config=PythonProfilingConfig(
            start_step=9,
            num_steps=1,
            python_profiler=PythonProfiler.CPROFILE,
            cprofile_timer=cProfileTimer.TOTAL_TIME
        )
    )
)
```

For more information about available profiling options, see [DetailedProfilingConfig](https://github.com/aws/sagemaker-py-sdk), [DataloaderProfilingConfig](https://github.com/aws/sagemaker-py-sdk), and [PythonProfilingConfig](https://github.com/aws/sagemaker-py-sdk) in the Amazon SageMaker Python SDK.

**Updating Debugger System Monitoring and Framework Profiling Configuration while a Training Job is Running**

If you want to enable or update the Debugger monitoring and profiling configuration for a training job that is currently running, use the following SageMaker estimator extension methods:

- To enable Debugger system monitoring for a running training job and receive a Debugger profiling report, use the following:

```python
estimator.enable_default_profiling()
```
When you use the `enable_default_profiling` method, Debugger initiates the default system monitoring and the `ProfileReport` built-in rule, which generates a comprehensive profiling report at the end of the training job. This method can be called only if the current training job is running without both Debugger monitoring and profiling.

For more information, see `estimator.enable_default_profiling` in the Amazon SageMaker Python SDK.

- To enable Debugger built-in rules, system monitoring, and framework profiling with customizable configuration parameters, use the following:

```
estimator.update_profiler(  
    rules=[ProfilerRule.sagemaker(rule_configs.BuiltInRule()),  
          ProfilerRule.sagemaker(rule_configs.SystemMonitoringRule(system_monitor_interval_millis=500)),  
          ProfilerRule.sagemaker(rule_configs.FrameworkProfileProfile())  
)
```

For more information, see `estimator.update_profiler` in the Amazon SageMaker Python SDK.

**Turn Off Debugger**

If you want to completely turn off Debugger, do one of the following:

- Before starting a training job, do the following:

  To turn off profiling, include the `disable_profiler` parameter to your estimator and set it to `True`.

  **Warning**
  
  If you disable it, you won't be able to view the comprehensive Studio Debugger insights dashboard and the autogenerated profiling report.

  To turn off debugging, set the `debugger_hook_config` parameter to `False`.

  **Warning**
  
  If you disable it, you won't be able to collect output tensors and cannot debug your model parameters.

```
estimator=Estimator(    
    ...    
    disable_profiler=True    
    debugger_hook_config=False
)
```

For more information about the Debugger-specific parameters, see `SageMaker Estimator` in the Amazon SageMaker Python SDK.

- While a training job is running, do the following:

  To disable both monitoring and profiling while your training job is running, use the following estimator classmethod:

  ```python
  estimator.disable_profiling()
  ```

  To disable framework profiling only and keep system monitoring, use the `update_profiler` method:

  ```python
  estimator.update_profiler(disable_framework_metrics=True)
  ```
For more information about the estimator extension methods, see the `estimator.disable_profiling` and `estimator.update_profiler` classmethods in the Amazon SageMaker Python SDK documentation.

### Configure Built-in Profiler Rules Managed by Amazon SageMaker Debugger

Amazon SageMaker Debugger's built-in profiler rules analyze system metrics and framework operations collected during the training of a model. Debugger offers the `ProfilerRule` API operation that helps configure the rules to monitor training job progress and detect anomalies. For example, the rules can detect whether gradients are getting too large or too small, whether a model is overfitting or overtraining, and whether a training job does not decrease loss function and improve. To see a full list of available built-in rules, see the `List of Debugger Built-in Rules` (p. 2365).

**Note**
The built-in rules are prepared in Amazon SageMaker processing containers and fully managed by SageMaker Debugger. By default, Debugger initiates the `ProfilerReport` (p. 2368) rule for all SageMaker training jobs, without any Debugger-specific rule parameter specified to the SageMaker estimators. The `ProfilerReport` rule invokes all of the following built-in rules for monitoring system bottlenecks and profiling framework metrics:

- BatchSize (p. 2369)
- CPUBottleneck (p. 2370)
- GPUMemoryIncrease (p. 2371)
- IOBottleneck (p. 2372)
- LoadBalancing (p. 2374)
- LowGPUUtilization (p. 2374)
- OverallSystemUsage (p. 2376)
- MaxInitializationTime (p. 2376)
- OverallFrameworkMetrics (p. 2377)
- StepOutlier (p. 2377)

Debugger saves the profiling report in a default S3 bucket. The format of the default S3 bucket URI is `s3://sagemaker-<region>-<12digit_account_id>/<training-job-name>/rule-output/`. For more information about how to download the profiling report, see the `SageMaker Debugger Profiling Report` (p. 2334). SageMaker Debugger fully manages the built-in rules and analyzes your training job in parallel. For more information about billing, see the `Amazon SageMaker Studio is available at no additional charge` section of the Amazon SageMaker Pricing page.

In the following topics, learn how to use the Debugger built-in rules.

**Topics**
- Use Debugger Built-in Profiler Rules with the Default Parameter Settings (p. 2315)
- Use Debugger Built-in Profiler Rules with Custom Parameter Values (p. 2316)

### Use Debugger Built-in Profiler Rules with the Default Parameter Settings

To specify Debugger built-in rules in an estimator, you need to configure a `rules` list object. The following example code shows the basic structure of listing the Debugger built-in rules:

```python
from sagemaker.debugger import Rule, ProfilerRule, rule_configs
```
For example, to inspect the overall training performance and progress of your model, construct a SageMaker estimator with the following built-in rule configuration.

```python
from sagemaker.debugger import Rule, rule_configs

rules=
    ProfilerRule.sagemaker(rule_configs.BuiltInProfilerRuleName_1()),
    ProfilerRule.sagemaker(rule_configs.BuiltInProfilerRuleName_2()),
    ...
    ProfilerRule.sagemaker(rule_configs.BuiltInProfilerRuleName_n()),
    ...
# You can also append more debugging rules in the Rule.sagemaker(rule_configs.*())
format.
```

When you start the training job, Debugger collects system resource utilization data every 500 milliseconds and the loss and accuracy values every 500 steps by default. Debugger analyzes the resource utilization to identify if your model is having bottleneck problems. The loss_not_decreasing, overfit, overtraining, and stalled_training_rule monitors if your model is optimizing the loss function without those training issues. If the rules detect training anomalies, the rule evaluation status changes to IssueFound. You can set up automated actions, such as notifying training issues and stopping training jobs using Amazon CloudWatch Events and AWS Lambda. For more information, see Action on Amazon SageMaker Debugger Rules (p. 2293).

Use Debugger Built-in Profiler Rules with Custom Parameter Values

If you want to adjust the built-in rule parameter values and customize tensor collection regex, configure the base_config and rule_parameters parameters for the ProfilerRule.sagemaker and Rule.sagemaker class methods. In case of the Rule.sagemaker class methods, you can also customize tensor collections through the collections_to_save parameter. The instruction of how to use the CollectionConfig class is provided at Configure Tensor Collections Using the CollectionConfig API (p. 2282).

Use the following configuration template for built-in rules to customize parameter values. By changing the rule parameters as you want, you can adjust the sensitivity of the rules to be triggered.

- The base_config argument is where you call the built-in rule methods.
- The rule_parameters argument is to adjust the default key values of the built-in rules listed in List of Debugger Built-in Rules (p. 2365).

For more information about the Debugger rule class, methods, and parameters, see SageMaker Debugger Rule class in the Amazon SageMaker Python SDK.

```python
from sagemaker.debugger import Rule, ProfilerRule, rule_configs, CollectionConfig

rules=[
    ProfilerRule.sagemaker(
        base_config=rule_configs.BuiltInProfilerRuleName(),
        rule_parameters={
            "key": "value"
        }
    )
]"
The parameter descriptions and value customization examples are provided for each rule at List of Debugger Built-in Rules (p. 2365).

For a low-level JSON configuration of the Debugger built-in rules using the CreateTrainingJob API, see Configure Debugger Using Amazon SageMaker API (p. 2415).

### Amazon SageMaker Debugger in Amazon SageMaker Studio

Use the Amazon SageMaker Debugger dashboards in Amazon SageMaker Studio to analyze your model performance and system bottlenecks while running training jobs on Amazon Elastic Compute Cloud (Amazon EC2) instances. Gain insights into your training jobs and improve your model training performance and accuracy with the Debugger dashboards. By default, Debugger monitors system metrics (CPU, GPU, CPU and GPU memory, network, and data I/O) every 500 milliseconds and basic output tensors (loss and accuracy) every 500 iterations for training jobs. You can also further customize Debugger configuration parameter values and adjust the saving intervals through the Studio UI or using the Amazon SageMaker Python SDK.

**Important**

If you’re using existing Studio apps, restart them to use the new features. For instructions on how to restart and update your Studio environment, see Update Amazon SageMaker Studio.

### Topics

- Open the Amazon SageMaker Debugger Insights Dashboard (p. 2317)
- Amazon SageMaker Debugger Insights Dashboard Controller (p. 2319)
- Amazon SageMaker Debugger Insights Dashboard (p. 2323)
- Shut Down the Amazon SageMaker Debugger Insights Instance (p. 2330)
- Amazon SageMaker Debugger in Studio Experiments (p. 2331)

### Open the Amazon SageMaker Debugger Insights Dashboard

Open the Debugger insights dashboard in Studio to see profiling progress, results of resource utilization, and system bottlenecks of your training job running on Amazon EC2 instances.
Note
The Studio Debugger insights dashboard runs a Studio app on an ml.m5.4xlarge instance to process and render the visualizations. Each Debugger insights tab runs one Studio kernel session. Multiple kernel sessions for multiple Debugger insights tabs run on the single instance. When you close a Debugger insights tab, the corresponding kernel session is also closed. The Studio app remains active and accrues charges for the ml.m5.4xlarge instance usage. For information about pricing, see the Amazon SageMaker Pricing page.

Important
When you are done using the Debugger insights dashboard, you must shut down the ml.m5.4xlarge instance to avoid accruing charges. For instructions on how to shut down the instance, see Shut Down the Amazon SageMaker Debugger Insights Instance (p. 2330).

To open the Debugger insights dashboard
1. Choose the SageMaker Components and registries icon (.Mapper).
2. Open the dropdown list, and choose Experiments and trials.
3. Look up your training job name. If you have not assigned a SageMaker Experiments trial component to the training job, the job is collected under the Unassigned trial components list.
4. Right-click (or an equivalent UI interaction) to open the context menu of the training job trial component. There are two menu items to access the Debugger features in Studio: Open Debugger for insights and Open in trial details.
5. Choose Open Debugger for insights. This opens a Debug [your-training-job-name] tab. On this tab, Debugger provides an overview of your model training performance on Amazon EC2 instances and identifies system bottleneck problems. While monitoring the system resource utilization, you can also enable profiling to capture framework metrics that consist of data from neural network operations executed during the forward and backward pass and data loading. For more information about how to enable profiling using the Debugger insights dashboard controller, see Enable and Configure Debugger Profiling for Detailed Insights (p. 2319).

Debugger correlates the system resource utilization metrics with the framework metrics and helps identify resource-intensive operators that might be the root cause of the system bottlenecks. You can
also download an aggregated Debugger profiling report. For more information, see Amazon SageMaker Debugger Insights Dashboard Controller (p. 2319).

Amazon SageMaker Debugger Insights Dashboard Controller

There are different components of the Debugger controller for monitoring and profiling. In this guide, you learn about the Debugger controller components.

**Note**
The Studio Debugger insights dashboard runs a Studio app on an ml.m5.4xlarge instance to process and render the visualizations. Each Debugger insights tab runs one Studio kernel session. Multiple kernel sessions for multiple Debugger insights tabs run on the single instance. When you close a Debugger insights tab, the corresponding kernel session is also closed. The Studio app remains active and accrues charges for the ml.m5.4xlarge instance usage. For information about pricing, see the Amazon SageMaker Pricing page.

**Important**
When you are done using the Debugger insights dashboard, shut down the ml.m5.4xlarge instance to avoid accruing charges. For instructions on how to shut down the instance, see Shut Down the Amazon SageMaker Debugger Insights Instance (p. 2330).

SageMaker Debugger Insights Controller UI

Using the Debugger controller located at the upper-left corner of the insights dashboard, you can refresh the dashboard, configure or update Debugger settings for monitoring system metrics and profiling framework metrics, stop a training job, and download a Debugger profiling report.

- If you want to manually refresh the **Debug [your-training-job-name]** page, choose the refresh button (the round arrow at the upper-left corner) as shown in the preceding screenshot.
- **Monitoring** is on by default for any SageMaker training job. By monitoring your training job, Debugger only collects system metrics to detect resource utilization problems, such as CPU bottlenecks and GPU underutilization. For a complete list of resource utilization problems that Debugger monitors, see Debugger Built-in Rules for Monitoring Hardware System Resource Utilization (System Metrics) (p. 2366).
- To download a comprehensive Debugger profiling report with details and analysis of a training job, choose **Download report**. For more information about the Debugger profiling report, see SageMaker Debugger Profiling Report (p. 2334).

Enable and Configure Debugger Profiling for Detailed Insights

When you enable **Profiling**, Debugger starts collecting framework metrics. Framework metrics are model data collected from the ML framework operations of your model, such as forward pass, backward pass, batch normalization, and data loader processes. Debugger correlates system performance bottlenecks with the framework operations and runs the Debugger Built-in Rules for Profiling Framework Metrics (p. 2366).
Note
After you've enabled profiling, Debugger collects every framework operation call that's executed in each step: operations for convolving down input layers during forward pass, updating weights of millions of neurons during backward pass, and data loader processes. While profiling can help you understand model performance at a deeper level, collecting framework metrics might impact your training time and performance. We recommend that you enable profiling to inspect your model up to two steps at a time. For more information about how to configure Debugger for framework profiling using Amazon SageMaker Python SDK, see Configure Debugger Framework Profiling (p. 2310) and Updating Debugger System Monitoring and Framework Profiling Configuration while a Training Job is Running (p. 2313).

If you want to enable profiling while your training job is running, use the following steps to start profiling.

1. In Studio, turn on Profiling to enable Debugger framework profiling. This opens a Debugger monitoring and profiling configuration page.

2. The Configure Debugger monitoring and profiling, S3 bucket URI and Collect monitoring data every fields are already set to the default values.

You can choose to change the monitoring interval using the dropdown list. Select from the following available options: 100 milliseconds, 200 milliseconds, 500 milliseconds (default), 1 second, 5 seconds, and 1 minute.
Specify values for the following fields:

- **S3 bucket URI**: Specify the base S3 bucket URI.
- **Collect monitoring data every**: Select a time interval to collect system metrics.

  **Note**
  If you choose one of the lower time intervals, you increase the granularity of monitoring system metrics. It allows you to capture spikes and anomalies with a higher time resolution. However, as the size of system metrics to process proportionally increases, it might impact the overall training and processing time.

3. In **Advanced settings for profiling**, configure framework metrics profiling options. Specify **Start step** (or **Start time**) and **Number of steps to profile** (or **Time duration to profile**) to profile. You can also leave the input fields blank. The default values are automatically configured to use the current step and for 1-step duration.
• **Detailed profiling**: Specify a target step or time range to profile framework operations using the native framework profilers (TensorFlow profiler and PyTorch profiler). For example, if you’re using TensorFlow, the Debugger hooks enable the TensorFlow profiler to collect TensorFlow-specific framework metrics. Detailed profiling enables you to profile all framework operators at a pre-step (before the first step), within steps, and between steps of a training job.

**Note**
The detailed profiling might significantly increase GPU memory consumption. It is not recommended to enable the detailed profiling for more than a couple of steps.

• **Python profiling**: Specify a target step or time range to profile Python functions. You can also choose between two Python profilers: cProfile and Pyinstrument.
  
  • **cProfile** – The standard Python profiler. cProfile collects for every Python operator called during training. With cProfile, Debugger saves cumulative time and annotation of each function call, providing a complete detail of Python functions. In deep learning, for example, the most frequently called functions might be the convolutional filters and backward pass operators, and cProfile profiles every single of them. For the cProfile option, you can further select a timer option: total time, CPU time, and off-CPU time. While you can profile every function calls executing on processors (both CPU and GPU) in CPU time, you can also identify I/O or network bottlenecks with the off-CPU time option. The default is total time, and Debugger profiles both CPU and off-CPU time. With cProfile, you are able to drill down to every single functions when analyzing the profile data.
  
  • **Pyinstrument** – Pyinstrument is a low overhead Python profiler that works based on sampling. With the Pyinstrument option, Debugger samples profiling events every millisecond. Because Pyinstrument measures elapsed wallclock time instead of CPU time, the Pyinstrument option can be a better choice over the cProfile option for reducing profiling noises (filtering out irrelevant function calls that are cumulatively fast) and capturing operators that are actually compute intensive (cumulatively slow) for training your model. With Pyinstrument, you are able to see a tree of function calls and better understand the structure and root cause of the slowness.

**Note**
Enabling Python profiling might result in slowing down the overall training time. In case of cProfile, Python operators that are the most frequently called are profiled at every call, so the processing time on profiling increases with respect to the number of calls. For Pyinstrument, the cumulative profiling time increases with respect to time because of its sampling mechanism.

• **Dataloader profiling**: Specify a target step or time range to profile deep learning framework data loader processes. Debugger collects every data loader event of the frameworks.
Note
The data loader profiling can lower the training performance while collecting information from data loaders. We don't recommend that you enable the data loader profiling for more than a couple of steps.
Debugger is pre-configured to annotate data loader processes only for the AWS deep learning containers. Debugger cannot profile data loader processes on any other custom or external containers.

4. Choose Confirm to finish your profiling configuration. When the configuration is successfully updated, you should be able to see a Debugger configuration updated successfully confirmation message, as shown in following image.

Amazon SageMaker Debugger Insights Dashboard

When you initiate a SageMaker training job, Debugger starts monitoring hardware system resource utilization of Amazon EC2 instances by default. You can track the system utilization rate, statistics overview, and bottleneck detection status through the insights dashboard. This guide walks you through the content of the Debugger insights dashboard under the following tabs: Overview, Nodes, and Model insights.

Note
The Studio Debugger insights dashboard runs a Studio app on an ml.m5.4xlarge instance to process and render the visualizations. Each Debugger insights tab runs one Studio kernel session. Multiple kernel sessions for multiple Debugger insights tabs run on the single instance. When you close a Debugger insights tab, the corresponding kernel session is also closed. The Studio app remains active and accrues charges for the ml.m5.4xlarge instance usage. For information about pricing, see the Amazon SageMaker Pricing page.

Important
When you are done using the Debugger insights dashboard, shut down the ml.m5.4xlarge instance to avoid accruing charges. For instructions on how to shut down the instance, see Shut Down the Amazon SageMaker Debugger Insights Instance (p. 2330).

Important
In the reports, plots and recommendations are provided for informational purposes and are not definitive. You are responsible for making your own independent assessment of the information.

Topics
- Debugger Insights – Overview (p. 2323)
- Debugger Insights – Nodes (p. 2326)
- Debugger Insights – Model Insights (p. 2329)

Debugger Insights – Overview

On the Overview tab, you can find a training job summary, resource utilization summary, resource intensive operations, and insights.

Training job summary

The Training job summary section shows the overall training time spent on different phases of training: initialization, training loop, and finalization. The pie chart shows the time usage percentage and absolute time amount spent on the different training phases. For example, you can have a high-level overview of
how long it takes for initializing a training job, check if the initialization is taking too long due to data downloading, leaving the GPUs idle.

This section has the following features:

- The **Training progress over time** chart shows the timeline of the different training phases over time. If you’re using spot training, you can also find the spot interruptions in the timeline chart.
- The **Training job details** panel shows the exact time stamps and utilization rate percentage numbers.
  - **Start time**: The exact time when the training job started.
  - **End time**: The exact time when the training job finished.
  - **Job duration**: The total training time from the **Start time** to the **End time**.
  - **Training loop start**: The exact time when the first step of the first epoch has started.
  - **Training loop end**: The exact time when the last step of the last epoch has finished.
  - **Training loop duration**: The total time between the training loop start time and the training loop end time.
  - **Initialization**: Time spent on initializing the training job, such as compiling the training script, initiating Amazon EC2 instances, and downloading training data.
  - **Finalization**: Time spent on finalizing the training job, such as finishing the model training, updating the model artifacts, and closing the Amazon EC2 instances.
  - **Initialization (%)**: The percentage of time spent on **Initialization** over the total **Job duration**.
  - **Training loop (%)**: The percentage of time spent on **Training loop** over the total **Job duration**.
  - **Finalization (%)**: The percentage of time spent on **Finalization** over the total **Job duration**.

**Resource utilization summary**

This summary table shows hardware system resource utilization statistics of all workers (algo-n). System metrics include total CPU utilization, total GPU utilization, total CPU memory utilization, total GPU memory utilization, total I/O wait time, and total network in bytes. The table shows the minimum and the maximum values, and p99, p90, and p50 percentiles.
The **Resource intensive operations** section provides more detailed profiling results that show which training job operations were compute intensive. In the following example, it shows that the convolutional neural network backward pass operators were the most resource intensive on the GPUs.

<table>
<thead>
<tr>
<th>Top operations on GPU</th>
<th>Cumulative time</th>
<th>GPU operator</th>
</tr>
</thead>
<tbody>
<tr>
<td>34.51</td>
<td>13905349</td>
<td>CudnnConvolutionBackward</td>
</tr>
<tr>
<td>34.48</td>
<td>15895879</td>
<td>cudnn_convolution_backward</td>
</tr>
<tr>
<td>6.13</td>
<td>2469970</td>
<td>conv2d</td>
</tr>
<tr>
<td>6.11</td>
<td>2460408</td>
<td>convolution</td>
</tr>
<tr>
<td>6.08</td>
<td>2450894</td>
<td>_convolution</td>
</tr>
<tr>
<td>6.03</td>
<td>2431585</td>
<td>cudnn_convolution</td>
</tr>
<tr>
<td>3.35</td>
<td>1351617</td>
<td>CudnnBatchNormBackward</td>
</tr>
<tr>
<td>3.31</td>
<td>1332746</td>
<td>cudnn_batch_norm_backward</td>
</tr>
</tbody>
</table>

**Insights**

In the **Insights** pane, you can find training issues detected by Debugger built-in rules. You can expand each entry in the list to find useful insights, suggestions, a description of the rule, and criteria for initiating the rule.

For more information about the Debugger built-in rules, see [List of Debugger Built-in Rules](p. 2365).
On the Nodes tab, Debugger provides detailed graphs that track each compute node on which your training jobs are running.

CPU and Network utilization

The first two graphs show CPU utilization and network utilization over time. By default, the graphs show the mean values: the average of CPU and network utilization over the total number of CPU cores. You can select one or more CPU cores by selecting the labels to graph them on a single chart and compare utilization across cores. The timeline graphs are interactive, and the two graphs are synced up. You can drag and zoom in and out to get a closer look at specific time windows.
The following graphs show GPU utilization and GPU memory utilization over time. By default, the graphs show the mean utilization rate over time. You can select the GPU core labels to see the utilization rate of each core. Taking the mean of utilization rate over the total number of GPU cores shows the mean utilization of the entire hardware system resource. By looking at the mean utilization rate, you can check the overall system resource usage of an Amazon EC2 instance. The following figure shows an example training job on an ml.p3.16xlarge instance with 8 GPU cores. You can monitor if the training job is well distributed, fully utilizing all GPUs.
Overall system utilization over time

The following heatmap shows the entire system utilization over time projected onto the two-dimensional plot. Every CPU and GPU core is listed in the vertical axis, and the utilization is recorded over time with colors. See the labeled colorbar on the right side of the plot to find out which color level corresponds to which utilization rate. For example, in the following heatmap, after the initialization phase has ended, around Sun 23:18, you can find that the training job fully utilizes an ml.p3.16xlarge instance: the GPU cores are fully utilized and the CPUs are moderately used for processing Python operations. There were several CPU bottleneck problems scattered across the CPUs at different times.

System resource utilization over time and framework event phase

The **System metrics over time** graph shows the overall CPU, GPU, and data I/O utilization. The **Framework metrics over time** graph shows the framework metrics, which are the framework event phases that you can correlate with the **System metrics over time** graph.

You can select a time interval of interest in the system resource usage timeline, and the framework event phase spots the interval to show what events happened during the selected time interval. In each event phase block, you can find which time interval was actually spent for the training loop and break the training loop into backward pass and forward pass events. Overall, you can see that actual training time intervals are occupying only a small percentage over the entire training time.
Time spent in training

The following graph shows framework metrics from the last 30 steps of the last training loop, with cumulative time spent by different events in each step.

Debugger Insights – Model Insights

On the Model insights tab, you can browse autogenerated training reports for SageMaker XGBoost training jobs. The report provides insights into XGBoost training jobs, such as improvement in accuracy over time, loss value with respect to iteration, class imbalance, and other statistics to evaluate model performance. Depending on the type of supervised learning (binary classification, multi classification,
and regression), the **Model insights** tab is rendered automatically based on the Debugger's XGBoost training HTML report.

**Note**
This feature is available for SageMaker XGBoost training jobs. The training jobs must be initiated using the SageMaker XGBoost training containers version 1.2-1 or later.

**Note**
In the report, plots and recommendations are provided for informational purposes only and are not definitive. You are responsible for making your own independent assessment of the information.

To load model insights content, enable the CreateXgboostReport (p. 2378) rule when you start the training job. For more information about enabling the rule through the SageMaker estimator, see Construct a SageMaker XGBoost Estimator with the Debugger XGBoost Report Rule (p. 2345).

For more information about the content on the model insights tab, see Debugger XGBoost Training Report Walkthrough.

To download the HTML report, follow the instructions at Download the Debugger XGBoost Training Report.

The following GIF image shows an example view of the **Model insights** tab for a SageMaker XGBoost training job.

![Model insights tab example](image)

**Shut Down the Amazon SageMaker Debugger Insights Instance**

When you are not using the Debugger insights dashboard, shut down the instance on which it runs to avoid incurring additional fees.

**To shut down the Debugger insights instance in Studio**
1. In Studio, select the **Running Instances and Kernels** icon.

2. Under the **RUNNING APPS** list, look for the **sagemaker-debugger-1.0** app. Select the shutdown icon next to the app. The Debugger insights dashboards run on an `ml.m5.4xlarge` instance. This instance also disappears from the **RUNNING INSTANCES** when you shut down the **sagemaker-debugger-1.0** app.

**Amazon SageMaker Debugger in Studio Experiments**

In this section, you learn how to use the Debugger in Studio Experiments. You can select any training jobs from the experiment trial list to see the model output data graphs, such as accuracy and loss curves, debugging built-in rule status, and Debugger configuration information for debugging.

**Visualize Tensors Using Debugger and Studio**

Studio provides visualizations to interpret tensor outputs that are captured by Debugger.

**Loss Curves While Training Is in Progress**

The following screenshot shows visualizations of loss curves for training. The training is in progress.
Analyzing Training Jobs: Comparing Loss Curves Across Multiple Jobs

Studio enables you to compare across multiple jobs (in this case, the loss). This helps you identify the best-performing training jobs.

Initiating Rules and Viewing Logs from Jobs

When rules are initiated for anomalous conditions, Studio presents logs for the failing rule to help you to analyze the causes of the condition.
SageMaker Debugger Interactive Reports

Receive training and profiling reports autogenerated by Debugger. The Debugger reports provide insights into your training jobs and suggest recommendations to improve your model performance. The following screenshot shows a collage of the Debugger profiling report. To learn more, see SageMaker Debugger Profiling Report (p. 2334).

**Note**
You can download a Debugger reports while your training job is running or after the job has finished. During training, Debugger concurrently updates the report reflecting the current rules' evaluation status. You can download a complete Debugger report only after the training job has completed.

**Important**
In the reports, plots and and recommendations are provided for informational purposes and are not definitive. You are responsible for making your own independent assessment of the information.

**Topics**
- SageMaker Debugger Profiling Report (p. 2334)
- SageMaker Debugger XGBoost Training Report (p. 2345)
SageMaker Debugger Profiling Report

For any SageMaker training jobs, the Debugger ProfilerReport (p. 2368) rule invokes all of the monitoring and profiling rules (p. 2366) and aggregates the rule analysis into a comprehensive report. Following this guide, download the report using the Amazon SageMaker Python SDK or the S3 console, and learn what you can interpret from the profiling results.

**Important**
In the report, plots and and recommendations are provided for informational purposes and are not definitive. You are responsible for making your own independent assessment of the information.

**Topics**
- Download a Debugger Profiling Report (p. 2334)
- Debugger Profiling Report Walkthrough (p. 2337)

Download a Debugger Profiling Report

Download the Debugger profiling report while your training job is running or after the job has finished using the Amazon SageMaker Python SDK and AWS Command Line Interface (CLI).

**Tip**
You can also download the report with one click and no additional scripting through the SageMaker Studio Debugger insights dashboard. To find out how to download the report from Studio, see Open the Amazon SageMaker Debugger Insights Dashboard (p. 2317).

Download using SageMaker Python SDK and AWS CLI

1. Check the current job's default S3 output base URI.

   ```python
   estimator.output_path
   ```
2. Check the current job name.
   
   ```python
   estimator.latest_training_job.job_name
   ```

3. The Debugger profiling report is stored under `<default-s3-output-base-uri>/ <training-job-name>/rule-output`. Configure the rule output path as follows:
   
   ```python
   rule_output_path = estimator.output_path + estimator.latest_training_job.job_name + 
   "//rule-output"
   ```

4. To check if the report is generated, list directories and files recursively under the `rule_output_path` using `aws s3 ls` with the `--recursive` option.
   
   ```bash
   ! aws s3 ls {rule_output_path} --recursive
   ```

   This should return a complete list of files under an autogenerated folder that’s named as `ProfilerReport-1234567890`. The folder name is a combination of strings: `ProfilerReport` and a unique 10-digit tag based on the Unix timestamp when the ProfilerReport rule is initiated.

   The `profiler-report.html` is an autogenerated profiling report by Debugger. The remaining files are the built-in rule analysis components stored in JSON and a Jupyter notebook that are used to aggregate them into the report.

5. Download the files recursively using `aws s3 cp`. The following command saves all of the rule output files to the `ProfilerReport-1234567890` folder under the current working directory.
   
   ```bash
   ! aws s3 cp {rule_output_path} ./ --recursive
   ```

   **Tip**
   If using a Jupyter notebook server, run `!pwd` to double check the current working directory.

6. Under the `/ProfilerReport-1234567890/profiler-output` directory, open `profiler-report.html`. If using JupyterLab, choose **Trust HTML** to see the autogenerated Debugger profiling report.

7. Open the `profiler-report.ipynb` file to explore how the report is generated. You can also customize and extend the profiling report using the Jupyter notebook file.

---

**Download using Amazon S3 Console**

1. Sign in to the AWS Management Console and open the Amazon S3 console at [https://console.aws.amazon.com/s3/](https://console.aws.amazon.com/s3/).
2. Search for the base S3 bucket. For example, if you haven’t specified any base job name, the base S3 bucket name should be in the following format: sagemaker-<region>-111122223333. Look up the base S3 bucket through the Find bucket by name field.

3. In the base S3 bucket, look up the training job name by specifying your job name prefix into the Find objects by prefix input field. Choose the training job name.

4. In the training job’s S3 bucket, there must be three subfolders for training data collected by Debugger: debug-output/, profiler-output/, and rule-output/. Choose rule-output/.

5. In the rule-output/ folder, choose ProfilerReport-1234567890, and choose profiler-output/ folder. The profiler-output/ folder contains profiler-report.html (the autogenerated profiling report in html), profiler-report.ipynb (a Jupyter notebook with scripts that are used for generating the report), and a profiler-report/ folder (contains rule analysis JSON files that are used as components of the report).

6. Select the profiler-report.html file, choose Actions, and Download.
7. Open the downloaded `profiler-report.html` file in a web browser.

**Note**
If you started your training job without configuring the Debugger-specific parameters, Debugger generates the report based only on the system monitoring rules because the Debugger parameters are not configured to save framework metrics. To enable framework metrics profiling and receive an extended Debugger profiling report, configure the `profiler_config` parameter when constructing or updating SageMaker estimators.
To learn how to configure the `profiler_config` parameter before starting a training job, see [Configure Debugger Framework Profiling](p. 2310).
To update the current training job and enable framework metrics profiling, see [Update Debugger Framework Profiling Configuration](p. 2313).

**Debugger Profiling Report Walkthrough**

This section walks you through the Debugger profiling report section by section. The profiling report is generated based on the built-in rules for monitoring and profiling. The report shows result plots only for the rules that found issues.

**Important**
In the report, plots and and recommendations are provided for informational purposes and are not definitive. You are responsible for making your own independent assessment of the information.

**Topics**
- [Training Job Summary](p. 2338)
- [System Usage Statistics](p. 2339)
Training Job Summary

At the beginning of the report, Debugger provides a summary of your training job. In this section, you can overview the time durations and timestamps at different training phases.

Training job summary

The following table gives a summary about the training job. The table includes information about when the training job started and ended, how much time initialization, training loop and finalization took. Your training job started on 11/26/2020 at 09:12:42 and ran for 707 seconds.

<table>
<thead>
<tr>
<th>#</th>
<th>Job Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Start time 20:12:42</td>
</tr>
<tr>
<td>1</td>
<td>End time 20:24:59</td>
</tr>
<tr>
<td>2</td>
<td>Job duration 737 seconds</td>
</tr>
<tr>
<td>3</td>
<td>Training loop start 20:20:17</td>
</tr>
<tr>
<td>4</td>
<td>Training loop end 20:24:59</td>
</tr>
<tr>
<td>5</td>
<td>Training loop duration 446 seconds</td>
</tr>
<tr>
<td>6</td>
<td>Initialization time 288 seconds</td>
</tr>
<tr>
<td>7</td>
<td>Finalization time 9 seconds</td>
</tr>
<tr>
<td>8</td>
<td>Initialization 36 %</td>
</tr>
<tr>
<td>9</td>
<td>Training loop 50 %</td>
</tr>
<tr>
<td>10</td>
<td>Finalization 0 %</td>
</tr>
</tbody>
</table>

The summary table contains the following information:

- **start_time** – The exact time when the training job started.
- **end_time** – The exact time when the training job finished.
- **job_duration_in_seconds** – The total training time from the **start_time** to the **end_time**.
- **training_loop_start** – The exact time when the first step of the first epoch has started.
- **training_loop_end** – The exact time when the last step of the last epoch has finished.
- **training_loop_duration_in_seconds** – The total time between the training loop start time and the training loop end time.
- **initialization_in_seconds** – Time spent on initializing the training job. The initialization phase covers the period from the **start_time** to the **training_loop_start** time. The initialization time is spent on compiling the training script, starting the training script, creating and initializing the model, initiating EC2 instances, and downloading training data.
- **finalization_in_seconds** – Time spent on finalizing the training job, such as finishing the model training, updating the model artifacts, and closing the EC2 instances. The finalization phase covers the period from the **training_loop_end** time to the **end_time**.
- **initialization (%)** – The percentage of time spent on initialization over the total **job_duration_in_seconds**.
• **training loop (%)** – The percentage of time spent on training loop over the total job_duration_in_seconds.

• **finalization (%)** – The percentage of time spent on finalization over the total job_duration_in_seconds.

**System Usage Statistics**

In this section, you can see an overview of system utilization statistics.

**System usage statistics**

The 95th quantile of the total GPU utilization on node algo-2 is 74%. GPUs on node algo-2 are well utilized.

The following table shows usage statistics per worker node such as total CPU and GPU utilization, total CPU and memory footprint. The table also includes total IO wait time and total sent/received bytes. The table shows min and max values as well as p99, p95 and p50 percentiles.

<table>
<thead>
<tr>
<th>#</th>
<th>node</th>
<th>metric</th>
<th>unit</th>
<th>max</th>
<th>p99</th>
<th>p95</th>
<th>p50</th>
<th>min</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>algo-1</td>
<td>Network</td>
<td>bytes</td>
<td>218817581.57</td>
<td>168.02</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>algo-1</td>
<td>I/O</td>
<td>percentage</td>
<td>13.2953125</td>
<td>5.59283125</td>
<td>0.00000</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>algo-1</td>
<td>GPU memory</td>
<td>percentage</td>
<td>32.25</td>
<td>25.26</td>
<td>21</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>algo-1</td>
<td>GPU</td>
<td>percentage</td>
<td>75</td>
<td>74.5</td>
<td>74.25</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>algo-1</td>
<td>CPU memory</td>
<td>percentage</td>
<td>5.05</td>
<td>5.01</td>
<td>4.98</td>
<td>2.17</td>
<td>0.55</td>
</tr>
<tr>
<td>4</td>
<td>algo-1</td>
<td>CPU</td>
<td>percentage</td>
<td>32.956625</td>
<td>22.62913125</td>
<td>0.00000</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>algo-2</td>
<td>Network</td>
<td>bytes</td>
<td>4135.24</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
<td>algo-2</td>
<td>I/O</td>
<td>percentage</td>
<td>20.1875</td>
<td>8.15525</td>
<td>0.00000</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>9</td>
<td>algo-2</td>
<td>GPU memory</td>
<td>percentage</td>
<td>38</td>
<td>31.75</td>
<td>21.75</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>algo-2</td>
<td>GPU</td>
<td>percentage</td>
<td>75</td>
<td>74.5</td>
<td>74.25</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>algo-2</td>
<td>CPU memory</td>
<td>percentage</td>
<td>5.05</td>
<td>5.02</td>
<td>4.99</td>
<td>2.17</td>
<td>0.55</td>
</tr>
<tr>
<td>5</td>
<td>algo-2</td>
<td>CPU</td>
<td>percentage</td>
<td>35.004374999999</td>
<td>25.699999875000000</td>
<td>18.334068750000000</td>
<td>3.778281250000000</td>
<td>0.00000</td>
</tr>
</tbody>
</table>

The Debugger profiling report includes the following information:

• **node** – Lists the name of nodes. If using distributed training on multi nodes (multiple EC2 instances), the node names are in format of a1go-n.

• **metric** – The system metrics collected by Debugger: CPU, GPU, CPU memory, GPU memory, I/O, and Network metrics.

• **unit** – The unit of the system metrics.

• **max** – The maximum value of each system metric.

• **p99** – The 99th percentile of each system utilization.

• **p95** – The 95th percentile of each system utilization.

• **p50** – The 50th percentile (median) of each system utilization.

• **min** – The minimum value of each system metric.

**Framework metrics summary**

In this section, the following pie charts show the breakdown of framework operations on CPUs and GPUs.
Each of the pie charts analyzes the collected framework metrics in various aspects as follows:

- **Ratio between TRAIN/EVAL phase and others** – Shows the ratio between time durations spent on different training phases.
- **Ratio between forward and backward pass** – Shows the ratio between time durations spent on forward and backward pass in the training loop.
- **Ratio between CPU/GPU operators** – Shows the ratio between time spent on operators running on CPU or GPU, such as convolutional operators.
- **General metrics recorded in framework** – Shows the ratio between time spent on major framework metrics, such as data loading, forward and backward pass.

**Overview: CPU Operators**

This section provides information of the CPU operators in detail. The table shows the percentage of the time and the absolute cumulative time spent on the most frequently called CPU operators.
Overview: GPU Operators

The following table shows a list of operators that your training job on GPU. The most expensive operator on GPU was "ConvolutionBackward" with 54.4% of the total execution time. The table provides details on the percentage and cumulative time spent on each operator.

<table>
<thead>
<tr>
<th>Percentage</th>
<th>Cumulative Time</th>
<th>GPU Operator</th>
</tr>
</thead>
<tbody>
<tr>
<td>34.46</td>
<td>1384565956</td>
<td>ConvolutionBackward</td>
</tr>
<tr>
<td>34.44</td>
<td>1384565956</td>
<td>Convolution_Backward</td>
</tr>
<tr>
<td>0.16</td>
<td>24893690</td>
<td>conv2d</td>
</tr>
<tr>
<td>0.13</td>
<td>24893690</td>
<td>convolution</td>
</tr>
<tr>
<td>0.11</td>
<td>24893690</td>
<td>_convolution</td>
</tr>
<tr>
<td>0.06</td>
<td>24893690</td>
<td>_convolution</td>
</tr>
<tr>
<td>3.34</td>
<td>13487744</td>
<td>ConvolutionBackwardNorm</td>
</tr>
<tr>
<td>3.3</td>
<td>13300000</td>
<td>_convolution</td>
</tr>
</tbody>
</table>

Rules Summary

This section provides information on the rules evaluation results, analysis, rule descriptions, and suggestions. The following table outlines the rules evaluated:

<table>
<thead>
<tr>
<th>Description</th>
<th>Recommendation</th>
<th>Number of times rule triggered</th>
<th>Number of datapoints</th>
<th>Rule parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Load Balancing</td>
<td>Choose different distributed training strategy or different distributed training framework</td>
<td>263</td>
<td>5467</td>
<td>ElasticNet, 8.2</td>
</tr>
<tr>
<td>Load Pathology</td>
<td>Choose different distributed training strategy or different distributed training framework</td>
<td>324</td>
<td>6986</td>
<td>ElasticNet, 8.2</td>
</tr>
<tr>
<td>Batch Size</td>
<td>Run on a smaller instance type or increase batch size</td>
<td>271</td>
<td>5466</td>
<td>ElasticNet, 8.2</td>
</tr>
<tr>
<td>GPU Memory Increase</td>
<td>Choose a larger instance type with more memory, if it is not a memory or cache bottleneck</td>
<td>33</td>
<td>5467</td>
<td>ElasticNet, 8.2</td>
</tr>
<tr>
<td>CPU Bottleneck</td>
<td>Check if CPU usage is high but GPU usage is low or vice versa</td>
<td>18</td>
<td>10398</td>
<td>ElasticNet, 8.2</td>
</tr>
<tr>
<td>I/O Bottleneck</td>
<td>Check if I/O usage is high but GPU usage is low or vice versa</td>
<td>18</td>
<td>10398</td>
<td>ElasticNet, 8.2</td>
</tr>
<tr>
<td>SnapAfter</td>
<td>Check if the training initialization is taking too much time</td>
<td>0</td>
<td>4603</td>
<td>ElasticNet, 8.2</td>
</tr>
<tr>
<td>Weight Initialization</td>
<td>Check if the training initialization is taking too much time</td>
<td>0</td>
<td>4603</td>
<td>ElasticNet, 8.2</td>
</tr>
</tbody>
</table>
Analyzing the Training Loop – Step Durations

In this section, you can find a detailed statistics of step durations on each GPU core of each node. Debugger evaluates mean, maximum, p99, p95, p50, and minimum values of step durations, and evaluate step outliers. The following histogram shows the step durations captured on different worker nodes and GPUs. You can enable or disable the histogram of each worker by choosing the legends on the right side. You can check if there is a particular GPU that's causing step duration outliers.

GPU Utilization Analysis

This section shows the detailed statistics about GPU core utilization based on LowGPUUtilization rule. It also summarizes the GPU utilization statistics, mean, p95, and p5 to determine if the training job is underutilizing GPUs.

Batch Size

This section shows the detailed statistics of total CPU utilization, individual GPU utilizations, and GPU memory footprints. The BatchSize rule determines if you need to change the batch size to better utilize the GPUs. You can check whether the batch size is too small resulting in underutilization or too large causing overutilization and out of memory issues. In the plot, the boxes show the p25 and p75 percentile ranges (filled with dark purple and bright yellow respectively) from the median (p50), and the error bars show the 5th percentile for the lower bound and 95th percentile for the upper bound.
CPU Bottlenecks

In this section, you can drill down into the CPU bottlenecks that the CPUBottleneck rule detected from your training job. The rule checks if the CPU utilization is above cpu_threshold (90% by default) and also if the GPU utilization is below gpu_threshold (10% by default).

- **Low GPU usage caused by CPU bottlenecks** – Shows the ratio of data points between the ones with GPU utilization above and below the threshold and the ones that matches the CPU bottleneck criteria.
- **Ratio between TRAIN/EVAL phase and others** – Shows the ratio between time durations spent on different training phases.
- **Ratio between forward and backward pass** – Shows the ratio between time durations spent on forward and backward pass in the training loop.

The pie charts show the following information:

- Low GPU usage caused by CPU bottlenecks
- Ratio between TRAIN/EVAL phase and others
- Ratio between forward and backward pass
• **Ratio between CPU/GPU operators** – Shows the ratio between time durations spent on GPUs and CPUs by Python operators, such as data loader processes and forward and backward pass operators.

• **General metrics recorded in framework** – Shows major framework metrics and the ratio between time durations spent on the metrics.

**I/O Bottlenecks**

In this section, you can find a summary of I/O bottlenecks. The rule evaluates the I/O wait time and GPU utilization rates and monitors if the time spent on the I/O requests exceeds a threshold percent of the total training time. It might indicate I/O bottlenecks where GPUs are waiting for data to arrive from storage.

**LoadBalancing in Multi-GPU Training**

In this section, you can identify workload balancing issue across GPUs.

**GPU Memory Analysis**

In this section, you can analyze the GPU memory utilization collected by the GPUMemoryIncrease rule. In the plot, the boxes show the p25 and p75 percentile ranges (filled with dark purple and bright yellow respectively) from the median (p50), and the error bars show the 5th percentile for the lower bound and 95th percentile for the upper bound.
SageMaker Debugger XGBoost Training Report

For SageMaker XGBoost training jobs, use the Debugger CreateXgboostReport (p. 2378) rule to receive a comprehensive training report of the training progress and results. Following this guide, specify the CreateXgboostReport (p. 2378) rule while constructing an XGBoost estimator, download the report using the Amazon SageMaker Python SDK or the Amazon S3 console, and gain insights into the training results.

Important
In the report, plots and and recommendations are provided for informational purposes and are not definitive. You are responsible for making your own independent assessment of the information.

Topics
- Construct a SageMaker XGBoost Estimator with the Debugger XGBoost Report Rule (p. 2345)
- Download the Debugger XGBoost Training Report (p. 2346)
- Debugger XGBoost Training Report Walkthrough (p. 2348)

Construct a SageMaker XGBoost Estimator with the Debugger XGBoost Report Rule

The CreateXgboostReport (p. 2378) rule collects the following output tensors from your training job:

- hyperparameters – Saves at the first step.
- metrics – Saves loss and accuracy every 5 steps.
- feature_importance – Saves every 5 steps.
- predictions – Saves every 5 steps.
- labels – Saves every 5 steps.

The output tensors are saved at a default S3 bucket. For example, s3://sagemaker-<region>-<12digit_account_id>/<base-job-name>/debug-output/.

When you construct a SageMaker estimator for an XGBoost training job, specify the rule as shown in the following example code.

Using the SageMaker generic estimator

```python
import boto3
import sagemaker
from sagemaker.estimator import Estimator
from sagemaker import image_uris
from sagemaker.debugger import Rule, rule_configs

rules = [
    Rule.sagemaker(rule_configs.create_xgboost_report())
]

region = boto3.Session().region_name
xgboost_container = sagemaker.image_uris.retrieve("xgboost", region, "1.2-1")

estimator = Estimator(
    role=sagemaker.get_execution_role(),
    image_uri=xgboost_container,
    base_job_name="debugger-xgboost-report-demo",
    instance_count=1,
    instance_type="ml.m5.2xlarge",
    )
```
# Add the Debugger XGBoost report rule

```python
rules=rules
```

estimator.fit(wait=False)

---

### Download the Debugger XGBoost Training Report

Download the Debugger XGBoost training report while your training job is running or after the job has finished using the Amazon SageMaker Python SDK and AWS Command Line Interface (CLI).

**Download using the SageMaker Python SDK and AWS CLI**

1. Check the current job’s default S3 output base URI.

   ```python
   estimator.output_path
   ```

2. Check the current job name.

   ```python
   estimator.latest_training_job.job_name
   ```

3. The Debugger XGBoost report is stored under `<default-s3-output-base-uri>/<training-job-name>/rule-output`. Configure the rule output path as follows:

   ```python
   rule_output_path = estimator.output_path + ""/
   estimator.latest_training_job.job_name + ""/rule-output"
   ```

4. To check if the report is generated, list directories and files recursively under the `rule_output_path` using `aws s3 ls` with the `--recursive` option.

   ```bash
   ! aws s3 ls {rule_output_path} --recursive
   ```

   This should return a complete list of files under autogenerated folders that are named `CreateXgboostReport` and `ProfilerReport-1234567890`. The XGBoost training report is stored in the `CreateXgboostReport`, and the profiling report is stored in the `ProfilerReport-1234567890` folder. To learn more about the profiling report generated by default with the XGBoost training job, see *SageMaker Debugger Profiling Report* (p. 2334).

5. Download the files recursively using `aws s3 cp`. The following command saves all of the rule output files to the `ProfilerReport-1234567890` folder under the current working directory.

   ```bash
   ! aws s3 cp {rule_output_path} ./ --recursive
   ```

The `xgboost_report.html` is an autogenerated XGBoost training report by Debugger. The `xgboost_report.ipynb` is a Jupyter notebook that’s used to aggregate training results into the report. You can download all of the files, browse the HTML report file, and modify the report using the notebook.

6. Download the files recursively using `aws s3 cp`. The following command saves all of the rule output files to the `ProfilerReport-1234567890` folder under the current working directory.

   ```bash
   ! aws s3 cp {rule_output_path} ./ --recursive
   ```
Tip
If you are using a Jupyter notebook server, run !pwd to verify the current working directory.

6. Under the /CreateXgboostReport directory, open xgboost_report.html. If you are using JupyterLab, choose Trust HTML to see the autogenerated Debugger training report.

7. Open the xgboost_report.ipynb file to explore how the report is generated. You can customize and extend the training report using the Jupyter notebook file.

Download using the Amazon S3 console

1. Sign in to the AWS Management Console and open the Amazon S3 console at https://console.aws.amazon.com/s3/.

2. Search for the base S3 bucket. For example, if you haven't specified any base job name, the base S3 bucket name should be in the following format: sagemaker-<region>-111122223333. Look up the base S3 bucket through the Find bucket by name field.

3. In the base S3 bucket, look up the training job name by entering your job name prefix in Find objects by prefix and then choosing the training job name.
4. In the training job's S3 bucket, choose **rule-output/** subfolder. There must be three subfolders for training data collected by Debugger: **debug-output/**, **profiler-output/**, and **rule-output/**.

5. In the **rule-output/** folder, choose the **CreateXgboostReport/** folder. The folder contains **xbgoost_report.html** (the autogenerated report in html) and **xbgoost_report.ipynb** (a Jupyter notebook with scripts that are used for generating the report).

6. Choose the **xbgoost_report.html** file, choose **Download actions**, and then choose **Download**.

7. Open the downloaded **xbgoost_report.html** file in a web browser.

Debugger XGBoost Training Report Walkthrough

This section walks you through the Debugger XGBoost training report. The report is automatically aggregated depending on the output tensor regex, recognizing what type of your training job is among binary classification, multiclass classification, and regression.
Important
In the report, plots and recommendations are provided for informational purposes and are not definitive. You are responsible for making your own independent assessment of the information.

Topics
- Distribution of True Labels of the Dataset (p. 2349)
- Loss versus Step Graph (p. 2349)
- Feature Importance (p. 2350)
- Confusion Matrix (p. 2351)
- Evaluation of the Confusion Matrix (p. 2352)
- Accuracy Rate of Each Diagonal Element Over Iteration (p. 2353)
- Receiver Operating Characteristic Curve (p. 2354)
- Distribution of Residuals at the Last Saved Step (p. 2355)
- Absolute Validation Error per Label Bin Over Iteration (p. 2356)

Distribution of True Labels of the Dataset
This histogram shows the distribution of labeled classes (for classification) or values (for regression) in your original dataset. Skewness in your dataset could contribute to inaccuracies. This visualization is available for the following model types: binary classification, multiclassification, and regression.

Loss versus Step Graph
This is a line chart that shows the progression of loss on training data and validation data throughout training steps. The loss is what you defined in your objective function, such as mean squared error. You can gauge whether the model is overfit or underfit from this plot. This section also provides insights that you can use to determine how to resolve the overfit and underfit problems. This visualization is available for the following model types: binary classification, multiclassification, and regression.
Feature Importance

There are three different types of feature importance visualizations provided: Weight, Gain and Coverage. We provide detailed definitions for each of the three in the report. Feature importance visualizations help you learn what features in your training dataset contributed to the predictions. Feature importance visualizations are available for the following model types: binary classification, multiclassification, and regression.
Confusion Matrix

This visualization is only applicable to binary and multiclass classification models. Accuracy alone might not be sufficient for evaluating the model performance. For some use cases, such as healthcare and fraud detection, it’s also important to know the false positive rate and false negative rate. A confusion matrix gives you the additional dimensions for evaluating your model performance.
Evaluation of the Confusion Matrix

This section provides you with more insights on the micro, macro, and weighted metrics on precision, recall, and F1-score for your model.
Overall Accuracy
Overall Accuracy: 0.919

Micro Performance Metrics
Performance metrics calculated globally by counting the total true positives, false negatives, and false positives.

Micro Precision: 0.919
Micro Recall: 0.919
Micro F1-score: 0.919

Macro Performance Metrics
Performance metrics calculated for each label, and find their unweighted mean. This does not take the class imbalance problem into account.

Macro Precision: 0.919
Macro Recall: 0.918
Macro F1-score: 0.918

Weighted Performance Metrics
Performance metrics calculated for each label and their average weighted by support (the number of true instances for each label). This extends the macro option to take the class imbalance into account. It might result in an F-score that is not between precision and recall.

Weighted Precision: 0.92
Weighted Recall: 0.919
Weighted F1-score: 0.919

Classification Report
The summary of the precision, recall, and F1-score for each class.

<table>
<thead>
<tr>
<th>precision</th>
<th>recall</th>
<th>F1-score</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>0.95</td>
<td>0.97</td>
<td>0.96</td>
</tr>
<tr>
<td>1.0</td>
<td>0.94</td>
<td>0.98</td>
<td>0.96</td>
</tr>
<tr>
<td>2.0</td>
<td>0.93</td>
<td>0.90</td>
<td>0.92</td>
</tr>
<tr>
<td>3.0</td>
<td>0.91</td>
<td>0.89</td>
<td>0.90</td>
</tr>
<tr>
<td>4.0</td>
<td>0.92</td>
<td>0.89</td>
<td>0.90</td>
</tr>
<tr>
<td>5.0</td>
<td>0.94</td>
<td>0.89</td>
<td>0.91</td>
</tr>
<tr>
<td>6.0</td>
<td>0.95</td>
<td>0.94</td>
<td>0.95</td>
</tr>
<tr>
<td>7.0</td>
<td>0.92</td>
<td>0.94</td>
<td>0.93</td>
</tr>
<tr>
<td>8.0</td>
<td>0.87</td>
<td>0.87</td>
<td>0.87</td>
</tr>
<tr>
<td>9.0</td>
<td>0.85</td>
<td>0.90</td>
<td>0.88</td>
</tr>
</tbody>
</table>

accuracy: 0.92 12000
macro avg: 0.92 0.92 0.92 12000
weighted avg: 0.92 0.92 0.92 12000

Accuracy Rate of Each Diagonal Element Over Iteration
This visualization is only applicable to binary classification and multiclass classification models. This is a line chart that plots the diagonal values in the confusion matrix throughout the training steps for each class. This plot shows you how the accuracy of each class progresses throughout the training steps. You can identify the under-performing classes from this plot.
Receiver Operating Characteristic Curve

This visualization is only applicable to binary classification models. The Receiver Operating Characteristic curve is commonly used to evaluate binary classification model performance. The y-axis of the curve is True Positive Rate (TPF) and x-axis is false positive rate (FPR). The plot also displays the value for the area under the curve (AUC). The higher the AUC value, the more predictive your classifier. You can also use the ROC curve to understand the trade-off between TPR and FPR and identify the optimum classification threshold for your use case. The classification threshold can be adjusted to tune the behavior of the model to reduce more of one or another type of error (FP/FN).
Distribution of Residuals at the Last Saved Step

This visualization is a column chart that shows the residual distributions in the last step Debugger captures. In this visualization, you can check whether the residual distribution is close to normal distribution that’s centered at zero. If the residuals are skewed, your features may not be sufficient for predicting the labels.
Absolute Validation Error per Label Bin Over Iteration

This visualization is only applicable to regression models. The actual target values are split into 10 intervals. This visualization shows how validation errors progress for each interval throughout the training steps in line plots. Absolute validation error is the absolute value of difference between prediction and actual during validation. You can identify the underperforming intervals from this visualization.
Analyze Data Using the SMDebug Client Library

While your training job is running or after it has completed, you can access the training data collected by Debugger using the Amazon SageMaker Python SDK and the SMDebug client library. The SMDebug library provides analysis and visualization tools that enable you to drill down into your training job data.

To install the library and use the SMDebug analysis tools (in a JupyterLab notebook or an iPython kernel)

! pip install -U smdebug

The following topics walk you through how to use the SMDebug tools to visualize and analyze the training data collected by Debugger.

Analyze system and framework metrics

- Access the Monitoring and Profiling Data (p. 2357)
- Plot the System Metrics and Framework Metrics Data (p. 2358)
- Access the Profiling Data Using the Pandas Data Parsing Tool (p. 2359)
- Access the Python Profiling Stats Data (p. 2360)
- Merge Timelines of Different Profiling Trace Files (p. 2362)
- Profiling Data Loader (p. 2364)

Access the Monitoring and Profiling Data

The SMDebug TrainingJob class reads data from the S3 bucket where the system and framework metrics are saved.

To set up a TrainingJob object and retrieve profiling event files of a training job

```python
from smdebug.profiler.analysis.notebook_utils.training_job import TrainingJob
tj = TrainingJob(training_job_name, region)
```

Tip

You need to specify the training_job_name and region parameters to log to a training job. There are two ways to specify the training job information:

- Use the SageMaker Python SDK while the estimator is still attached to the training job.

```python
import sagemaker
training_job_name=estimator.latest_training_job.job_name
region=sagemaker.Session().boto_region_name
```

- Pass strings directly.

```python
training_job_name="your-training-job-name-YYYY-MM-DD-HH-MM-SS-SSS"
region="us-west-2"
```

Note

By default, SageMaker Debugger collects system metrics to monitor hardware resource utilization and system bottlenecks. Running the following functions, you might receive error messages regarding unavailability of framework metrics. To retrieve framework profiling data and gain insights into framework operations, you must enable framework profiling.
• If you use SageMaker Python SDK to manipulate your training job request, pass the `framework_profile_params` to the `profiler_config` argument of your estimator. To learn more, see Configure SageMaker Debugger Framework Profiling.

• If you use Studio, turn on profiling using the Profiling toggle button in the Debugger insights dashboard. To learn more, see SageMaker Debugger Insights Dashboard Controller.

To retrieve a description of the training job description and the S3 bucket URI where the metric data are saved

```python
tj.describe_training_job()
tj.get_config_and_profiler_s3_output_path()
```

To check if the system and framework metrics are available from the S3 URI

```python
tj.wait_for_sys_profiling_data_to_be_available()
tj.wait_for_framework_profiling_data_to_be_available()
```

To create system and framework reader objects after the metric data become available

```python
system_metrics_reader = tj.get_systems_metrics_reader()
framework_metrics_reader = tj.get_framework_metrics_reader()
```

To refresh and retrieve the latest training event files

The reader objects have an extended method, `refresh_event_file_list()`, to retrieve the latest training event files.

```python
system_metrics_reader.refresh_event_file_list()
framework_metrics_reader.refresh_event_file_list()
```

Plot the System Metrics and Framework Metrics Data

You can use the system and algorithm metrics objects for the following visualization classes to plot timeline graphs and histograms.

**Note**
To visualize the data with narrowed-down metrics in the following visualization object plot methods, specify `select_dimensions` and `select_events` parameters. For example, if you specify `select_dimensions=['GPU']`, the plot methods filter the metrics that include the "GPU" keyword. If you specify `select_events=['total']`, the plot methods filter the metrics that include the "total" event tags at the end of the metric names. If you enable these parameters and give the keyword strings, the visualization classes return the charts with filtered metrics.

• The MetricsHistogram class

```python
from smdebug.profiler.analysis.notebook_utils.metrics_histogram import MetricsHistogram

metrics_histogram = MetricsHistogram(system_metrics_reader)
metrics_histogram.plot(
    starttime=0,
    endtime=system_metrics_reader.get_timestamp_of_latest_available_file(),
    select_dimensions=['CPU', 'GPU', 'I/O'],  # optional
    select_events=['total']                      # optional
)
```

• The StepTimelineChart class
from smdebug.profiler.analysis.notebook_utils.step_timeline_chart import StepTimelineChart
view_step_timeline_chart = StepTimelineChart(framework_metrics_reader)

• The StepHistogram class

from smdebug.profiler.analysis.notebook_utils.step_histogram import StepHistogram
step_histogram = StepHistogram(framework_metrics_reader)
step_histogram.plot(
    starttime=step_histogram.last_timestamp - 5 * 1000 * 1000,
    endtime=step_histogram.last_timestamp,
    show_workers=True
)

• The TimelineCharts class

from smdebug.profiler.analysis.notebook_utils.timeline_charts import TimelineCharts
view_timeline_charts = TimelineCharts(
    system_metrics_reader,
    framework_metrics_reader,
    select_dimensions=["CPU", "GPU", "I/O"],  # optional
    select_events=["total"]  # optional
)
view_timeline_charts.plot_detailed_profiler_data([700,710])

• The Heatmap class

from smdebug.profiler.analysis.notebook_utils.heatmap import Heatmap
view_heatmap = Heatmap(
    system_metrics_reader,
    framework_metrics_reader,
    select_dimensions=["CPU", "GPU", "I/O"],  # optional
    select_events=["total"],  # optional
    plot_height=450
)

Access the Profiling Data Using the Pandas Data Parsing Tool

The following PandasFrame class provides tools to convert the collected profiling data to Pandas data frame.

from smdebug.profiler.analysis.utils.profiler_data_to_pandas import PandasFrame

The PandasFrame class takes the tj object's S3 bucket output path, and its methods get_all_system_metrics() get_all_framework_metrics() return system metrics and framework metrics in the Pandas data format.

pf = PandasFrame(tj.profiler_s3_output_path)
system_metrics_df = pf.get_all_system_metrics()
framework_metrics_df = pf.get_all_framework_metrics(
    selected_framework_metrics=[
        'Step:ModeKeys.TRAIN',
        'Step:ModeKeys.GLOBAL'
    ]
)
Access the Python Profiling Stats Data

The Python profiling provides framework metrics related to Python functions and operators in your training scripts and the SageMaker deep learning frameworks.

Training Modes and Phases for Python Profiling

To profile specific intervals during training to partition statistics for each of these intervals, Debugger provides tools to set modes and phases.

For training modes, use the following `PythonProfileModes` class:

```python
from smdebug.profiler.python_profile_utils import PythonProfileModes
```

This class provides the following options:

- `PythonProfileModes.TRAIN` – Use if you want to profile the target steps in the training phase. This mode option available only for TensorFlow.
- `PythonProfileModes.EVAL` – Use if you want to profile the target steps in the evaluation phase. This mode option available only for TensorFlow.
- `PythonProfileModes.PREDICT` – Use if you want to profile the target steps in the prediction phase. This mode option available only for TensorFlow.
- `PythonProfileModes.GLOBAL` – Use if you want to profile the target steps in the global phase, which includes the previous three phases. This mode option available only for PyTorch.
- `PythonProfileModes.PRE_STEP_ZERO` – Use if you want to profile the target steps in the initialization stage before the first training step of the first epoch starts. This phase includes the initial job submission, uploading the training scripts to EC2 instances, preparing the EC2 instances, and downloading input data. This mode option available for both TensorFlow and PyTorch.
- `PythonProfileModes.POST_HOOK_CLOSE` – Use if you want to profile the target steps in the finalization stage after the training job has done and the Debugger hook is closed. This phase includes profiling data while the training jobs are finalized and completed. This mode option available for both TensorFlow and PyTorch.

For training phases, use the following `StepPhase` class:

```python
from smdebug.profiler.analysis.utils.python_profile_analysis_utils import StepPhase
```

This class provides the following options:

- `StepPhase.START` – Use to specify the start point of the initialization phase.
- `StepPhase.STEP_START` – Use to specify the start step of the training phase.
- `StepPhase.FORWARD_PASS_END` – Use to specify the steps where the forward pass ends. This option available only for PyTorch.
- `StepPhase.STEP_END` – Use to specify the end steps in the training phase. This option available only for TensorFlow.
- `StepPhase.END` – Use to specify the ending point of the finalization (post-hook-close) phase. If the callback hook is not closed, the finalization phase profiling does not occur.

Python Profiling Analysis Tools

Debugger supports the Python profiling with two profiling tools:
• cProfile – The standard python profiler. cProfile collects framework metrics on CPU time for every function called when profiling was enabled.

• Pyinstrument – This is a low overhead Python profiler sampling profiling events every milliseconds.

To learn more about the Python profiling options and what's collected, see Start a Training Job with the Default System Monitoring and Customized Framework Profiling with Different Profiling Options (p. 2312).

The following methods of the PythonProfileAnalysis, cProfileAnalysis, PyinstrumentAnalysis classes are provided to fetch and analyze the Python profiling data. Each function loads the latest data from the default S3 URI.

```python
from smdebug.profiler.analysis.python_profile_analysis import PythonProfileAnalysis, cProfileAnalysis, PyinstrumentAnalysis
```

To set Python profiling objects for analysis, use the cProfileAnalysis or PyinstrumentAnalysis classes as shown in the following example code. It shows how to set a cProfileAnalysis object, and if you want to use PyinstrumentAnalysis, replace the class name.

```python
python_analysis = cProfileAnalysis(
    local_profile_dir=tf_python_stats_dir,
    s3_path=tj.profiler_s3_output_path
)
```

The following methods are available for the cProfileAnalysis and PyinstrumentAnalysis classes to fetch the Python profiling stats data:

• `python_analysis.fetch_python_profile_stats_by_time(start_time_since_epoch_in_secs, end_time_since_epoch_in_secs)` – Takes in a start time and end time, and returns the function stats of step stats whose start or end times overlap with the provided interval.

• `python_analysis.fetch_python_profile_stats_by_step(start_step, end_step, mode, start_phase, end_phase)` – Takes in a start step and end step and returns the function stats of all step stats whose profiled steps satisfy `start_step <= step < end_step`.

• `start_step` and `end_step` (str) – Specify the start step and end step to fetch the Python profiling stats data.

• `mode` (str) – Specify the mode of training job using the PythonProfileModes enumerator class. The default is PythonProfileModes.TRAIN. Available options are provided in the Training Modes and Phases for Python Profiling (p. 2360) section.

• `start_phase` (str) – Specify the start phase in the target step(s) using the StepPhase enumerator class. This parameter enables profiling between different phases of training. The default is StepPhase.STEP_START. Available options are provided in the Training Modes and Phases for Python Profiling (p. 2360) section.

• `end_phase` (str) – Specify the end phase in the target step(s) using the StepPhase enumerator class. This parameter sets up the end phase of training. Available options are as same as the ones for the start_phase parameter. The default is StepPhase.STEP_END. Available options are provided in the Training Modes and Phases for Python Profiling (p. 2360) section.

• `python_analysis.fetch_profile_stats_between_modes(start_mode, end_mode)` – Fetches stats from the Python profiling between the start and end modes.

• `python_analysis.fetch_pre_step_zero_profile_stats()` – Fetches the stats from the Python profiling until step 0.

• `python_analysis.fetch_post_hook_close_profile_stats()` – Fetches stats from the Python profiling after the hook is closed.
• `python_analysis.list_profile_stats()` – Returns a DataFrame of the Python profiling stats. Each row holds the metadata for each instance of profiling and the corresponding stats file (one per step).

• `python_analysis.list_available_node_ids()` – Returns a list the available node IDs for the Python profiling stats.

The `cProfileAnalysis` class specific methods:

• `fetch_profile_stats_by_training_phase()` – Fetches and aggregates the Python profiling stats for every possible combination of start and end modes. For example, if a training and validation phases are done while detailed profiling is enabled, the combinations are `(PRE_STEP_ZERO, TRAIN), (TRAIN, TRAIN), (TRAIN, EVAL), (EVAL, EVAL), and (EVAL, POST_HOOK_CLOSE)`. All stats files within each of these combinations are aggregated.

• `fetch_profile_stats_by_job_phase()` – Fetches and aggregates the Python profiling stats by job phase. The job phases are `initialization` (profiling until step 0), `training_loop` (training and validation), and `finalization` (profiling after the hook is closed).

**Merge Timelines of Different Profiling Trace Files**

The SMDebug client library provide profiling analysis and visualization tools for merging timelines of system metrics, framework metrics, and Python profiling data collected by Debugger.

**Tip**
Before proceeding, you need to set a TrainingJob object that will be utilized throughout the examples in this page. For more information about setting up a TrainingJob object, see Access the Monitoring and Profiling Data (p. 2357).

The `MergedTimeline` class provides tools to integrate and correlate different profiling information in a single timeline. After Debugger captures profiling data and annotations from different phases of a training job, JSON files of trace events are saved in a default `tracefolder` directory.

• For annotations in the Python layers, the trace files are saved in `*pythontimeline.json`.

• For annotations in the TensorFlow C++ layers, the trace files are saved in `*model_timeline.json`.

• TensorFlow profiler saves events in a `*trace.json.gz` file.

**Tip**
If you want to list all of the JSON trace files, use the following AWS CLI command:

```
! aws s3 ls {tj.profiler_s3_output_path} --recursive | grep '\.json$'
```

As shown in the following animated screenshot, putting and aligning the trace events captured from the different profiling sources in a single plot can provide an overview of the entire events occurring in different phases of the training job.
Tip
To interact with the merged timeline on the tracing app using a keyboard, use the W key for zooming in, the A key for shifting to the left, the S key for zooming out, and the D key for shifting to the right.

The multiple event trace JSON files can be merged into one trace event JSON file using the following MergedTimeline API operation and class method from the smdebug.profiler.analysis.utils.merge_timelines module.

```python
from smdebug.profiler.analysis.utils.merge_timelines import MergedTimeline

combined_timeline = MergedTimeline(path, file_suffix_filter, output_directory)
combined_timeline.merge_timeline(start, end, unit)
```

The MergedTimeline API operation passes the following parameters:

- **path (str)** – Specify a root folder (/profiler-output) that contains system and framework profiling trace files. You can locate the profiler-output using the SageMaker estimator classmethod or the TrainingJob object. For example, estimator.latest_job_profiler_artifacts_path() or tj.profiler_s3_output_path.
- **file_suffix_filter (list)** – Specify a list of file suffix filters to merge timelines. Available suffix filters are ["model_timeline.json", "pythontimeline.json", "trace.json.gz"]. If this parameter is not manually specified, all of the trace files are merged by default.
- **output_directory (str)** – Specify a path to save the merged timeline JSON file. The default is to the directory specified for the path parameter.

The merge_timeline() classmethod passes the following parameters to execute the merging process:

- **start (int)** – Specify start time (in microseconds and in Unix time format) or start step to merge timelines.
- **end (int)** – Specify end time (in microseconds and in Unix time format) or end step to merge timelines.
• unit (str) – Choose between "time" and "step". The default is "time".

Using the following example codes, execute the merge_timeline() method and download the merged JSON file.

• Merge timeline with the "time" unit option. The following example code merges all available trace files between the Unix start time (the absolute zero Unix time) and the current Unix time, which means that you can merge the timelines for the entire training duration.

```python
import time
from smdebug.profiler.analysis.utils.merge_timelines import MergedTimeline
from smdebug.profiler.profiler_constants import CONVERT_TO_MICROSECS

combined_timeline = MergedTimeline(tj.profiler_s3_output_path, output_directory=".")
combined_timeline.merge_timeline(0, int(time.time() * CONVERT_TO_MICROSECS))
```

• Merge timeline with the "step" unit option. The following example code merges all available timelines between step 3 and step 9.

```python
from smdebug.profiler.analysis.utils.merge_timelines import MergedTimeline

combined_timeline = MergedTimeline(tj.profiler_s3_output_path, output_directory=".")
combined_timeline.merge_timeline(3, 9, unit="step")
```

Open the Chrome tracing app at chrome://tracing on a Chrome browser, and open the JSON file. You can explore the output to plot the merged timeline.

### Profiling Data Loader

In PyTorch, data loader iterators, such as SingleProcessingDataLoaderIter and MultiProcessingDataLoaderIter, are initiated at the beginning of every iteration over a dataset. During the initialization phase, PyTorch turns on worker processes depending on the configured number of workers, establishes data queue to fetch data and pin_memory threads.

To use the PyTorch data loader profiling analysis tool, import the following PT_dataloader_analysis class:

```python
from smdebug.profiler.analysis.utils.pytorch_dataloader_analysis import PT_dataloader_analysis

pt_analysis = PT_dataloader_analysis(pf)
```

The following functions are available for the pt_analysis object:

- `pt_analysis.analyze_dataloaderIter_initialization()`

The SMDebug S3SystemMetricsReader class reads the system metrics from the S3 bucket specified to the s3_trial_path parameter.

- `pt_analysis.analyze_dataloaderIter_initialization()`

The analysis outputs the median and maximum duration for these initializations. If there are outliers, (i.e duration is greater than 2 * median), the function prints the start and end times for those durations. These can be used to inspect system metrics during those time intervals.
List of Built-in Rules

The following list shows what analysis is available from this class method:

- Which type of data loader iterators were initialized.
- The number of workers per iterator.
- Inspect whether the iterator was initialized with or without pin_memory.
- Number of times the iterators were initialized during training.

```
pt_analysis.analyze_dataloaderWorkers()
```

The following list shows what analysis is available from this class method:

- The number of worker processes that were spun off during the entire training.
- Median and maximum duration for the worker processes.
- Start and end time for the worker processes that are outliers.

```
pt_analysis.analyze_dataloader_getnext()
```

The following list shows what analysis is available from this class method:

- Number of GetNext calls made during the training.
- Median and maximum duration in microseconds for GetNext calls.
- Start time, End time, duration and worker id for the outlier GetNext call duration.

```
pt_analysis.analyze_batchtime(start_timestamp, end_timestamp,
select_events=[".*"], select_dimensions=[".*"])  
```

Debugger collects the start and end times of all the GetNext calls. You can find the amount of time spent by the training script on one batch of data. Within the specified time window, you can identify the calls that are not directly contributing to the training. These calls can be from the following operations: computing the accuracy, adding the losses for debugging or logging purposes, and printing the debugging information. Operations like these can be compute intensive or time consuming. We can identify such operations by correlating the Python profiler, system metrics, and framework metrics.

The following list shows what analysis is available from this class method:

- Profile time spent on each data batch, BatchTime_in_seconds, by finding the difference between start times of current and subsequent GetNext calls.
- Find the outliers in BatchTime_in_seconds and start and end time for those outliers.
- Obtain the system and framework metrics during those BatchTime_in_seconds timestamps. This indicates where the time was spent.

```
pt_analysis.plot_the_window()
```

Plots a timeline charts between a start timestamp and the end timestamp.

List of Debugger Built-in Rules

Use the Debugger built-in rules provided by Amazon SageMaker Debugger and analyze tensors emitted while training your models. The Debugger built-in rules monitor various common conditions that are critical for the success of a training job. You can call the built-in rules using Amazon SageMaker Python SDK or the low-level SageMaker API operations. Depending on deep learning frameworks of your choice, there are four scopes of validity for the built-in rules as shown in the following table.

**Note**
The maximum numbers of built-in rules for a training job are 20 for ProfilerRule and 20 for Rule. SageMaker Debugger fully manages the built-in rules and analyzes your training job in parallel. For more information about billing, see the Amazon SageMaker Studio is available at no additional charge section of the Amazon SageMaker Pricing page.
Important
To use the new Debugger features, you need to upgrade the SageMaker Python SDK and the SMDebug client library. In your iPython kernel, Jupyter notebook, or JupyterLab environment, run the following code to install the latest versions of the libraries and restart the kernel.

```python
import sys
import IPython
!{sys.executable} -m pip install -U sagemaker smdebug
IPython.Application.instance().kernel.do_shutdown(True)
```

Debugger ProfilerRule

The following rules are the Debugger built-in rules that are callable using the ProfilerRule.sagemaker classmethod.

### Debugger Built-in Rules for Generating Profiling Reports

<table>
<thead>
<tr>
<th>Scope of Validity</th>
<th>Built-in Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profiling Report for any SageMaker training job</td>
<td>• ProfilerReport (p. 2368)</td>
</tr>
</tbody>
</table>

### Debugger Built-in Rules for Monitoring Hardware System Resource Utilization (System Metrics)

<table>
<thead>
<tr>
<th>Scope of Validity</th>
<th>Built-in Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Generic system monitoring rules for any SageMaker training job</td>
<td>• BatchSize (p. 2369)</td>
</tr>
<tr>
<td></td>
<td>• CPUBottleneck (p. 2370)</td>
</tr>
<tr>
<td></td>
<td>• GPUMemoryIncrease (p. 2371)</td>
</tr>
<tr>
<td></td>
<td>• IOBottleneck (p. 2372)</td>
</tr>
<tr>
<td></td>
<td>• LoadBalancing (p. 2374)</td>
</tr>
<tr>
<td></td>
<td>• LowGPUUtilization (p. 2374)</td>
</tr>
<tr>
<td></td>
<td>• OverallSystemUsage (p. 2376)</td>
</tr>
</tbody>
</table>

### Debugger Built-in Rules for Profiling Framework Metrics

<table>
<thead>
<tr>
<th>Scope of Validity</th>
<th>Built-in Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Profiling rules for deep learning frameworks (TensorFlow and PyTorch)</td>
<td>• MaxInitializationTime (p. 2376)</td>
</tr>
<tr>
<td></td>
<td>• OverallFrameworkMetrics (p. 2377)</td>
</tr>
<tr>
<td></td>
<td>• StepOutlier (p. 2377)</td>
</tr>
</tbody>
</table>

Debugger Rule

The following rules are the Debugger built-in rules that are callable using the Rule.sagemaker classmethod.

### Debugger Built-in Rules for Generating Training Reports

<table>
<thead>
<tr>
<th>Scope of Validity</th>
<th>Built-in Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training Report for SageMaker XGboost training job</td>
<td>• create_xgboost_report (p. 2378)</td>
</tr>
</tbody>
</table>
### Debugger Built-in Rules for Debugging Model Training Data (Output Tensors)

<table>
<thead>
<tr>
<th>Scope of Validity</th>
<th>Built-in Rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deep learning frameworks (TensorFlow, MXNet, and PyTorch)</td>
<td>• dead_relu (p. 2379)</td>
</tr>
<tr>
<td></td>
<td>• exploding_tensor (p. 2380)</td>
</tr>
<tr>
<td></td>
<td>• poor_weight_initialization (p. 2381)</td>
</tr>
<tr>
<td></td>
<td>• saturated_activation (p. 2383)</td>
</tr>
<tr>
<td></td>
<td>• vanishing_gradient (p. 2386)</td>
</tr>
<tr>
<td></td>
<td>• weight_update_ratio (p. 2387)</td>
</tr>
<tr>
<td>Deep learning frameworks (TensorFlow, MXNet, and PyTorch) and the XGBoost algorithm</td>
<td>• all_zero (p. 2388)</td>
</tr>
<tr>
<td></td>
<td>• class_imbalance (p. 2390)</td>
</tr>
<tr>
<td></td>
<td>• loss_not_decreasing (p. 2392)</td>
</tr>
<tr>
<td></td>
<td>• overfit (p. 2394)</td>
</tr>
<tr>
<td></td>
<td>• overtraining (p. 2395)</td>
</tr>
<tr>
<td></td>
<td>• similar_across_runs (p. 2397)</td>
</tr>
<tr>
<td></td>
<td>• stalled_training_rule (p. 2398)</td>
</tr>
<tr>
<td></td>
<td>• tensor_variance (p. 2399)</td>
</tr>
<tr>
<td></td>
<td>• unchanged_tensor (p. 2401)</td>
</tr>
<tr>
<td>Deep learning applications</td>
<td>• check_input_images (p. 2403)</td>
</tr>
<tr>
<td></td>
<td>• nlp_sequence_ratio (p. 2404)</td>
</tr>
<tr>
<td>XGBoost algorithm</td>
<td>• confusion (p. 2405)</td>
</tr>
<tr>
<td></td>
<td>• feature_importance_overweight (p. 2408)</td>
</tr>
<tr>
<td></td>
<td>• tree_depth (p. 2409)</td>
</tr>
</tbody>
</table>

**To use the built-in rules with default parameter values** – use the following configuration format:

```python
from sagemaker.debugger import Rule, ProfilerRule, rule_configs

rules = [
    ProfilerRule.sagemaker(rule_configs.BuiltInRuleName_1()),
    ProfilerRule.sagemaker(rule_configs.BuiltInRuleName_2()),
    ...
    ProfilerRule.sagemaker(rule_configs.BuiltInRuleName_n()),
    Rule.sagemaker(rule_configs.built_in_rule_name_1()),
    Rule.sagemaker(rule_configs.built_in_rule_name_2()),
    ...
    Rule.sagemaker(rule_configs.built_in_rule_name_n())
]
```

**To use the built-in rules with customizing the parameter values** – use the following configuration format:

```python
from sagemaker.debugger import Rule, ProfilerRule, rule_configs

rules = [
    ProfilerRule.sagemaker(
        base_config=rule_configs.BuiltInRuleName(),
        rule_parameters={
            "key": "value"
        }
    )
]```
To find available keys for the rule_parameters parameter, see the parameter description tables.

Sample rule configuration codes are provided for each built-in rule below the parameter description tables.

- For a full instruction and examples of using the Debugger built-in rules, see Debugger Built-in Rules Example Code (p. 2290).
- For a full instruction of using the built-in rules with the low-level SageMaker API operations, see Configure Debugger Using Amazon SageMaker API (p. 2415).

### ProfilerReport

The ProfilerReport rule invokes all of the built-in rules for monitoring and profiling. It creates a profiling report and updates when the individual rules are triggered. You can download a comprehensive profiling report while a training job is running or after the training job is complete. You can adjust the rule parameter values to customize sensitivity of the built-in monitoring and profiling rules. The following example code shows the basic format to adjust the built-in rule parameters through the ProfilerReport rule.

```
rules=[
    ProfilerRule.sagemaker(
        rule_configs.ProfilerReport(
            CPUBottleneck_cpu_threshold = 90,
            IOBottleneck_threshold = 90
        )
    )
]
```

If you trigger this ProfilerReport rule without any customized parameter as shown in the following example code, then the ProfilerReport rule triggers all of the built-in rules for monitoring and profiling with their default parameter values.

```
rules=[ProfilerRule.sagemaker(rule_configs.ProfilerReport())]
```

The following example code shows how to specify and adjust the CPUBottleneck rule's cpu_threshold parameter and the IOBottleneck rule's threshold parameter.

```
rules=[
    ProfilerRule.sagemaker(
        rule_configs.ProfilerReport(
            CPUBottleneck_cpu_threshold = 90,
            IOBottleneck_threshold = 90
        )
    )
]`
Parameter Descriptions for the OverallSystemUsage Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>&lt;BuiltInRuleName&gt;_&lt;parameter_name&gt;</td>
<td>Customizable parameter to adjust thresholds of other built-in monitoring and profiling rules.</td>
</tr>
</tbody>
</table>

BatchSize

The BatchSize rule helps detect if GPU is underutilized due to a small batch size. To detect this issue, this rule monitors the average CPU utilization, GPU utilization, and GPU memory utilization. If utilization on CPU, GPU, and GPU memory is low on average, it may indicate that the training job can either run on a smaller instance type or can run with a bigger batch size. However, increasing the batch size can lead to processing or data loading bottlenecks because more data preprocessing time is required in each iteration.

Parameter Descriptions for the BatchSize Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>cpu_threshold_p95</td>
<td>Defines the threshold for 95th quantile of CPU utilization in percentage.</td>
</tr>
<tr>
<td>gpu_threshold_p95</td>
<td>Defines the threshold for 95th quantile of GPU utilization in percentage.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------------------------</td>
<td>------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>default_value: 70 (in percentage)</td>
<td></td>
</tr>
<tr>
<td>gpu_memory_threshold_p95</td>
<td>Defines the threshold for 95th quantile of GPU memory utilization in percentage.</td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 70 (in percentage)</td>
</tr>
<tr>
<td>patience</td>
<td>Defines the number of data points to skip until the rule starts evaluation.</td>
</tr>
<tr>
<td></td>
<td>The first several steps of training jobs usually show high volume of data</td>
</tr>
<tr>
<td></td>
<td>processes, so keep the rule patient and prevent it from being invoked too</td>
</tr>
<tr>
<td></td>
<td>soon with a given number of profiling data that you specify with this</td>
</tr>
<tr>
<td></td>
<td>parameter.</td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 100</td>
</tr>
<tr>
<td>window</td>
<td>Window size for computing quantiles.</td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 500</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval that timeline files are scanned.</td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 60000000 (in microseconds)</td>
</tr>
</tbody>
</table>

**CPUBottleneck**

The CPUBottleneck rule helps detect if GPU is underutilized due to CPU bottlenecks. Rule returns True if number of CPU bottlenecks exceeds a predefined threshold.

**Parameter Descriptions for the CPUBottleneck Rule**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the</td>
</tr>
<tr>
<td></td>
<td>current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td>Required</td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>threshold</td>
<td>Defines the threshold for proportion of bottlenecked time to the total training time. If the proportion exceeds the percentage specified to the threshold parameter, the rule switches the rule status to True.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 50 (in percentage)</td>
</tr>
<tr>
<td>gpu_threshold</td>
<td>A threshold that defines low GPU utilization.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 10 (in percentage)</td>
</tr>
<tr>
<td>cpu_threshold</td>
<td>A threshold that defines high CPU utilization.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 90 (in percentage)</td>
</tr>
<tr>
<td>patience</td>
<td>Defines the number of data points to skip until the rule starts evaluation. The first several steps of training jobs usually show high volume of data processes, so keep the rule patient and prevent it from being invoked too soon with a given number of profiling data that you specify with this parameter.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 100</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval with which timeline files are scanned.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 60000000 (in microseconds)</td>
</tr>
</tbody>
</table>

**GPUMemoryIncrease**

The GPUMemoryIncrease rule helps detect a large increase in memory usage on GPUs.
### Parameter Descriptions for the GPUMemoryIncrease Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>increase</td>
<td>Defines the threshold for absolute memory increase.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 10 (in percentage)</td>
</tr>
<tr>
<td>patience</td>
<td>Defines the number of data points to skip until the rule starts evaluation. The first several steps of training jobs usually show high volume of data processes, so keep the rule patient and prevent it from being invoked too soon with a given number of profiling data that you specify with this parameter.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 100</td>
</tr>
<tr>
<td>window</td>
<td>Window size for computing quantiles.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 500</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval that timeline files are scanned.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 60000000 (in microseconds)</td>
</tr>
</tbody>
</table>

### IOBottleneck

This rule helps to detect if GPU is underutilized due to data IO bottlenecks. Rule returns True if number of IO bottlenecks exceeds a predefined threshold.
### Parameter Descriptions for the IOBottleneck Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>threshold</td>
<td>Defines the threshold when Rule to return True.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 50 (in percentage)</td>
</tr>
<tr>
<td>gpu_threshold</td>
<td>A threshold that defines when GPU is considered underutilized.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 70 (in percentage)</td>
</tr>
<tr>
<td>io_threshold</td>
<td>A threshold that defines high IO wait time.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 50 (in percentage)</td>
</tr>
<tr>
<td>patience</td>
<td>Defines the number of data points to skip until the rule starts evaluation. The first several steps of training jobs usually show high volume of data processes, so keep the rule patient and prevent it from being invoked too soon with a given number of profiling data that you specify with this parameter.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 1000</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval that timeline files are scanned.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 60000000 (in microseconds)</td>
</tr>
</tbody>
</table>
LoadBalancing

The LoadBalancing rule helps detect issues in workload balancing among multiple GPUs.

Parameter Descriptions for the LoadBalancing Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>threshold</td>
<td>Defines the workload percentage.</td>
</tr>
<tr>
<td>patience</td>
<td>Defines the number of data points to skip until the rule starts evaluation. The first several steps of training jobs usually show high volume of data processes, so keep the rule patient and prevent it from being invoked too soon with a given number of profiling data that you specify with this parameter.</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval that timeline files are scanned.</td>
</tr>
</tbody>
</table>

LowGPUtilization

The LowGPUtilization rule helps detect if GPU utilization is low or suffers from fluctuations. This is checked for each GPU on each worker. Rule returns True if 95th quantile is below threshold_p95 which indicates underutilization. Rule returns true if 95th quantile is above threshold_p95 and 5th quantile is below threshold_p5 which indicates fluctuations.
### Parameter Descriptions for the LowGPUtilization Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>threshold_p95</td>
<td>A threshold for 95th quantile below which GPU is considered to be underutilized.</td>
</tr>
<tr>
<td>threshold_p5</td>
<td>A threshold for 5th quantile. Default is 10 percent.</td>
</tr>
<tr>
<td>patience</td>
<td>Defines the number of data points to skip until the rule starts evaluation. The first several steps of training jobs usually show high volume of data processes, so keep the rule patient and prevent it from being invoked too soon with a given number of profiling data that you specify with this parameter.</td>
</tr>
<tr>
<td>window</td>
<td>Window size for computing quantiles.</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval that timeline files are scanned.</td>
</tr>
</tbody>
</table>

**Base Trial**

- **Required**
- **Valid values:** String

**Threshold p95**

- **Optional**
- **Valid values:** Integer
- **Default value:** 70 (in percentage)

**Threshold p5**

- **Optional**
- **Valid values:** Integer
- **Default values:** 10 (in percentage)

**Patience**

- **Optional**
- **Valid values:** Integer
- **Default values:** 1000

**Window**

- **Optional**
- **Valid values:** Integer
- **Default values:** 500

**Scan Interval (us)**

- **Optional**
- **Valid values:** Integer
- **Default values:** 60000000 (in microseconds)
### OverallSystemUsage

The OverallSystemUsage rule measures overall system usage per worker node. The rule currently only aggregates values per node and computes their percentiles.

**Parameter Descriptions for the OverallSystemUsage Rule**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval to scan timeline files.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 60000000 (in microseconds)</td>
</tr>
</tbody>
</table>

### MaxInitializationTime

The MaxInitializationTime rule helps detect if the training initialization is taking too much time. The rule waits until the first step is available.

**Parameter Descriptions for the MaxInitializationTime Rule**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>threshold</td>
<td>Defines the threshold in minutes to wait for the first step to become available.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 20 (in minutes)</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval with which timeline files are scanned.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 60000000 (in microseconds)</td>
</tr>
</tbody>
</table>
OverallFrameworkMetrics

The OverallFrameworkMetrics rule summarizes the time spent on framework metrics, such as forward and backward pass, and data loading.

Parameter Descriptions for the OverallFrameworkMetrics Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger. Required Valid values: String</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval to scan timeline files. Optional Valid values: Integer Default values: 60000000 (in microseconds)</td>
</tr>
</tbody>
</table>

StepOutlier

The StepOutlier rule helps detect outliers in step durations. This rule returns True if there are outliers with step durations larger than stddev sigmas of the entire step durations in a time range.

Parameter Descriptions for the StepOutlier Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger. Required Valid values: String</td>
</tr>
<tr>
<td>stddev</td>
<td>Defines a factor by which to multiply the standard deviation. For example, the rule is invoked by default when a step duration is larger or smaller than 5 times the standard deviation. Optional Valid values: Integer Default value: 5 (in minutes)</td>
</tr>
<tr>
<td>mode</td>
<td>Mode under which steps have been saved and on which Rule should run on. Per default rule will run on steps from EVAL and TRAIN phase Optional</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td><strong>Parameter Name</strong></td>
<td><strong>Description</strong></td>
</tr>
<tr>
<td>n_outliers</td>
<td>How many outliers to ignore before rule returns True</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 10</td>
</tr>
<tr>
<td>scan_interval_us</td>
<td>Time interval with which timeline files are scanned.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default values: 60000000 (in microseconds)</td>
</tr>
</tbody>
</table>

### CreateXgboostReport

The `CreateXgboostReport` rule collects output tensors from an XGBoost training job and autogenerates a comprehensive training report. You can download a comprehensive profiling report while a training job is running or after the training job is complete, and check progress of training or the final result of the training job. The `CreateXgboostReport` rule collects the following output tensors by default:

- `hyperparameters` – Saves at the first step
- `metrics` – Saves loss and accuracy every 5 steps
- `feature_importance` – Saves every 5 steps
- `predictions` – Saves every 5 steps
- `labels` – Saves every 5 steps

### Parameter Descriptions for the CreateXgboostReport Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
</tbody>
</table>

```python
rules=[
    Rule.sagemaker(
        rule_configs.create_xgboost_report()
    )
]
```
DeadRelu

This rule detects when the percentage of rectified linear unit (ReLU) activation functions in a trial are considered dead because their activation activity has dropped below a threshold. If the percent of inactive ReLUs in a layer is greater than the `threshold_layer` value of inactive ReLUs, the rule returns True.

**Parameter Descriptions for the DeadRelu Rule**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| base_trial       | The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger. Required
|                  | Valid values: String                                                                                                   |
| tensor_regex     | A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched. Optional
|                  | Valid values: List of strings or a comma-separated string
|                  | Default value: ".*relu_output"                                                                                      |
| threshold_inactivity | Defines a level of activity below which a ReLU is considered to be dead. A ReLU might be active in the beginning of a trial and then slowly die during the training process. If the ReLU is active less than the `threshold_inactivity`, it is considered to be dead. Optional
|                  | Valid values: Float
|                  | Default values: 1.0 (in percentage)                                                                                   |
| threshold_layer  | Returns True if the percentage of inactive ReLUs in a layer is greater than `threshold_layer`. Returns False if the percentage of inactive ReLUs in a layer is less than `threshold_layer`. Optional
|                  | Valid values: Float
|                  | Default values: 50.0 (in percentage)                                                                                 |
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.dead_relu(),
        rule_parameters={
            "tensor_regex": ".*relu_output|.*ReLU_output",
            "threshold_inactivity": "1.0",
            "threshold_layer": "50.0"
        },
        collections_to_save=[
            CollectionConfig(
                name="custom_relu_collection",
                parameters={
                    "include_regex": ".*relu_output|.*ReLU_output",
                    "save_interval": "500"
                }
            )
        ]
    )
]  

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

**Note**

This rule is not available for the XGBoost algorithm.

### ExplodingTensor

This rule detects whether the tensors emitted during training have non-finite values, either infinite or NaN (not a number). If a non-finite value is detected, the rule returns `True`.

#### Parameter Descriptions for the ExplodingTensor Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>collection_names</td>
<td>The list of collection names whose tensors the rule inspects.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>tensor_regex</td>
<td>A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
</tbody>
</table>
| only_nan       | True to monitor the base_trial tensors only for NaN values and not for infinity.  
False to treat both NaN and infinity as exploding values and to monitor for both. |

```
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.exploding_tensor(),
        rule_parameters={
            "tensor_regex": ".*gradient",
            "only_nan": "False"
        },
        collections_to_save=[
            CollectionConfig(
                name="gradients",
                parameters={
                    "save_interval": "500"
                }
            )
        ]
    )
]
```

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

**Note**
This rule is not available for the XGBoost algorithm.

**PoorWeightInitialization**

This rule detects if your model parameters have been poorly initialized.

Good initialization breaks the symmetry of the weights and gradients in a neural network and maintains commensurate activation variances across layers. Otherwise, the neural network doesn't learn effectively. Initializers like Xavier aim to keep variance constant across activations, which is especially relevant for training very deep neural nets. Too small an initialization can lead to vanishing gradients. Too large an initialization can lead to exploding gradients. This rule checks the variance of activation inputs across layers, the distribution of gradients, and the loss convergence for the initial steps to determine if a neural network has been poorly initialized.

**Parameter Descriptions for the PoorWeightInitialization Rule**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>activation_inputs_regex</td>
<td>A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched.</td>
</tr>
<tr>
<td>threshold</td>
<td>If the ratio between minimum and maximum variance of weights per layer exceeds the threshold at a step, the rule returns True.</td>
</tr>
<tr>
<td>distribution_range</td>
<td>If the minimum difference between 5th and 95th percentiles of the gradient distribution is less than the distribution_range, the rule returns True.</td>
</tr>
<tr>
<td>patience</td>
<td>The number of steps to wait until the loss is considered to be no longer decreasing.</td>
</tr>
<tr>
<td>steps</td>
<td>The number of steps this rule analyzes. You typically need to check only the first few iterations.</td>
</tr>
</tbody>
</table>
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.poor_weight_initialization(),
        rule_parameters={
            "activation_inputs_regex": ".*relu_input|.*ReLU_input",
            "threshold": "10.0",
            "distribution_range": "0.001",
            "patience": "5",
            "steps": "10"
        },
        collections_to_save=[
            CollectionConfig(
                name="custom_relu_collection",
                parameters={
                    "include_regex": ".*relu_input|.*ReLU_input",
                    "save_interval": "500"
                }
            )
        ]
    )
]

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

Note

This rule is not available for the XGBoost algorithm.

### SaturatedActivation

This rule detects if the tanh and sigmoid activation layers are becoming saturated. An activation layer is saturated when the input of the layer is close to the maximum or minimum of the activation function. The minimum and maximum of the tanh and sigmoid activation functions are defined by their respective min_threshold and max_thresholds values. If the activity of a node drops below the threshold_inactivity percentage, it is considered saturated. If more than a threshold_layer percent of the nodes are saturated, the rule returns True.

### Parameter Descriptions for the SaturatedActivation Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>collection_names</td>
<td>The list of collection names whose tensors the rule inspects.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>tensor_regex</td>
<td>A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td>rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched.</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: String</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;.*tanh_input|.*sigmoid_input&quot;.</td>
</tr>
<tr>
<td></td>
<td>threshold_tanh_min                                                                                                               The minimum and maximum thresholds that define the extremes of the input for a tanh activation function, defined as: (min_threshold, max_threshold). The default values are determined based on a vanishing gradient threshold of 0.0000001.</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default values: -9.4999</td>
</tr>
<tr>
<td></td>
<td>threshold_tanh_max                                                                                                              The minimum and maximum thresholds that define the extremes of the input for a tanh activation function, defined as: (min_threshold, max_threshold). The default values are determined based on a vanishing gradient threshold of 0.0000001.</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default values: 9.4999</td>
</tr>
<tr>
<td></td>
<td>threshold_sigmoid_min                                                              The minimum and maximum thresholds that define the extremes of the input for a sigmoid activation function, defined as: (min_threshold, max_threshold). The default values are determined based on a vanishing gradient threshold of 0.0000001.</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default values: -23</td>
</tr>
</tbody>
</table>
### List of Built-in Rules

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
<th>Optional</th>
<th>Valid values</th>
<th>Default values</th>
</tr>
</thead>
<tbody>
<tr>
<td>threshold_sigmoid_max</td>
<td>The minimum and maximum thresholds that define the extremes of the input for a sigmoid activation function, defined as: ((\text{min_threshold}, \text{max_threshold})). The default values are determined based on a vanishing gradient threshold of 0.0000001.</td>
<td>Optional</td>
<td>Float</td>
<td>16.99999</td>
</tr>
<tr>
<td>threshold_inactivity</td>
<td>The percentage of inactivity below which the activation layer is considered to be saturated. The activation might be active in the beginning of a trial and then slowly become less active during the training process.</td>
<td>Optional</td>
<td>Float</td>
<td>1.0</td>
</tr>
<tr>
<td>threshold_layer</td>
<td>Returns True if the number of saturated activations in a layer is greater than the threshold_layer percentage.</td>
<td>Optional</td>
<td>Float</td>
<td>50.0</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.saturated_activation(),
        rule_parameters={
            "tensor_regex": ".*tanh_input\|.*sigmoid_input",
            "threshold_tanh_min": "-9.4999",
            "threshold_tanh_max": "9.4999",
            "threshold_sigmoid_min": "-23",
            "threshold_sigmoid_max": "16.99999",
            "threshold_inactivity": "1.0",
            "threshold_layer": "50.0"
        },
        collections_to_save=[
            CollectionConfig(
                name="custom_activations_collection",
                parameters={
                    "include_regex": "\.*tanh_input\|.*sigmoid_input",
                    "save_interval": "500"
                }
            )
        ]
    )
]```

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For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

**Note**
This rule is not available for the XGBoost algorithm.

### VanishingGradient

This rule detects if the gradients in a trial become extremely small or drop to a zero magnitude. If the mean of the absolute values of the gradients drops below a specified threshold, the rule returns True.

**Parameters Descriptions for the VanishingGradient Rule**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>threshold</td>
<td>The value at which the gradient is determined to be vanishing.</td>
</tr>
</tbody>
</table>

- **base_trial**
  - Required
  - Valid values: String
  - Default value: 0.0000001

- **threshold**
  - Optional
  - Valid values: Float

```python
built_in_rules = [  
    Rule.sagemaker(  
        base_config=rule_configs.vanishing_gradient(),  
        rule_parameters={  
            "threshold": "0.0000001"  
        },  
        collections_to_save=[  
            CollectionConfig(  
                name="gradients",  
                parameters={  
                    "save_interval": "500"  
                }  
            )  
        ]  
    )  
]
```

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

**Note**
This rule is not available for the XGBoost algorithm.
WeightUpdateRatio

This rule keeps track of the ratio of updates to weights during training and detects if that ratio gets too large or too small. If the ratio of updates to weights is larger than the large_threshold value or if this ratio is smaller than small_threshold, the rule returns True.

Conditions for training are best when the updates are commensurate to gradients. Excessively large updates can push the weights away from optimal values, and very small updates result in very slow convergence. This rule requires weights to be available for two training steps, and train.save_interval needs to be set equal to num_steps.

Parameter Descriptions for the WeightUpdateRatio Rule

<table>
<thead>
<tr>
<th>Parameter Name,</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>num_steps</td>
<td>The number of steps across which the rule checks to determine if the tensor has changed. The number of steps across which you want to compare the weight ratios. If you pass no value, the rule runs by default against the current step and the immediately previous saved step. If you override the default by passing a value for this parameter, the comparison is done between weights at step $s$ and at a step $\geq s - num_steps$.</td>
</tr>
<tr>
<td>large_threshold</td>
<td>The maximum value that the ratio of updates to weight can take before the rule returns True.</td>
</tr>
<tr>
<td>small_threshold</td>
<td>The minimum value that the ratio of updates to weight can take, below which the rule returns True.</td>
</tr>
</tbody>
</table>

- **base_trial**
  - **Required**
  - **Valid values:** String
  - **Default value:** None

- **num_steps**
  - **Optional**
  - **Valid values:** Integer
  - **Default value:** None

- **large_threshold**
  - **Optional**
  - **Valid values:** Float
  - **Default value:** 10.0

- **small_threshold**
  - **Optional**
  - **Valid values:** Float
  - **Default value:** 0.00000001
### Built-in Rules

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>epsilon</td>
<td>A small constant used to ensure that Debugger does not divide by zero when computing the ratio updates to weigh.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.000000001</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.weight_update_ratio(),
        rule_parameters={
            "num_steps": "100",
            "large_threshold": "10.0",
            "small_threshold": "0.00000001",
            "epsilon": "0.000000001"
        },
        collections_to_save=[
            CollectionConfig(
                name="weights",
                parameters={
                    "train.save_interval": "100"
                }
            )
        ]
    )
]
```

For an example of how to configure and deploy a built-in rule, see [Configure Debugger Built-in Rules](p. 2287).

**Note**

This rule is not available for the XGBoost algorithm.

## AllZero

This rule detects if all or a specified percentage of the tensor values are zero.

This rule can be applied either to one of the supported deep learning frameworks (TensorFlow, MXNet, and PyTorch) or to the XGBoost algorithm. You must specify either the `collection_names` or `tensor_regex` parameter. If both the parameters are specified, the rule inspects the union of tensors from both sets.

For an example of how to configure and deploy a built-in rule, see [Configure Debugger Built-in Rules](p. 2287).

### Parameters Descriptions for the AllZero Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td>Required</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>collection_names</td>
<td>The list of collection names whose tensors the rule inspects.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>tensor_regex</td>
<td>A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>threshold</td>
<td>Specifies the percentage of values in the tensor that needs to be zero for this rule to be invoked.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: 100 (in percentage)</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.all_zero(),
        rule_parameters={
            "tensor_regex": ".+",
            "threshold": "100"
        },
        collections_to_save=[
            CollectionConfig(
                name="all",
                parameters={
                    "save_interval": "500"
                }
            )
        ]
    )
]```
ClassImbalance

This rule measures sampling imbalances between classes and throws errors if the imbalance exceeds a threshold or if too many mispredictions for underrepresented classes occur as a result of the imbalance.

Classification models require well-balanced classes in the training dataset or a proper weighting/sampling of classes during training. The rule performs the following checks:

- It counts the occurrences per class. If the ratio of number of samples between smallest and largest class is larger than the `threshold_imbalance`, an error is thrown.
- It checks the prediction accuracy per class. If resampling or weighting has not been correctly applied, then the model can reach high accuracy for the class with many training samples, but low accuracy for the classes with few training samples. If a fraction of mispredictions for a certain class is above `threshold_misprediction`, an error is thrown.

This rule can be applied either to one of the supported deep learning frameworks (TensorFlow, MXNet, and PyTorch) or to the XGBoost algorithm.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

### Parameter Descriptions for the ClassImbalance Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>base_trial</code></td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td><code>threshold_imbalance</code></td>
<td>The acceptable imbalance between the number of samples in the smallest class and in the largest class. Exceeding this threshold value throws an error.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: 10</td>
</tr>
<tr>
<td><code>threshold_misprediction</code></td>
<td>A limit on the fraction of mispredictions allowed for each class. Exceeding this threshold throws an error. The underrepresented classes are most at risk of crossing this threshold.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.7</td>
</tr>
<tr>
<td><code>samples</code></td>
<td>The number of labels that have to be processed before an imbalance is evaluated. The rule might not be triggered until it has seen sufficient samples across several steps. The more classes</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
</tbody>
</table>
| that your dataset contains, the larger this sample number should be.  | **Optional**  
|Valid values: Integer  |Default value: 500 (assuming a dataset like MNIST with 10 classes)  |
| **argmax** | If True, np.argmax is applied to the prediction tensor. Required when you have a vector of probabilities for each class. It is used to determine which class has the highest probability.  |**Conditional**  
|Valid values: Boolean  |Default value: False  |
| **labels_regex** | The name of the tensor that contains the labels.  |**Optional**  
|Valid values: String  |Default value: ".*labels"  |
| **predictions_regex** | The name of the tensor that contains the predictions.  |**Optional**  
|Valid values: String  |Default value: ".*predictions"  |

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.class_imbalance(),
        rule_parameters={
            "threshold_imbalance": "10",
            "threshold_misprediction": "0.7",
            "samples": "500",
            "argmax": "False",
            "labels_regex": ".*labels",
            "predictions_regex": ".*predictions"
        },
        collections_to_save=[
            CollectionConfig(
                name="custom_output_collection",
                parameters={
                    "include_regex": ".*labels|.*predictions",
                    "save_interval": "500"
                }
            )
        ]
    )
]```
LossNotDecreasing

This rule detects when the loss is not decreasing in value at an adequate rate. These losses must be scalars.

This rule can be applied either to one of the supported deep learning frameworks (TensorFlow, MXNet, and PyTorch) or to the XGBoost algorithm. You must specify either the `collection_names` or `tensor_regex` parameter. If both the parameters are specified, the rule inspects the union of tensors from both sets.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

Parameter Descriptions for the LossNotDecreasing Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>base_trial</code></td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td><code>collection_names</code></td>
<td>The list of collection names whose tensors the rule inspects.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td><code>tensor_regex</code></td>
<td>A list of regex patterns that is used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td><code>use_losses_collection</code></td>
<td>If set to <code>True</code>, looks for losses in the collection named &quot;losses&quot; when the collection is present.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Boolean</td>
</tr>
<tr>
<td></td>
<td>Default value: <code>True</code></td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description                                                                                                                                                                                                                                                                                                                                stäufser</td>
</tr>
<tr>
<td>------------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>num_steps</td>
<td>The minimum number of steps after which the rule checks if the loss has decreased. Rule evaluation happens every num_steps. The rule compares the loss for this step with the loss at a step which is at least num_steps behind the current step. For example, suppose that the loss is being saved every three steps, but num_steps is set to 10. At step 21, loss for step 21 is compared with loss for step 9. The next step at which loss is checked is step 33, because ten steps after step 21 is step 31, and at step 31 and step 32 loss is not saved.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 10</td>
</tr>
<tr>
<td>diff_percent</td>
<td>The minimum percentage difference by which the loss should decrease between num_steps.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0.0 &lt; float &lt; 100</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.1 (in percentage)</td>
</tr>
<tr>
<td>increase_threshold_percent</td>
<td>The maximum threshold percent that loss is allowed to increase in case loss has been increasing</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: 0 &lt; float &lt; 100</td>
</tr>
<tr>
<td></td>
<td>Default value: 5 (in percentage)</td>
</tr>
<tr>
<td>mode</td>
<td>The name of the Debugger mode to query tensor values for rule checking. If this is not passed, the rule checks in order by default for the mode . EVAL, then mode . TRAIN, and then mode . GLOBAL.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String (EVAL, TRAIN, or GLOBAL)</td>
</tr>
<tr>
<td></td>
<td>Default value: GLOBAL</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.loss_not_decreasing(),
        rule_parameters={
            "tensor_regex": ".*",
            "use_losses_collection": "True",
            "num_steps": "10",
```
### Overfit

This rule detects if your model is being overfit to the training data by comparing the validation and training losses.

This rule can be applied either to one of the supported deep learning frameworks (TensorFlow, MXNet, and PyTorch) or to the XGBoost algorithm.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

**Note**

A standard way to prevent overfitting is to regularize your model.

#### Parameter Descriptions for the Overfit Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| base_trial     | The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.  

**Required**  

Valid values: String |
| tensor_regex    | A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched.  

**Optional**  

Valid values: List of strings or a comma-separated string  

Default value: None |
| start_step      | The step from which to start comparing the validation and training loss.  

**Optional** |
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>patience</td>
<td>The number of steps for which the ratio_threshold is allowed to exceed the value set before the model is considered to be overfit.</td>
</tr>
<tr>
<td>ratio_threshold</td>
<td>The maximum ratio of the difference between the mean validation loss and mean training loss to the mean training loss. If this threshold is exceeded for a patience number of steps, the model is being overfit and the rule returns True.</td>
</tr>
</tbody>
</table>

```
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.overfit(),
        rule_parameters={
            "tensor_regex": ".*",
            "start_step": "0",
            "patience": "1",
            "ratio_threshold": "0.1"
        },
        collections_to_save=[
            CollectionConfig(
                name="losses",
                parameters={
                    "train.save_interval": "100",
                    "eval.save_interval": "10"
                }
            )
        ]
    )
]
```

**Overtraining**

This rule detects if a model is being overtrained. After a number of training iterations on a well-behaved model (both training and validation loss decrease), the model approaches to a minimum of the loss function and does not improve anymore. If the model continues training it can happen that validation loss starts increasing, because the model starts overfitting. This rule sets up thresholds and conditions to determine if the model is not improving, and prevents overfitting problems due to overtraining.

This rule can be applied either to one of the supported deep learning frameworks (TensorFlow, MXNet, and PyTorch) or to the XGBoost algorithm.
For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

**Note**
Overtraining can be avoided by early stopping. For information on early stopping, see Stop Training Jobs Early (p. 2458). For an example that shows how to use spot training with Debugger, see Enable Spot Training with Amazon SageMaker Debugger.

### Parameter Descriptions for the Overtraining Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>patience_train</td>
<td>The number of steps to wait before the training loss is considered to not to be improving anymore.</td>
</tr>
<tr>
<td>patience_validation</td>
<td>The number of steps to wait before the validation loss is considered to not to be improving anymore.</td>
</tr>
<tr>
<td>delta</td>
<td>The minimum threshold by how much the error should improve before it is considered as a new optimum.</td>
</tr>
</tbody>
</table>

**Parameter Descriptions**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>base_trial</strong></td>
<td>Required</td>
</tr>
<tr>
<td><strong>patience_train</strong></td>
<td>Optional</td>
</tr>
<tr>
<td><strong>patience_validation</strong></td>
<td>Optional</td>
</tr>
<tr>
<td><strong>delta</strong></td>
<td>Optional</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>base_trial</strong></td>
<td>Valid values: String</td>
</tr>
<tr>
<td><strong>patience_train</strong></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td><strong>patience_validation</strong></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td><strong>delta</strong></td>
<td>Valid values: Float</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.overtraining(),
        rule_parameters={
            "patience_train": "5",
            "patience_validation": "10",
            "delta": "0.01"
        },
        collections_to_save=[
            CollectionConfig(  
                name="losses",  
                parameters={
                    "save_interval": "500"
                }
            )
        ]
    )
]```
**SimilarAcrossRuns**

This rule compares tensors gathered from a base trial with tensors from another trial.

This rule can be applied either to one of the supported deep learning frameworks (TensorFlow, MXNet, and PyTorch) or to the XGBoost algorithm.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

**Parameter Descriptions for the SimilarAcrossRuns Rule**

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>other_trials</td>
<td>A completed training job name whose tensors you want to compare to those tensors gathered from the current base_trial.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>collection_names</td>
<td>The list of collection names whose tensors the rule inspects.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>tensor_regex</td>
<td>A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match</td>
</tr>
<tr>
<td></td>
<td>the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only</td>
</tr>
<tr>
<td></td>
<td>scalar-valued tensors can be matched.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
</tbody>
</table>
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.similar_across_runs(),
        rule_parameters={
            "other_trials": "<specify-another-job-name>",
            "collection_names": "losses",
            "tensor_regex": ".*"
        },
        collections_to_save=[
            CollectionConfig(
                name="losses",
                parameters={
                    "save_interval": "500"
                }
            )
        ]
    )
]

StalledTrainingRule

StalledTrainingRule detects if there is no progress made on training job, and stops the training job if the rule fires. This rule requires tensors to be periodically saved in a time interval defined by its threshold parameter. This rule keeps on monitoring for new tensors, and if no new tensor has been emitted for threshold interval rule gets fired.

Parameter Descriptions for the StalledTrainingRule Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>threshold</td>
<td>A threshold that defines by how much time in seconds the rule waits for a tensor output until it fires a stalled training issue. Default value is 1800 seconds.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 1800</td>
</tr>
<tr>
<td>stop_training_on_fire</td>
<td>If set to True, watches if the base training job outputs tensors in &quot;threshold&quot; seconds.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Boolean</td>
</tr>
<tr>
<td></td>
<td>Default value: False</td>
</tr>
<tr>
<td>training_job_name_prefix</td>
<td>The prefix of base training job name. If stop_training_on_fire is true, the rule</td>
</tr>
</tbody>
</table>
Amazon SageMaker Developer Guide
List of Built-in Rules

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
</tbody>
</table>

TensorVariance

This rule detects if you have tensors with very high or low variances. Very high or low variances in a tensor could lead to neuron saturation, which reduces the learning ability of the neural network. Very high variance in tensors can also eventually lead to exploding tensors. Use this rule to detect such issues early.

This rule can be applied either to one of the supported deep learning frameworks (TensorFlow, MXNet, and PyTorch) or to the XGBoost algorithm. You must specify either the collection_names or tensor_regex parameter. If both the parameters are specified, the rule inspect the union of tensors from both sets.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

Parameter Descriptions for the TensorVariance Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
</tbody>
</table>

Optional

Valid values: String
### List of Built-in Rules

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>collection_names</td>
<td>The list of collection names whose tensors the rule inspects.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>tensor_regex</td>
<td>A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>max_threshold</td>
<td>The threshold for the upper bound of tensor variance.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>min_threshold</td>
<td>The threshold for the lower bound of tensor variance.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.tensor_variance(),
        rule_parameters={
            "collection_names": "weights",
            "max_threshold": "10",
            "min_threshold": "0.00001",
        },
        collections_to_save=[
            CollectionConfig(
                name="weights",
                parameters={
                    "save_interval": "500"
                }]
            )
        ]
```
UnchangedTensor

This rule detects whether a tensor is no longer changing across steps.

This rule runs the `numpy.allclose` method to check if the tensor isn't changing.

This rule can be applied either to one of the supported deep learning frameworks (TensorFlow, MXNet, and PyTorch) or to the XGBoost algorithm. You must specify either the `collection_names` or `tensor_regex` parameter. If both the parameters are specified, the rule inspects the union of tensors from both sets.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

Parameter Descriptions for the UnchangedTensor Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>collection_names</td>
<td>The list of collection names whose tensors the rule inspects.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>tensor_regex</td>
<td>A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered in the trials by default. Only scalar-valued tensors can be matched.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: List of strings or a comma-separated string</td>
</tr>
<tr>
<td></td>
<td>Default value: None</td>
</tr>
<tr>
<td>num_steps</td>
<td>The number of steps across which the rule checks to determine if the tensor has changed.</td>
</tr>
<tr>
<td></td>
<td>This checks the last <code>num_steps</code> that are available. They don’t need to be consecutive. If <code>num_steps</code></td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td>num_steps</td>
<td>is 2, at step s it doesn't necessarily check for s-1 and s. If s-1 isn't available, it checks the last available step along with s. In that case, it checks the last available step with the current step.</td>
</tr>
<tr>
<td>rtol</td>
<td>The relative tolerance parameter to be passed to the <code>numpy.allclose</code> method.</td>
</tr>
<tr>
<td>atol</td>
<td>The absolute tolerance parameter to be passed to the <code>numpy.allclose</code> method.</td>
</tr>
<tr>
<td>equal_nan</td>
<td>Whether to compare NaNs as equal. If True, NaNs in input array a are considered equal to NaNs in input array b in the output array. This parameter is passed to the <code>numpy.allclose</code> method.</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.unchanged_tensor(),
        rule_parameters={
            "collection_names": "losses",
            "tensor_regex": "",
            "num_steps": "3",
            "rtol": "1e-05",
            "atol": "1e-08",
            "equal_nan": "False"
        },
        collections_to_save=[
            CollectionConfig(name="losses",
                             parameters={
                                "save_interval": "500"
                             })
        ]
    )
]```

Optional
Valid values: Integer
Default value: 3

Optional
Valid values: Float
Default value: 1e-05

Optional
Valid values: Float
Default value: 1e-08

Optional
Valid values: Boolean
Default value: False

Valid values: Float
Default value: 1e-05

Valid values: Float
Default value: 1e-08

Valid values: Boolean
Default value: False
CheckInputImages

This rule checks if input images have been correctly normalized. Specifically, it detects if the mean of the sample data differs by more than a threshold value from zero. Many computer vision models require that input data has a zero mean and unit variance.

This rule is applicable to deep learning applications.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

Parameter Descriptions for the CheckInputImages Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td><strong>Required</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>threshold_mean</td>
<td>A threshold that defines by how much mean of the input data can differ from 0.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.2</td>
</tr>
<tr>
<td>threshold_samples</td>
<td>The number of images that have to be sampled before an error can be thrown. If the value is too low, the estimation of the dataset mean will be inaccurate.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 500</td>
</tr>
<tr>
<td>regex</td>
<td>The name of the input data tensor.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;.*hybridsequential0_input_0&quot; (the name of the input tensor for Apache MXNet models using HybridSequential)</td>
</tr>
<tr>
<td>channel</td>
<td>The position of the color channel in the input tensor shape array.</td>
</tr>
<tr>
<td></td>
<td><strong>Optional</strong></td>
</tr>
</tbody>
</table>

### List of Built-in Rules

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
</table>
| base_trial     | The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger. **Required**  
| tensor_regex   | A list of regex patterns used to restrict this comparison to specific scalar-valued tensors. The rule inspects only the tensors that match the regex patterns specified in the list. If no patterns are passed, the rule compares all tensors gathered |

**NLPSequenceRatio**

This rule calculates the ratio of specific tokens given the rest of the input sequence that is useful for optimizing performance. For example, you can calculate the percentage of padding end-of-sentence (EOS) tokens in your input sequence. If the number of EOS tokens is too high, an alternate bucketing strategy should be performed. You also can calculate the percentage of unknown tokens in your input sequence. If the number of unknown words is too high, an alternate vocabulary could be used.

This rule is applicable to deep learning applications.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

**Parameter Descriptions for the NLPSequenceRatio Rule**
<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>token_values</td>
<td>A string of a list of the numerical values of the tokens. For example, &quot;3, 0&quot;.</td>
</tr>
<tr>
<td>token_thresholds_percent</td>
<td>A string of a list of thresholds (in percentages) that correspond to each of the token_values. For example, &quot;50.0, 50.0&quot;.</td>
</tr>
</tbody>
</table>

```
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.nlp_sequence_ratio(),
        rule_parameters={
            "tensor_regex": ".*embedding0_input_0",
            "token_values": "0",
            "token_thresholds_percent": "50"
        },
        collections_to_save=[
            CollectionConfig(
                name="custom_inputs_collection",
                parameters={
                    "include_regex": ".*embedding0_input_0"
                }
            )
        ]
    )
]
```

**Confusion**

This rule evaluates the goodness of a confusion matrix for a classification problem.

It creates a matrix of size category_no*category_no and populates it with data coming from (labels, predictions) pairs. For each (labels, predictions) pair, the count in
confusion[labels][predictions] is incremented by 1. When the matrix is fully populated, the ratio of data on-diagonal values and off-diagonal values are evaluated as follows:

- For elements on the diagonal: \( \text{confusion}[i][i] / \sum_j(\text{confusion}[j][j]) \geq \text{min\_diag} \)
- For elements off the diagonal: \( \text{confusion}[j][i] / \sum_j(\text{confusion}[j][i]) \leq \text{max\_off\_diag} \)

This rule can be applied to the XGBoost algorithm.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

### Parameter Descriptions for the Confusion Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td></td>
<td>Required</td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td>category_no</td>
<td>The number of categories.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: Integer ( \geq 2 )</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;None&quot;</td>
</tr>
<tr>
<td>labels</td>
<td>The labels tensor collection or an 1-d vector of true labels.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;labels&quot;</td>
</tr>
<tr>
<td>predictions</td>
<td>The predictions tensor collection or an 1-d vector of estimated labels.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;predictions&quot;</td>
</tr>
<tr>
<td>labels_collection</td>
<td>The rule inspects the tensors in this collection for labels.</td>
</tr>
<tr>
<td></td>
<td>Optional</td>
</tr>
<tr>
<td></td>
<td>Valid values: String</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;labels&quot;</td>
</tr>
<tr>
<td>predictions_collection</td>
<td>The rule inspects the tensors in this collection for predictions.</td>
</tr>
</tbody>
</table>

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### List of Built-in Rules

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
<th>Optional</th>
<th>Valid values</th>
<th>Default value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>String</td>
<td>&quot;predictions&quot;</td>
</tr>
<tr>
<td>min_diag</td>
<td>The minimum threshold for the ratio of data on the diagonal.</td>
<td>Optional</td>
<td>0 ≤ float ≤ 1</td>
<td>0.9</td>
</tr>
<tr>
<td>max_off_diag</td>
<td>The maximum threshold for the ratio of data off the diagonal.</td>
<td>Optional</td>
<td>0 ≤ float ≤ 1</td>
<td>0.1</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.confusion(),
        rule_parameters=
        {
            "category_no": "10",
            "labels": "labels",
            "predictions": "predictions",
            "labels_collection": "labels",
            "predictions_collection": "predictions",
            "min_diag": "0.9",
            "max_off_diag": "0.1"
        },
        collections_to_save=[[CollectionConfig(name="labels",
                                                parameters=
                                                {
                                                    "save_interval": "500"
                                                }]
                              ,
                         CollectionConfig(name="predictions",
                                          parameters=
                                          {
                                              "include_regex": "500"
                                          })
                              ]
    )
]
```

**Note**

This rule infers default values for the optional parameters if their values aren't specified.
FeatureImportanceOverweight

This rule accumulates the weights of the n largest feature importance values per step and ensures that they do not exceed the threshold. For example, you can set the threshold for the top 3 features to not hold more than 80 percent of the total weights of the model.

This rule is valid only for the XGBoost algorithm.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

Parameter Descriptions for the FeatureImportanceOverweight Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>threshold</td>
<td>Defines the threshold for the proportion of the cumulative sum of the n largest features. The number n is defined by the nfeatures parameter.</td>
</tr>
<tr>
<td>nfeatures</td>
<td>The number of largest features.</td>
</tr>
<tr>
<td>tensor_regex</td>
<td>Regular expression (regex) of tensor names the rule to analyze.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Required</th>
<th>Valid values: String</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optional</td>
<td>Valid values: Float</td>
</tr>
<tr>
<td></td>
<td>Default value: 0.8</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: Integer</td>
</tr>
<tr>
<td></td>
<td>Default value: 3</td>
</tr>
<tr>
<td>Optional</td>
<td>Valid values: String</td>
</tr>
<tr>
<td></td>
<td>Default value: &quot;.*feature_importance/weight&quot;</td>
</tr>
</tbody>
</table>

```python
built_in_rules = [
    Rule.sagemaker(
        base_config=rule_configs.feature_importance_overweight(),
        rule_parameters={
            "threshold": "0.8",
            "nfeatures": "3",
            "tensor_regex": ".*feature_importance/weight"
        }
    )
]`
TreeDepth

This rule measures the depth of trees in an XGBoost model. XGBoost rejects splits if they do not improve loss. This regularizes the training. As a result, the tree might not grow as deep as defined by the `depth` parameter.

This rule is valid only for the XGBoost algorithm.

For an example of how to configure and deploy a built-in rule, see Configure Debugger Built-in Rules (p. 2287).

Parameter Descriptions for the TreeDepth Rule

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>base_trial</td>
<td>The base trial training job name. This parameter is automatically set to the current training job by Amazon SageMaker Debugger.</td>
</tr>
<tr>
<td>depth</td>
<td>The depth of the tree. The depth of the tree is obtained by computing the base 2 logarithm of the largest node ID.</td>
</tr>
</tbody>
</table>

built_in_rules = [
  Rule.sagemaker(
    base_config=rule_configs.tree_depth(),
    rule_parameters={
      "depth": "4"
    },
    collections_to_save=[
      CollectionConfig(
        name="feature_importance",
        parameters={
          "save_interval": "500"
        }
      )
    ]
  )
]
Create Debugger Custom Rules for Training Job Analysis

You can create custom rules to monitor your training job using the Debugger Rule APIs and the open source `smdebug Python library` that provide tools to build your own rule containers.

Topics

- Prerequisites for Creating Debugger Custom Rules (p. 2410)
- Use the Debugger Client Library `smdebug` to Create a Custom Rule Python Script (p. 2410)
- Use the Debugger APIs to Run Your Own Custom Rules (p. 2410)

Prerequisites for Creating Debugger Custom Rules

To create Debugger custom rules, you need the following prerequisites.

- SageMaker Debugger Rule.custom API
- The open source `smdebug Python library`
- Your own custom rule python script
- Amazon SageMaker Debugger Registry URLs for Custom Rule Evaluators (p. 2431)

Use the Debugger Client Library `smdebug` to Create a Custom Rule Python Script

The `smdebug` Rule API provides an interface to set up your own custom rules. The following python script is a sample of how to construct a custom rule, `CustomGradientRule`. This tutorial custom rule watches if the gradients are getting too large and set the default threshold as 10. The custom rule takes a base trial created by a SageMaker estimator when it initiates training job.

```python
from smdebug.rules.rule import Rule
class CustomGradientRule(Rule):
    def __init__(self, base_trial, threshold=10.0):
        super().__init__(base_trial)
        self.threshold = float(threshold)

    def invoke_at_step(self, step):
        for tname in self.base_trial.tensor_names(collection="gradients"):
            t = self.base_trial.tensor(tname)
            abs_mean = t.reduction_value(step, "mean", abs=True)
            if abs_mean > self.threshold:
                return True
        return False
```

You can add multiple custom rule classes as many as you want in the same python script and deploy them to any training job trials by constructing custom rule objects in the following section.

Use the Debugger APIs to Run Your Own Custom Rules

The following code sample shows how to configure a custom rule with the Amazon SageMaker Python SDK. This example assumes that the custom rule script you created in the previous step is located at `path/to/my_custom_rule.py`.

---

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from sagemaker.debugger import Rule, CollectionConfig

custom_rule = Rule.custom(
    name='MyCustomRule',
    image_uri='759209512951.dkr.ecr.us-west-2.amazonaws.com/sagemaker-debugger-rule-evaluator:latest',
    instance_type='ml.t3.medium',
    source='path/to/my_custom_rule.py',
    rule_to_invoke='CustomGradientRule',
    collections_to_save=[CollectionConfig("gradients")],
    rule_parameters={"threshold": "20.0"},
)

The following list explains the Debugger Rule.custom API arguments.

- **name (str):** Specify a custom rule name as you want.
- **image_uri (str):** This is the image of the container that has the logic of understanding your custom rule. It sources and evaluates the specified tensor collections you save in the training job. You can find the list of open source SageMaker rule evaluator images from Amazon SageMaker Debugger Registry URLs for Custom Rule Evaluators (p. 2431).
- **instance_type (str):** You need to specify an instance to build a rule docker container. This spins up the instance in parallel with a training container.
- **source (str):** This is the local path or the Amazon S3 URI to your custom rule script.
- **rule_to_invoke (str):** This specifies the particular Rule class implementation in your custom rule script. SageMaker supports only one rule to be evaluated at a time in a rule job.
- **collections_to_save (str):** This specifies which tensor collections you will save for the rule to run.
- **rule_parameters (dictionary):** This accepts parameter inputs in a dictionary format. You can adjust the parameters that you configured in the custom rule script.

After you set up the custom_rule object, you can use it for building a SageMaker estimator for any training jobs. Specify the entry_point to your training script. You do not need to make any change of your training script.

from sagemaker.tensorflow import TensorFlow

estimator = TensorFlow(
    role=sagemaker.get_execution_role(),
    base_job_name='smdebug-custom-rule-demo-tf-keras',
    entry_point='path/to/your_training_script.py',
    train_instance_type='ml.p2.xlarge',
    ...,
    rules = [custom_rule]
)
estimator.fit()

For more variations and advanced examples of using Debugger custom rules, see the following example notebooks.

- Monitor your training job with Amazon SageMaker Debugger custom rules
- PyTorch iterative model pruning of ResNet and AlexNet
- Trigger Amazon CloudWatch Events using Debugger Rules to Take an Action Based on Training Status with TensorFlow
Use Debugger with Custom Training Containers

Amazon SageMaker Debugger is available for any deep learning models that you bring to Amazon SageMaker. The AWS CLI, SageMaker Estimator API, and the Debugger APIs enable you to use any Docker base images to build and customize containers to train your models. To use Debugger with customized containers, you need to make a minimal change to your training script to implement the Debugger hook callback and retrieve tensors from training jobs.

You need the following resources to build a customized container with Debugger.

- Amazon SageMaker Python SDK
- The SMDebug open source client library
- A Docker base image of your choice
- Your training script with a Debugger hook registered – For more information about registering a Debugger hook to your training script, see Register Debugger Hook to Your Training Script (p. 2412).

For an end-to-end example of using Debugger with a custom training container, see the following example notebook.

- Build a Custom Training Container and Debug Training Jobs with Debugger

Tip
This custom container with Debugger guide is an extension of the Adapting Your Own Training Container (p. 3166) guide which walks you thorough how to build and push your custom training container to Amazon ECR.

Prepare to Build a Custom Training Container

To build a docker container, the basic structure of files should look like the following:

```plaintext
### debugger_custom_container_test_notebook.ipynb    # a notebook to run python snippet codes
### debugger_custom_container_test_folder            # this is a docker folder
###  your-training-script.py                        # your training script with Debugger hook
###  Dockerfile                                     # a Dockerfile to build your own container
```

Register Debugger Hook to Your Training Script

To debug your model training, you need to add a Debugger hook to your training script.

Note
This step is required to collect model parameters (output tensors) for debugging your model training. If you only want to monitor and profile, you can skip this hook registration step and exclude the debugger_hook_config parameter when constructing an estimator.

The following example code shows the structure of a training script using the Keras ResNet50 model and how to pass the Debugger hook as a Keras callback for debugging. To find a complete training script, see TensorFlow training script with SageMaker Debugger hook.

```python
# An example of training script (your-training-script.py)
import tensorflow.compat.v2 as tf
from tensorflow.keras.applications.resnet50 import ResNet50
import smdebug.tensorflow as smd
def train(batch_size, epoch, model, hook):
```
model.fit(X_train, Y_train,
    batch_size=batch_size,
    epochs=epoch,
    validation_data=(X_valid, Y_valid),
    shuffle=True,

    # smdebug modification: Pass the Debugger hook in the main() as a Keras callback
callbacks=[hook])

def main():
    parser=argparse.ArgumentParser(description="Train resnet50 cifar10")
    # hyperparameter settings
    parser.add_argument(...) 
    args = parser.parse_args()
    model=ResNet50(weights=None, input_shape=(32,32,3), classes=10)

    # Add the following line to register the Debugger hook for Keras.
    hook=smd.KerasHook.create_from_json_file()

    # Start the training.
    train(args.batch_size, args.epoch, model, hook)

if __name__ == '__main__':
    main()

For more information about registering the Debugger hook for the supported frameworks and algorithm, see the following links in the SMDebug client library:

- SMDebug TensorFlow hook
- SMDebug PyTorch hook
- SMDebug MXNet hook
- SMDebug XGBoost hook

In the following example notebooks' training scripts, you can find more examples about how to add the Debugger hooks to training scripts and collect output tensors in detail:

- Debugger in script mode with the TensorFlow 2.1 framework

To see the difference between using Debugger in a Deep Learning Container and in script mode, open this notebook and put it and the previous Debugger in a Deep Learning Container TensorFlow v2.1 notebook example side by side.

In script mode, the hook configuration part is removed from the script in which you set the estimator. Instead, the Debugger hook feature is merged into the training script, TensorFlow Keras ResNet training script in script mode. The training script imports the smdebug library in the required TensorFlow Keras environment to communicate with the TensorFlow ResNet50 algorithm. It also manually implements the smdebug hook functionality by adding the callbacks=[hook] argument inside the train function (in line 49), and by adding the manual hook configuration (in line 89) provided through SageMaker Python SDK.

This script mode example runs the training job in the TF 2.1 framework for direct comparison with the zero script change in the TF 2.1 example. The benefit of setting up Debugger in script mode is the flexibility to choose framework versions not covered by AWS Deep Learning Containers.
- **Using Amazon SageMaker Debugger in a PyTorch Container in Script Mode**

  This notebook enables Debugger in script mode in PyTorch v1.3.1 framework. PyTorch v1.3.1 is supported by SageMaker containers, and this example shows details of how to modify a training script.

  The SageMaker PyTorch estimator is already in script mode by default. In the notebook, the line to activate `script_mode` is not included in the estimator configuration.

  This notebook shows detailed steps to change an original PyTorch training script to a modified version with Debugger enabled. Additionally, this example shows how you can use Debugger built-in rules to detect training issues such as the vanishing gradients problem, and the Debugger trial features to call and analyze the saved tensors.

### Create and Configure a Dockerfile

Open your SageMaker JupyterLab and create a new folder, `debugger_custom_container_test_folder` in this example, to save your training script and Dockerfile. The following code example is a Dockerfile that includes essential docker build commands. Paste the following code into the Dockerfile text file and save it. Upload your training script to the same folder.

```bash
# Specify a docker base image
FROM tensorflow/tensorflow:2.2.0rc2-gpu-py3
RUN /usr/bin/python3 -m pip install --upgrade pip
RUN pip install --upgrade protobuf
# Install required packages to enable the SageMaker Python SDK and the smdebug library
RUN pip install sagemaker-training
RUN pip install smdebug
CMD ["bin/bash"]
```

If you want to use a pre-built AWS Deep Learning Container image, see [Available AWS Deep Learning Containers Images](#).

### Build and Push the Custom Training Container to Amazon ECR

Create a test notebook, `debugger_custom_container_test_notebook.ipynb`, and run the following code in the notebook cell. This will access the `debugger_byoc_test_docker` directory, build the docker with the specified `algorithm_name`, and push the docker container to your Amazon ECR.

```python
import boto3

account_id = boto3.client('sts').get_caller_identity().get('Account')
ecr_repository = 'sagemaker-debugger-mnist-byoc-tf2'
tag = ':latest'
region = boto3.session.Session().region_name
uri_suffix = 'amazonaws.com'
if region in ['cn-north-1', 'cn-northwest-1']:
    uri_suffix = 'amazonaws.com.cn'
byoc_image_uri = '{}.dkr.ecr.{}.{}'.format(account_id, region, uri_suffix, ecr_repository + tag)

!docker build -t $ecr_repository docker
!$(aws ecr get-login --region $region --no-include-email)
!aws ecr create-repository --repository-name $ecr_repository
!docker tag {ecr_repository + tag} $byoc_image_uri
```
Configure Debugger Using Amazon SageMaker API

The preceding topics focus on using Debugger through Amazon SageMaker Python SDK, which is a wrapper around AWS SDK for Python (Boto3) and SageMaker API operations. This offers a high-level experience of accessing the Amazon SageMaker API operations. In case you need to manually configure the SageMaker API operations using AWS Boto3 or AWS Command Line Interface (CLI) for other SDKs, such as Java, Go, and C++, this section covers how to configure the following low-level API operations.

Topics
- JSON (AWS CLI) (p. 2416)
- AWS Boto3 (p. 2420)
Amazon SageMaker Debugger built-in rules can be configured for a training job using the `DebugHookConfig`, `DebugRuleConfiguration`, `ProfilerConfig`, and `ProfilerRuleConfiguration` objects through the SageMaker `CreateTrainingJob` API operation. You need to specify the right image URI in the `RuleEvaluatorImage` parameter, and the following examples walk you through how to set up the JSON strings to request `CreateTrainingJob`.

The following code shows a complete JSON template to run a training job with required settings and Debugger configurations. Save the template as a JSON file in your working directory and run the training job using AWS CLI. For example, save the following code as `debugger-training-job-cli.json`.

```
{
    "TrainingJobName": "debugger-aws-cli-test",
    "RoleArn": "arn:aws:iam::111122223333:role/service-role/AmazonSageMaker-ExecutionRole-
    YYYYMMDDT123456",
    "AlgorithmSpecification": {
        "TrainingImage": "763104351884.dkr.ecr.us-west-2.amazonaws.com/tensorflow-
        training:2.4.1-gpu-py37-cu110-ubuntu18.04",
        "TrainingInputMode": "File",
        "EnableSageMakerMetricsTimeSeries": false
    },
    "HyperParameters": {
        "sagemaker_program": "entry_point/tf-hvd-train.py",
        "sagemaker_submit_directory": "s3://sagemaker-us-west-2-111122223333/debugger-boto3-
        profiling-test/source.tar.gz"
    },
    "OutputDataConfig": {
        "S3OutputPath": "s3://sagemaker-us-west-2-111122223333/debugger-aws-cli-test/
        output"
    },
    "DebugHookConfig": {
        "S3OutputPath": "s3://sagemaker-us-west-2-111122223333/debugger-aws-cli-test/debug-
        output",
        "CollectionConfigurations": [
            {
                "CollectionName": "losses",
                "CollectionParameters": {
                    "train.save_interval": "50"
                }
            }
        ],
        "DebugRuleConfigurations": [
            {
                "RuleConfigurationName": "LossNotDecreasing",
                "RuleEvaluatorImage": "895741380848.dkr.ecr.us-west-2.amazonaws.com/sagemaker-
                debugger-rules:latest",
                "RuleParameters": {"rule_to_invoke": "LossNotDecreasing"}
            }
        ],
        "ProfilerConfig": {
            "S3OutputPath": "s3://sagemaker-us-west-2-111122223333/debugger-aws-cli-test/
            profiler-output",
            "ProfilingIntervalInMilliseconds": 500,
            "ProfilingParameters": {
```
"DebugHookConfig": {
  "S3OutputPath": "s3://<default-bucket>/<training-job-name>/debug-output",
  "CollectionConfigurations": [
    {
      "CollectionName": "gradients",
      "CollectionParameters": {
        "save_interval": "500"
      }
    }
  ]
}

This will make the training job save the tensor collection, gradients, every save_interval of 500 steps. To find available CollectionName values, see Debugger Built-in Collections in the SMDebug client library documentation. To find available CollectionParameters parameter keys and values, see the sagemaker.debugger.CollectionConfig class in the SageMaker Python SDK documentation.

To enable Debugger rules for debugging the output tensors

The following DebugRuleConfigurations API example shows how to run the built-in VanishingGradient rule on the saved gradients collection.
"DebugRuleConfigurations": [  
  {    
    "RuleConfigurationName": "VanishingGradient",    
    "RuleEvaluatorImage": "503895931360.dkr.ecr.us-east-1.amazonaws.com/sagemaker-debugger-rules:latest",    
    "RuleParameters": {       
      "rule_to_invoke": "VanishingGradient",       
      "threshold": "20.0"    
    }  
  }  
]

With a configuration like the one in this sample, Debugger starts a rule evaluation job for your training job using the VanishingGradient rule on the collection of gradients tensor. To find a complete list of available Docker images for using the Debugger rules, see Use Debugger Docker Images for Built-in or Custom Rules (p. 2429). To find the key-value pairs for RuleParameters, see List of Debugger Built-in Rules (p. 2365).

To configure a Debugger built-in rule for profiling system and framework metrics

The following example code shows how to specify the ProfilerConfig API operation to enable collecting system and framework metrics.

To enable Debugger profiling to collect system and framework metrics

Target Step

"ProfilerConfig": {    
  // Optional. Path to an S3 bucket to save profiling outputs    
  "S3OutputPath": "s3://<default-bucket>/<training-job-name>/profiler-output",    
  // Available values for ProfilingIntervalInMilliseconds: 100, 200, 500, 1000 (1 second), 5000 (5 seconds), and 60000 (1 minute) milliseconds.    
  "ProfilingIntervalInMilliseconds": 500,    
  "ProfilingParameters": {      
    "DataloaderProfilingConfig": "{ \"StartStep\": 5, \"NumSteps\": 3, \"MetricsRegex\": \".*\" }",      
    "DetailedProfilingConfig": "{ \"StartTimeInSecSinceEpoch\": 1234567890, \"DurationInSeconds\": 10, \"MetricsRegex\": \".*\" }"    
  }  
}

Target Time Duration

"ProfilerConfig": {    
  // Optional. Path to an S3 bucket to save profiling outputs    
  "S3OutputPath": "s3://<default-bucket>/<training-job-name>/profiler-output",    
  // Available values for ProfilingIntervalInMilliseconds: 100, 200, 500, 1000 (1 second), 5000 (5 seconds), and 60000 (1 minute) milliseconds.    
  "ProfilingIntervalInMilliseconds": 500,    
  "ProfilingParameters": {      
    "DataloaderProfilingConfig": "{ \"StartTimeInSeconds\": 1234567890, \"DurationInSeconds\": 10, \"MetricsRegex\": \".*\" }",      
    "DetailedProfilingConfig": "{ \"StartTimeInSecSinceEpoch\": 1234567890, \"DurationInSeconds\": 10, \"MetricsRegex\": \".*\" }"    
  }  
}

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To enable Debugger rules for profiling the metrics

The following example code shows how to configure the ProfilerReport rule.

```
"ProfilerRuleConfigurations": [
  {
    "RuleConfigurationName": "ProfilerReport",
    "RuleParameters": {
      "rule_to_invoke": "ProfilerReport",
      "CPUBottleneck_cpu_threshold": "90",
      "IOBottleneck_threshold": "90"
    }
  }
]
```

To find a complete list of available Docker images for using the Debugger rules, see Use Debugger Docker Images for Built-in or Custom Rules (p. 2429). To find the key-value pairs for RuleParameters, see List of Debugger Built-in Rules (p. 2365).

**Update Debugger Profiling Configuration Using the UpdateTrainingJob API Operation**

Debugger profiling configuration can be updated while your training job is running by using the UpdateTrainingJob API operation. Configure new ProfilerConfig and ProfilerRuleConfiguration objects, and specify the training job name to the TrainingJobName parameter.

```
{
  "ProfilerConfig": {
    "DisableProfiler": boolean,
    "ProfilingIntervalInMilliseconds": number,
    "ProfilingParameters": {
      "string": "string"
    }
  },
  "ProfilerRuleConfigurations": [
    {
      "RuleConfigurationName": "string",
      "RuleEvaluatorImage": "string",
      "RuleParameters": {
        "string": "string"
      }
    }
  ],
  "TrainingJobName": "your-training-job-name-YYYY-MM-DD-HH-MM-SS-SSS"
}
```
Add Debugger Custom Rule Configuration to the CreateTrainingJob API Operation

A custom rule can be configured for a training job using the `DebugHookConfig` and `DebugRuleConfiguration` objects in the `CreateTrainingJob` API operation. The following code sample shows how to configure a custom `ImproperActivation` rule written with the `smdebug` library using this SageMaker API operation. This example assumes that you’ve written the custom rule in `custom_rules.py` file and uploaded it to an Amazon S3 bucket. The example provides pre-built Docker images that you can use to run your custom rules. These are listed at Amazon SageMaker Debugger Registry URLs for Custom Rule Evaluators (p. 2431). You specify the URL registry address for the pre-built Docker image in the `RuleEvaluatorImage` parameter.

```
"DebugHookConfig": {
  "S3OutputPath": "s3://<default-bucket>/<training-job-name>/debug-output",
  "CollectionConfigurations": [
    {
      "CollectionName": "relu_activations",
      "CollectionParameters": {
        "include_regex": "relu",
        "save_interval": "500",
        "end_step": "5000"
      }
    }
  ],
  "DebugRulesConfigurations": [
    {
      "RuleConfigurationName": "improper_activation_job",
      "InstanceType": "ml.c4.xlarge",
      "VolumeSizeInGB": 400,
      "RuleParameters": {
        "source_s3_uri": "s3://bucket/custom_rules.py",
        "rule_to_invoke": "ImproperActivation",
        "collection_names": "relu_activations"
      }
    }
  ]
}
```

To find a complete list of available Docker images for using the Debugger rules, see Use Debugger Docker Images for Built-in or Custom Rules (p. 2429). To find the key-value pairs for `RuleParameters`, see List of Debugger Built-in Rules (p. 2365).

AWS Boto3

Amazon SageMaker Debugger built-in rules can be configured for a training job using the `create_training_job()` function of the AWS Boto3 SageMaker client. You need to specify the right image URI in the `RuleEvaluatorImage` parameter, and the following examples walk you through how to set up the request body for the `create_training_job()` function.

The following code shows a complete example of how to configure Debugger for the `create_training_job()` request body and start a training job in `us-west-2`, assuming that a training script `entry_point/train.py` is prepared using TensorFlow. To find an end-to-end example notebook, see Profiling TensorFlow Multi GPU Multi Node Training Job with Amazon SageMaker Debugger (Boto3).

**Note**

Ensure that you use the correct Docker container images. To find available AWS Deep Learning Container images, see Available Deep Learning Containers Images. To find a complete list of
available Docker images for using the Debugger rules, see Use Debugger Docker Images for Built-in or Custom Rules (p. 2429).

```python
import sagemaker, boto3
import datetime, tarfile

# Start setting up a SageMaker session and a Boto3 SageMaker client
session = sagemaker.Session()
region = session.boto_region_name
bucket = session.default_bucket()

# Upload a training script to a default Amazon S3 bucket of the current SageMaker session
source = 'source.tar.gz'
project = 'debugger-boto3-test'
tar = tarfile.open(source, 'w:gz')
tar.add('entry_point/train.py')
tar.close()
s3 = boto3.client('s3')
s3.upload_file(source, bucket, project+'/'+source)

# Set up a Boto3 session client for SageMaker
sm = boto3.Session(region_name=region).client("sagemaker")

# Start a training job
sm.create_training_job(
    TrainingJobName='debugger-boto3-'+datetime.datetime.now().strftime('%Y-%m-%d-%H-%M-%S'),
    HyperParameters={
        'sagemaker_submit_directory': 's3://'+bucket+'/'+project+'/'+source,
        'sagemaker_program': '/entry_point/train.py' # training scrip file location and
name under the sagemaker_submit_directory
    },
    AlgorithmSpecification={
        # Specify a training Docker container image URI (Deep Learning Container or your
own training container) to TrainingImage.
        'TrainingImage': '763104351884.dkr.ecr.us-west-2.amazonaws.com/tensorflow-
training:2.4.1-gpu-py37-cu110-ubuntu18.04',
        'TrainingInputMode': 'File',
        'EnableSageMakerMetricsTimeSeries': False
    },
    RoleArn='arn:aws:iam::111122223333:role/service-role/AmazonSageMaker-
ExecutionRole-20201014T161125',
    OutputDataConfig={
        'S3OutputPath': 's3://'+bucket+'/'+project+'/'+output'},
    ResourceConfig={
        'InstanceType': 'ml.p3.8xlarge',
        'InstanceCount': 1,
        'VolumeSizeInGB': 30
    },
    StoppingCondition={
        'MaxRuntimeInSeconds': 86400
    },
    DebugHookConfig={
        'S3OutputPath': 's3://'+bucket+'/'+project+'/'+debug-output',
        'CollectionConfigurations': [
            {'CollectionName': 'losses',
             'CollectionParameters': {
                'train.save_interval': '500',
                'eval.save_interval': '50'
             }
        ]
    },
)
```
DebugRuleConfigurations=[
    {
        'RuleConfigurationName': 'LossNotDecreasing',
        'RuleParameters': {'rule_to_invoke': 'LossNotDecreasing'}
    },
    {
        'ProfilerConfig': {
            'S3OutputPath': 's3://'+bucket+'/'+project+'/profiler-output',
            'ProfilingIntervalInMilliseconds': 500,
            'ProfilingParameters': {
                'DataloaderProfilingConfig': '{"StartStep": 5, "NumSteps": 3, "MetricsRegex": ".*", }',
                'DetailedProfilingConfig': '{"StartStep": 5, "NumSteps": 3, }',
                'PythonProfilingConfig': '{"StartStep": 5, "NumSteps": 3, "ProfilerName": "cprofile", "cProfileTimer": "total_time"}',
                'LocalPath': '/opt/ml/output/profiler/' # Optional. Local path for profiling outputs
            }
        },
        'ProfilerRuleConfigurations':[{
            'RuleConfigurationName': 'ProfilerReport',
            'RuleParameters': {'rule_to_invoke': 'ProfilerReport'}
        }]
    }
]

To configure a Debugger rule for debugging model parameters

The following code samples show how to configure a built-in VanishingGradient rule using this SageMaker API.

To enable Debugger to collect output tensors

Specify the Debugger hook configuration as follows:

DebugHookConfig=
    {
        'S3OutputPath': 's3://<default-bucket>/<training-job-name>/debug-output',
        'CollectionConfigurations': [
            {
                'CollectionName': 'gradients',
                'CollectionParameters': {
                    'train.save_interval': '500',
                    'eval.save_interval': '50'
                }
            }
        ]
    }

This will make the training job save a tensor collection, gradients, every save_interval of 500 steps. To find available CollectionName values, see Debugger Built-in Collections in the SMDebug client library documentation. To find available CollectionParameters parameter keys and values, see the sagemaker.debugger.CollectionConfig class in the SageMaker Python SDK documentation.

To enable Debugger rules for debugging the output tensors

The following DebugRuleConfigurations API example shows how to run the built-in VanishingGradient rule on the saved gradients collection.
Configure Debugger Using SageMaker API

DebugRuleConfigurations=[
    {
        'RuleConfigurationName': 'VanishingGradient',
        'RuleParameters': {
            'rule_to_invoke': 'VanishingGradient',
            'threshold': '20.0'
        }
    }
]

With a configuration like the one in this sample, Debugger starts a rule evaluation job for your training job using the VanishingGradient rule on the collection of gradients tensor. To find a complete list of available Docker images for using the Debugger rules, see Use Debugger Docker Images for Built-in or Custom Rules (p. 2429). To find the key-value pairs for RuleParameters, see List of Debugger Built-in Rules (p. 2365).

To configure a Debugger built-in rule for profiling system and framework metrics

The following example code shows how to specify the ProfilerConfig API operation to enable collecting system and framework metrics.

To enable Debugger profiling to collect system and framework metrics

Target Step

ProfilerConfig=
    {'S3OutputPath': 's3://<default-bucket>/<training-job-name>/profiler-output', # Optional. Path to an S3 bucket to save profiling outputs
        'ProfilingIntervalInMilliseconds': 500,
        'ProfilingParameters': {
            'DataloaderProfilingConfig': '{
                "StartStep": 5,
                "NumSteps": 3,
                "MetricsRegex": ".*"
            }',
            'DetailedProfilingConfig': '{
                "StartStep": 5,
                "NumSteps": 3
            }',
            'PythonProfilingConfig': '{
                "StartStep": 5,
                "NumSteps": 3,
                "ProfilerName": "cprofile", # Available options: cprofile, pyinstrument
                "cProfileTimer": "total_time" # Include only when using cprofile. Available options: cpu, off_cpu, total_time
            }',
            'LocalPath': '/opt/ml/output/profiler/' # Optional. Local path for profiling outputs
        }
    }

Target Time Duration

ProfilerConfig=
    {'S3OutputPath': 's3://<default-bucket>/<training-job-name>/profiler-output', # Optional. Path to an S3 bucket to save profiling outputs
        'ProfilingIntervalInMilliseconds': 500,
        'ProfilingParameters': {
            'DataloaderProfilingConfig': '{
                "StartStep": 5,
                "NumSteps": 3,
                "MetricsRegex": ".*"
            }',
            'DetailedProfilingConfig': '{
                "StartStep": 5,
                "NumSteps": 3
            }',
            'PythonProfilingConfig': '{
                "StartStep": 5,
                "NumSteps": 3,
                "ProfilerName": "cprofile", # Available options: cprofile, pyinstrument
                "cProfileTimer": "total_time" # Include only when using cprofile. Available options: cpu, off_cpu, total_time
            }',
            'LocalPath': '/opt/ml/output/profiler/' # Optional. Local path for profiling outputs
        }
    }

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# Available values for ProfilingIntervalInMilliseconds: 100, 200, 500, 1000 (1 second), 5000 (5 seconds), and 60000 (1 minute) milliseconds.

'ProfilingIntervalInMilliseconds': 500,
'ProfilingParameters': {
    'DataloaderProfilingConfig': '{
        "StartTimeInSecSinceEpoch": 12345567789,
        "DurationInSeconds": 10,
        "MetricsRegex": ".*"
    },
    'DetailedProfilingConfig': '{
        "StartTimeInSecSinceEpoch": 12345567789,
        "DurationInSeconds": 10
    },
    'PythonProfilingConfig': '{
        "StartTimeInSecSinceEpoch": 12345567789,
        "DurationInSeconds": 10,
        "ProfilerName": "cprofile", # Available options: cprofile, pyinstrument
        "cProfileTimer": "total_time" # Include only when using cprofile.
        Available options: cpu, off_cpu, total_time
    },
    'LocalPath': '/opt/ml/output/profiler/' # Optional. Local path for profiling outputs
}

To enable Debugger rules for profiling the metrics

The following example code shows how to configure the ProfilerReport rule.

ProfilerRuleConfigurations=

    ProfilerRuleConfigurations=[
    {
        'RuleConfigurationName': 'ProfilerReport',
        'RuleParameters': {
            'rule_to_invoke': 'ProfilerReport',
            'CPUBottleneck_cpu_threshold': '90',
            'IOBottleneck_threshold': '90'
        }
    }
    ]

To find a complete list of available Docker images for using the Debugger rules, see Use Debugger Docker Images for Built-in or Custom Rules (p. 2429). To find the key-value pairs for RuleParameters, see List of Debugger Built-in Rules (p. 2365).

# Update Debugger Profiling Configuration Using the UpdateTrainingJob API Operation

Debugger profiling configuration can be updated while your training job is running by using the update_training_job() function of the AWS Boto3 SageMaker client. Configure new ProfilerConfig and ProfilerRuleConfiguration objects, and specify the training job name to the TrainingJobName parameter.

ProfilerConfig=

    ProfilerConfig={
        'DisableProfiler': boolean,
        'ProfilingIntervalInMilliSeconds': number,
        'ProfilingParameters': {
            'string': 'string'
        }
    },

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Add Debugger Custom Rule Configuration to the CreateTrainingJob API Operation

A custom rule can be configured for a training job using the `DebugHookConfig` and `DebugRuleConfiguration` objects using the AWS Boto3 SageMaker client's `create_training_job()` function. The following code sample shows how to configure a custom `ImproperActivation` rule written with the `smdebug` library using this SageMaker API operation. This example assumes that you’ve written the custom rule in `custom_rules.py` file and uploaded it to an Amazon S3 bucket. The example provides pre-built Docker images that you can use to run your custom rules. These are listed at [Amazon SageMaker Debugger Registry URLs for Custom Rule Evaluators](p. 2431). You specify the URL registry address for the pre-built Docker image in the `RuleEvaluatorImage` parameter.

```
ProfilerRuleConfigurations=[
    {
        'RuleConfigurationName': 'string',
        'RuleEvaluatorImage': 'string',
        'RuleParameters': {
            'string': 'string'
        }
    }
],
TrainingJobName='your-training-job-name-YYYY-MM-DD-HH-MM-SS-SSS'
```

To find a complete list of available Docker images for using the Debugger rules, see [Use Debugger Docker Images for Built-in or Custom Rules](p. 2429). To find the key-value pairs for `RuleParameters`, see [List of Debugger Built-in Rules](p. 2365).

Best Practices for Amazon SageMaker Debugger

Use the following guidelines when you run training jobs with Debugger.

**Topics**
Choose a Machine Learning Framework

You can choose a machine learning framework and use SageMaker pre-built training containers or your own containers. Use Debugger to detect training and performance issues, and analyze training progress of your training job in SageMaker. SageMaker provides you options to use pre-built containers that are prepared for a number of machine learning framework environments to train your model on Amazon EC2. Any training job can be adapted to run in AWS Deep Learning Containers, SageMaker training containers, and custom containers.

Use Studio Debugger Insights Dashboard

With Studio Debugger insights dashboard, you are in control of your training jobs. Use the Studio Debugger dashboards to keep your model performance on Amazon EC2 instances in control and optimized. For any SageMaker training jobs running on Amazon EC2 instance, Debugger monitors resource utilization and basic model output data (loss and accuracy values). Through the Studio Debugger dashboards, gain insights into your training jobs and improve your model training performance. To learn more, see Amazon SageMaker Debugger in Amazon SageMaker Studio (p. 2317).

Download Debugger Reports and Gain More Insights

You can view aggregated results and gain insights in Debugger reports. Debugger aggregates training and profiling results collected from the built-in rule analysis into a report per training job. You can find more detailed information about your training results through the Debugger reports. To learn more, see SageMaker Debugger Interactive Reports (p. 2333).

Capture Data from Your Training Job and Save Data to Amazon S3

You can use a Debugger hook to save output tensors. After you choose a container and a framework that fit your training script, use a Debugger hook to configure which tensors to save and to which directory to save them, such as a Amazon S3 bucket. A Debugger hook helps you to build the configuration and to keep it in your account to use in subsequent analyses, where it is secured for use with the most privacy-sensitive applications. To learn more, see Configure SageMaker Debugger to Save Tensors (p. 2281).

Analyze the Data with a Fleet of Debugger Built-in Rules

You can use Debugger built-in rules to inspect tensors in parallel with a training job. To analyze the training performance data, Debugger provides built-in rules that watch for abnormal training process
behaviors. For example, a Debugger rule detects issues when the training process suffers from system bottleneck issues or training issues, such as vanishing gradients, exploding tensors, overfitting, or overtraining. If necessary, you can also build customized rules by creating a rule definition with your own criteria to define a training issue. To learn more about the Debugger rules, see Configure Debugger Built-in Rules (p. 2287) for detailed instructions of using the Amazon SageMaker Python SDK. For a full list of the Debugger built-in rules, see List of Debugger Built-in Rules (p. 2365). If you want to create a custom rule, see Create Debugger Custom Rules for Training Job Analysis (p. 2410).

**Take Actions Based on the Built-in Rule Status**

You can use Debugger with Amazon CloudWatch Events and AWS Lambda. You can automate actions based on the rule status, such as stopping training jobs early and setting up notifications through email or text. When the Debugger rules detect problems and triggers an "IssuesFound" evaluation status, CloudWatch Events detects the rule status changes and invokes the Lambda function to take actions. To configure automated actions to your training issues, see Create Actions on Rules Using Amazon CloudWatch and AWS Lambda (p. 2298).

**Dive Deep into the Data Using the SMDebug Client Library**

You can use the SMDebug tools to access and analyze training data collected by Debugger. The TrainingJob and create_trial classes load the metrics and tensors saved by Debugger. These classes provide extended class methods to analyze the data in real time or after the training has finished. The SMDebug library also provides visualization tools: merge timelines of framework metrics to aggregate different profiling, line charts and heatmap to track the system utilization, and histograms to find step duration outliers. To learn more about the SMDebug library tools, see Analyze Data Using the SMDebug Client Library (p. 2357).

**Monitor and Analyze Training Job Metrics**

Amazon CloudWatch supports high-resolution custom metrics, and its finest resolution is 1 second. However, the finer the resolution, the shorter the lifespan of the CloudWatch metrics. For the 1-second frequency resolution, the CloudWatch metrics are available for 3 hours. For more information about the resolution and the lifespan of the CloudWatch metrics, see GetMetricStatistics in the Amazon CloudWatch API Reference.

If you want to profile your training job with a finer resolution down to 100-millisecond (0.1 second) granularity and store the training metrics indefinitely in Amazon S3 for custom analysis at any time, consider using Amazon SageMaker Debugger. SageMaker Debugger provides built-in rules to automatically detect common training issues; it detects hardware resource utilization issues (such as CPU, GPU, and I/O bottlenecks) and non-converging model issues (such as overfit, vanishing gradients, and exploding tensors).

SageMaker Debugger also provides visualizations through Studio and its profiling report. Unlike CloudWatch metrics, which accumulates resource utilization rates of CPU and GPU cores and averages those out across multiple instances, Debugger tracks the utilization rate of each core. This enables you to identify unbalanced usage of hardware resources as you scale up to larger compute clusters. To explore the Debugger visualizations, see SageMaker Debugger Insights Dashboard Walkthrough, Debugger Profiling Report Walkthrough, and Analyze Data Using the SMDebug Client Library.

**Monitoring System Utilization and Detect Bottlenecks**

With Amazon SageMaker Debugger monitoring, you can measure hardware system resource utilization of Amazon EC2 instances. Monitoring is available for any SageMaker training job constructed with the SageMaker framework estimators (TensorFlow, PyTorch, and MXNet) and the generic SageMaker estimator (SageMaker built-in algorithms and your own custom containers). Debugger built-in rules for monitoring detect system bottleneck issues and notify you when they detect the bottleneck issues.
To learn how to enable Debugger system monitoring, see Configure Debugger Using Amazon SageMaker Python SDK (p. 2306) and then Configure Debugger Monitoring Hardware System Resource Utilization (p. 2309).

For a full list of available built-in rules for monitoring, see Debugger Built-in Rules for Monitoring Hardware System Resource Utilization (System Metrics) (p. 2366).

**Profiling Framework Operations**

With Amazon SageMaker Debugger profiling you can profile deep learning frameworks operations. You can profile your model training with the SageMaker TensorFlow training containers, the SageMaker PyTorch framework containers, and your own training containers. Using the profiling feature of Debugger, you can drill down into the Python operators and functions that are executed to perform the training job. Debugger supports detailed profiling, Python profiling, data loader profiling, and Horovod distributed training profiling. You can merge the profiled timelines to correlate with the system bottlenecks. Debugger built-in rules for profiling watch framework operation related issues, including excessive training initialization time due to data downloading before training starts and step duration outliers in training loops.

To learn how to configure Debugger for framework profiling, see Configure Debugger Using Amazon SageMaker Python SDK (p. 2306) and then Configure Debugger Framework Profiling (p. 2310).

For a complete list of available built-in rules for profiling, see Debugger Built-in Rules for Profiling Framework Metrics (p. 2366).

**Debugging Model Output Tensors**

Debugging is available for deep learning frameworks using AWS Deep Learning Containers and the SageMaker training containers. For fully supported framework versions (see the versions at Supported Frameworks and Algorithms (p. 2260)), Debugger automatically registers hooks to collect output tensors, and you can directly run your training script. For the versions with one asterisk sign, you need to manually register the hooks to collect tensors. Debugger provides preconfigured tensor collections with generalized names that you can utilize across the different frameworks. If you want to customize output tensor configuration, you can also use the CollectionConfig and DebuggerHookConfig API operations and the Amazon SageMaker Python SDK to configure your own tensor collections. Debugger built-in rules for debugging analyze the output tensors and identifies model optimization problems that blocks your model from minimizing the loss function. For example, the rules identify overfitting, overtraining, loss not decreasing, exploding tensors, and vanishing gradients.

To learn how to configure Debugger for debugging output tensors, see Step 2: Launch and Debug Training Jobs Using SageMaker Python SDK (p. 2278) and then Configure SageMaker Debugger to Save Tensors (p. 2281).

For a full list of available built-in rules for debugging, see Debugger Built-in Rules for Debugging Model Training Data (Output Tensors) (p. 2367).

**Amazon SageMaker Debugger Advanced Topics and Reference Documentation**

The following sections contain advanced topics, reference documentation for the API operations, exceptions, and known limitations for Debugger.

**Topics**

- Amazon SageMaker Debugger API Operations (p. 2429)
- Use Debugger Docker Images for Built-in or Custom Rules (p. 2429)
- Amazon SageMaker Debugger Exceptions (p. 2432)
Amazon SageMaker Debugger API Operations

Amazon SageMaker Debugger has API operations in several locations that are used to implement its monitoring and analysis of model training.

Amazon SageMaker Debugger also provides the open source `sagemaker-debugger` Python SDK that is used to configure built-in rules, define custom rules, and register hooks to collect output tensor data from training jobs.

The Amazon SageMaker Python SDK is a high-level SDK focused on machine learning experimentation. The SDK can be used to deploy built-in or custom rules defined with the SMDebug Python library to monitor and analyze these tensors using SageMaker estimators.

Debugger has added operations and types to the Amazon SageMaker API that enable the platform to use Debugger when training a model and to manage the configuration of inputs and outputs.

- `CreateTrainingJob` and `UpdateTrainingJob` use the following Debugger APIs to configure tensor collections, rules, rule images, and profiling options:
  - `CollectionConfiguration`
  - `DebugHookConfig`
  - `DebugRuleConfiguration`
  - `TensorBoardOutputConfig`
  - `ProfilerConfig`
  - `ProfilerRuleConfiguration`

- `DescribeTrainingJob` provides a full description of a training job, including the following Debugger configurations and rule evaluation statuses:
  - `DebugHookConfig`
  - `DebugRuleConfiguration`
  - `DebugRuleEvaluationStatus`
  - `ProfilerConfig`
  - `ProfilerRuleConfiguration`
  - `ProfilerRuleEvaluationStatus`

The rule configuration API operations use the SageMaker Processing functionality when analyzing a model training. For more information about SageMaker Processing, see `Process Data (p. 1022)`.

Use Debugger Docker Images for Built-in or Custom Rules

Amazon SageMaker provides two sets of Docker images for rules: one set for evaluating rules provided by SageMaker (built-in rules) and one set for evaluating custom rules provided in Python source files.

If you use the Amazon SageMaker Python SDK, you can simply use SageMaker high-level Debugger API operations with SageMaker Estimator API operations, without having to manually retrieve the Debugger Docker images and configure the `ConfigureTrainingJob` API.

If you are not using the SageMaker Python SDK, you have to retrieve a relevant pre-built container base image for the Debugger rules. Amazon SageMaker Debugger provides pre-built Docker images for built-in and custom rules, and the images are stored in Amazon Elastic Container Registry (Amazon ECR). To pull an image from an Amazon ECR repository (or to push an image to one), use the full name registry...
URL of the image using the CreateTrainingJob API. SageMaker uses the following URL patterns for the Debugger rule container image registry address.

\[
\text{<account_id>.dkr.ecr.<Region>.amazonaws.com/<ECR repository name>:<tag>}
\]

For the account ID in each AWS Region, Amazon ECR repository name, and tag value, see the following topics.

**Topics**
- Amazon SageMaker Debugger Registry URLs for Built-in Rule Evaluators (p. 2430)
- Amazon SageMaker Debugger Registry URLs for Custom Rule Evaluators (p. 2431)

**Amazon SageMaker Debugger Registry URLs for Built-in Rule Evaluators**

Use the following values for the components of the registry URLs for the images that provide built-in rules for Amazon SageMaker Debugger. For account IDs, see the following table.

**ECR Repository Name:** sagemaker-debugger-rules  
**Tag:** latest

**Example of a full registry URL:**

904829902805.dkr.ecr.ap-south-1.amazonaws.com/sagemaker-debugger-rules:latest

**Account IDs for Built-in Rules Container Images by AWS Region**

<table>
<thead>
<tr>
<th>Region</th>
<th>account_id</th>
</tr>
</thead>
<tbody>
<tr>
<td>af-south-1</td>
<td>314341159256</td>
</tr>
<tr>
<td>ap-east-1</td>
<td>199566480951</td>
</tr>
<tr>
<td>ap-northeast-1</td>
<td>430734990657</td>
</tr>
<tr>
<td>ap-northeast-2</td>
<td>578805364391</td>
</tr>
<tr>
<td>ap-south-1</td>
<td>904829902805</td>
</tr>
<tr>
<td>ap-southeast-1</td>
<td>972752614525</td>
</tr>
<tr>
<td>ap-southeast-2</td>
<td>184798709955</td>
</tr>
<tr>
<td>ca-central-1</td>
<td>519511493484</td>
</tr>
<tr>
<td>cn-north-1</td>
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</tr>
<tr>
<td>cn-northwest-1</td>
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</tr>
<tr>
<td>eu-west-2</td>
<td>250201462417</td>
</tr>
<tr>
<td>eu-west-3</td>
<td>447278800020</td>
</tr>
</tbody>
</table>
### Amazon SageMaker Debugger Registry URLs for Custom Rule Evaluators

Use the following values for the components of the registry URL for the images that provide custom rule evaluators for Amazon SageMaker Debugger. For account IDs, see the following table.

**ECR Repository Name:** sagemaker-debugger-rule-evaluator

**Tag:** latest

**Example of a full registry URL:**

```
552407032007.dkr.ecr.ap-south-1.amazonaws.com/sagemaker-debugger-rule-evaluator:latest
```

### Account IDs for Custom Rules Container Images by AWS Region

<table>
<thead>
<tr>
<th>Region</th>
<th>account_id</th>
</tr>
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<tbody>
<tr>
<td>af-south-1</td>
<td>515950693465</td>
</tr>
<tr>
<td>ap-east-1</td>
<td>645844755771</td>
</tr>
<tr>
<td>ap-northeast-1</td>
<td>670969264625</td>
</tr>
<tr>
<td>ap-northeast-2</td>
<td>326368420253</td>
</tr>
<tr>
<td>ap-south-1</td>
<td>552407032007</td>
</tr>
<tr>
<td>ap-southeast-1</td>
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<td>445670767460</td>
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<tr>
<td>ca-central-1</td>
<td>105842248657</td>
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<td>cn-north-1</td>
<td>617202126805</td>
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<tr>
<td>eu-south-1</td>
<td>335033873580</td>
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<tr>
<td>eu-west-1</td>
<td>606966180310</td>
</tr>
</tbody>
</table>
Amazon SageMaker Developer Guide
Advanced Topics and Reference

### Region

<table>
<thead>
<tr>
<th>Region</th>
<th>account_id</th>
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<tr>
<td>eu-west-2</td>
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</tr>
<tr>
<td>eu-west-3</td>
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</tr>
<tr>
<td>me-south-1</td>
<td>050406412588</td>
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<tr>
<td>sa-east-1</td>
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<tr>
<td>us-east-1</td>
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<tr>
<td>us-east-2</td>
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</tr>
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<tr>
<td>us-west-2</td>
<td>759209512951</td>
</tr>
<tr>
<td>us-gov-west-1</td>
<td>515361955729</td>
</tr>
</tbody>
</table>

#### Amazon SageMaker Debugger Exceptions

Amazon SageMaker Debugger is designed to be aware that tensors required to execute a rule might not be available at every step. As a result, it raises a few exceptions, which enable you to control what happens when a tensor is missing. These exceptions are available in the `smdebug.exceptions` module. You can import them as follows:

```python
from smdebug.exceptions import *
```

The following exceptions are available:

- **TensorUnavailableForStep** – The tensor requested is not available for the step. This might mean that this step might not be saved at all by the hook, or that this step might have saved some tensors but the requested tensor is not part of them. Note that when you see this exception, it means that this tensor can never become available for this step in the future. If the tensor has reductions saved for the step, it notifies you they can be queried.

- **TensorUnavailable** – This tensor is not being saved or has not been saved by the `smdebug` API. This means that this tensor is never seen for any step in `smdebug`.

- **StepUnavailable** – The step was not saved and Debugger has no data from the step.

- **StepNotYetAvailable** – The step has not yet been seen by `smdebug`. It might be available in the future if the training is still going on. Debugger automatically loads new data as it becomes available.

- **NoMoreData** – Raised when the training ends. Once you see this, you know that there are no more steps and no more tensors to be saved.

- **IndexReaderException** – The index reader is not valid.

- **InvalidWorker** – A worker was invoked that was not valid.

- **RuleEvaluationConditionMet** – Evaluation of the rule at the step resulted in the condition being met.

- **InsufficientInformationForRuleInvocation** – Insufficient information was provided to invoke the rule.

#### Considerations for Amazon SageMaker Debugger

Consider the following when using Amazon SageMaker Debugger.
Considerations for Distributed Training

The following list shows the scope of validity and considerations for using Debugger on training jobs with deep learning frameworks and various distributed training options.

- **Horovod**

**Scope of validity of using Debugger for training jobs with Horovod**

<table>
<thead>
<tr>
<th>Deep Learning Framework</th>
<th>Apache MXNet</th>
<th>TensorFlow 1.x</th>
<th>TensorFlow 2.x</th>
<th>TensorFlow 2.x with Keras</th>
<th>PyTorch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monitoring system bottlenecks</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Profiling framework operations</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Debugging model output tensors</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

- **SageMaker distributed data parallel**

**Scope of validity of using Debugger for training jobs with SageMaker distributed data parallel**

<table>
<thead>
<tr>
<th>Deep Learning Framework</th>
<th>TensorFlow 2.x</th>
<th>TensorFlow 2.x with Keras</th>
<th>PyTorch</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monitoring system bottlenecks</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Profiling framework operations</td>
<td>No*</td>
<td>No**</td>
<td>Yes</td>
</tr>
<tr>
<td>Debugging model output tensors</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

* Debugger does not support framework profiling for TensorFlow 2.x.

** SageMaker distributed data parallel does not support TensorFlow 2.x with Keras implementation.

- **SageMaker distributed model parallel** – Debugger does not support SageMaker distributed model parallel training.

- **Distributed training with SageMaker checkpoints** – Debugger is not available for training jobs when both the distributed training option and SageMaker checkpoints are enabled. You might see an error that looks like the following:

  SMDebug Does Not Currently Support Distributed Training Jobs With Checkpointing Enabled

To use Debugger for training jobs with distributed training options, you need to disable SageMaker checkpointing and add manual checkpointing functions to your training script. For more information about using Debugger with distributed training options and checkpoints, see Using SageMaker Distributed Data Parallel with Amazon SageMaker Debugger and Checkpoints (p. 2505) and Saving Checkpoints (p. 2569).
• **Parameter Server** – Debugger does not support parameter server-based distributed training.

• Profiling distributed training framework operations, such as the AllReduced operation of SageMaker distributed data parallel and Horovod operations, is not available.

**Considerations for Monitoring System Bottlenecks and Profiling Framework Operations**

• For AWS TensorFlow, data loader metrics cannot be collected using the default local_path setting of the FrameworkProfile class. The path has to be manually configured and end in "/". For example:

```python
FrameworkProfile(local_path="/opt/ml/output/profiler/")
```

• For AWS TensorFlow, the data loader profiling configuration cannot be updated while a training job is running.

• For AWS TensorFlow, a NoneType error might occur when you use analysis tools and notebook examples with TensorFlow 2.3 training jobs and the detailed profiling option.

• Python profiling and detailed profiling are only supported for Keras API.

• To access the deep profiling feature for TensorFlow and PyTorch, currently you must specify the latest AWS deep learning container images with CUDA 11. For example, you must specify the specific image URI in the TensorFlow and PyTorch estimator as follows:

  • For TensorFlow

```python
image_uri = f"763104351884.dkr.ecr.{region}.amazonaws.com/tensorflow-training:2.3.1-gpu-py37-cu110-ubuntu18.04"
```

  • For PyTorch

```python
image_uri = f"763104351884.dkr.ecr.{region}.amazonaws.com/pytorch-training:1.6.0-gpu-py36-cu110-ubuntu18.04"
```

**Considerations for Debugging Model Output Tensors**

• Avoid using functional API operations. Debugger cannot collect model output tensors from PyTorch and MXNet training scripts composed of functional API operations.

• Debugger cannot collect model output tensors from the `torch.nn.functional` API operations. When you write a PyTorch training script, it is recommended to use the `torch.nn` modules instead.

• Debugger cannot collect model output tensors from MXNet functional objects in hybrid blocks. For example, the ReLu activation (`F.relu`) outputs cannot be collected from the following example of `mxnet.gluon.HybridBlock` with `F` in the `hybrid_forward` function.

```python
import mxnet as mx
from mxnet.gluon import HybridBlock, nn

class Model(HybridBlock):
    def __init__(self, **kwargs):
        super(Model, self).__init__(**kwargs)
        # use name_scope to give child Blocks appropriate names.
        with self.name_scope():
            self.dense0 = nn.Dense(20)
            self.dense1 = nn.Dense(20)

    def hybrid_forward(F, x):
        x = F.relu(self.dense0(x))
        return F.relu(self.dense1(x))
```
model = Model()
model.initialize(ctx=mx.cpu(0))
model.hybridize()
model(mx.nd.zeros((10, 10), ctx=mx.cpu(0)))

Amazon SageMaker Debugger Usage Statistics

Consider the following when using autogenerated reports by Amazon SageMaker Debugger.

Debugger Profiling Report Usage


Debugger collects profiling report usage statistics by including code in the Jupyter notebook that collects the unique ProfilerReport rule's processing job ARN if the user opens the final profiler-report.html file.

Debugger only collects information about whether a user opens the final HTML report. It **DOES NOT** collect any information from training jobs, training data, training scripts, processing jobs, logs, or the content of the profiling report itself.

You can opt out of the collection of usage statistics using either of the following options.

(Recommended) Option 1: Opt Out before Running a Training Job

To opt out, you need to add the following Debugger ProfilerReport rule configuration to your training job request.

**SageMaker Python SDK**

```python
estimator=sagemaker.estimator.Estimator(
    ...
    rules=ProfilerRule.sagemaker(
        base_config=rule_configs.ProfilerReport()
        rule_parameters={"opt_out_telemetry": "True"}
    )
)
```

**AWS CLI**

```
"ProfilerRuleConfigurations": [
    {
        "RuleConfigurationName": "ProfilerReport-1234567890",
        "RuleParameters": {
            "rule_to_invoke": "ProfilerReport",
            "opt_out_telemetry": "True"
        }
    }
],
```

**AWS SDK for Python (Boto3)**

```python
ProfilerRuleConfigurations=[
```
Perform Automatic Model Tuning with SageMaker

Amazon SageMaker automatic model tuning, also known as hyperparameter tuning, finds the best version of a model by running many training jobs on your dataset using the algorithm and ranges of hyperparameters that you specify. It then chooses the hyperparameter values that result in a model that performs the best, as measured by a metric that you choose.

For example, suppose that you want to solve a binary classification problem on a marketing dataset. Your goal is to maximize the area under the curve (auc) metric of the algorithm by training an XGBoost Algorithm (p. 2038) model. You don't know which values of the eta, alpha, min_child_weight, and max_depth hyperparameters to use to train the best model. To find the best values for these hyperparameters, you can specify ranges of values that SageMaker hyperparameter tuning searches to find the combination of values that results in the training job that performs the best as measured by the objective metric that you chose. Hyperparameter tuning launches training jobs that use hyperparameter values in the ranges that you specified, and returns the training job with highest auc.

You can use SageMaker automatic model tuning with built-in algorithms, custom algorithms, and SageMaker pre-built containers for machine learning frameworks.

Amazon SageMaker automatic model tuning can use Amazon EC2 Spot instance to optimize costs when running training jobs. For more information on managed spot training, see Managed Spot Training in Amazon SageMaker (p. 2695).

Before you start using hyperparameter tuning, you should have a well-defined machine learning problem, including the following:
How Hyperparameter Tuning Works

When you build complex machine learning systems like deep learning neural networks, exploring all of the possible combinations is impractical. Hyperparameter tuning can accelerate your productivity by trying many variations of a model. It looks for the best model automatically by focusing on the most promising combinations of hyperparameter values within the ranges that you specify. To get good results, you need to choose the right ranges to explore.

**Note**
Because the algorithm itself is stochastic, it’s possible that the hyperparameter tuning model will fail to converge on the best answer, even if the best possible combination of values is within the ranges that you choose.

**Grid Search**

When using grid search, hyperparameter tuning chooses combinations of values from the range of categorical values that you specify when you create the job. Only categorical parameters are supported when using the grid search strategy. You do not need to specify the MaxNumberOfTrainingJobs. The number of training jobs created by the tuning job will be automatically calculated to be the total number of distinct categorical combinations possible. If specified, the value of MaxNumberOfTrainingJobs should equal the total number of distinct categorical combinations possible.

**Random Search**

When using random search, hyperparameter tuning chooses a random combination of values from within the ranges that you specify for hyperparameters for each training job it launches. Because the choice of hyperparameter values doesn’t depend on the results of previous training jobs, you can run the maximum number of concurrent training jobs without affecting the performance of the tuning.

Bayesian Optimization

Bayesian optimization treats hyperparameter tuning like a regression problem. Given a set of input features (the hyperparameters), hyperparameter tuning optimizes a model for the metric that you choose. To solve a regression problem, hyperparameter tuning makes guesses about which hyperparameter combinations are likely to get the best results, and runs training jobs to test these values. After testing a set of hyperparameter values, hyperparameter tuning uses regression to choose the next set of hyperparameter values to test.

Hyperparameter tuning uses an Amazon SageMaker implementation of Bayesian optimization.

When choosing the best hyperparameters for the next training job, hyperparameter tuning considers everything that it knows about this problem so far. Sometimes it chooses a combination of hyperparameter values close to the combination that resulted in the best previous training job to incrementally improve performance. This allows hyperparameter tuning to exploit the best known results. Other times, it chooses a set of hyperparameter values far removed from those it has tried. This allows it to explore the range of hyperparameter values to try to find new areas that are not yet well understood. The explore/exploit trade-off is common in many machine learning problems.

For more information about Bayesian optimization, see the following:

Basic Topics on Bayesian Optimization

- A Tutorial on Bayesian Optimization of Expensive Cost Functions, with Application to Active User Modeling and Hierarchical Reinforcement Learning
- Practical Bayesian Optimization of Machine Learning Algorithms
- Taking the Human Out of the Loop: A Review of Bayesian Optimization

Speeding up Bayesian Optimization

- Google Vizier: A Service for Black-Box Optimization
- Learning Curve Prediction with Bayesian Neural Networks
- Speeding up automatic hyperparameter optimization of deep neural networks by extrapolation of learning curves

Advanced Modeling and Transfer Learning

- Scalable Hyperparameter Transfer Learning
- Bayesian Optimization with Tree-structured Dependencies
- Bayesian Optimization with Robust Bayesian Neural Networks
- Scalable Bayesian Optimization Using Deep Neural Networks
- Input Warping for Bayesian Optimization of Non-stationary Functions

Hyperband

Hyperband is a multi-fidelity based tuning strategy that dynamically reallocates resources. Hyperband uses both intermediate and final results of training jobs to re-allocate epochs to well-utilized hyperparameter configurations and automatically stops those that underperform. It also seamlessly scales to using many parallel training jobs. These features can significantly speed up hyperparameter tuning over random search and Bayesian optimization strategies.

Hyperband should only be used to tune iterative algorithms that publish results at different resource levels. For example, Hyperband can be used to tune a neural network for image classification which publishes accuracy metrics after every epoch.
For more information about Hyperband, see the following links:

- Hyperband: A Novel Bandit-Based Approach to Hyperparameter Optimization
- Massively Parallel Hyperparameter Tuning
- BOHB: Robust and Efficient Hyperparameter Optimization at Scale
- Model-based Asynchronous Hyperparameter and Neural Architecture Search

**Hyperband with early stopping**

Training jobs can be stopped early when they are unlikely to improve the objective metric of the hyperparameter tuning job. This can help both reduce compute time and avoid overfitting your model. Hyperband uses an advanced internal mechanism to apply early stopping. Thus, the parameter `TrainingJobEarlyStoppingType` in the `HyperParameterTuningJobConfig` API must be set to `OFF` when using Hyperband's internal early stopping feature.

**Note**

Hyperparameter tuning might not improve your model. It is an advanced tool for building machine solutions, and, as such, should be considered part of the scientific development process.

**Define Metrics**

When you use one of the Amazon SageMaker built-in algorithms, you don't need to define metrics. Built-in algorithms automatically send metrics to hyperparameter tuning. You do need to choose one of the metrics that the built-in algorithm emits as the objective metric for the tuning job. For a list of metrics that a built-in algorithm emits, see the model tuning section for the appropriate algorithm listed in Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096).

To optimize hyperparameters for a machine learning model, a tuning job evaluates the training jobs it launches by using a metric that the training algorithm writes to logs. Amazon SageMaker hyperparameter tuning parses your algorithm’s `stdout` and `stderr` streams to find algorithm metrics, such as loss or validation-accuracy, that show how well the model is performing on the dataset.

**Note**

These are the same metrics that SageMaker sends to CloudWatch Logs. For more information, see Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675).

If you use your own algorithm for hyperparameter tuning, make sure that your algorithm emits at least one metric by writing evaluation data to `stderr` or `stdout`.

**Note**

Hyperparameter tuning sends an additional hyperparameter, `_tuning_objective_metric` to the training algorithm. This hyperparameter specifies the objective metric being used for the hyperparameter tuning job, so that your algorithm can use that information during training.

You can define up to 20 metrics for your tuning job to monitor. You choose one of those metrics to be the objective metric, which hyperparameter tuning uses to evaluate the training jobs. The hyperparameter tuning job returns the training job that returned the best value for the objective metric as the best training job.

You define metrics for a tuning job by specifying a name and a regular expression for each metric that your tuning job monitors. Design the regular expressions to capture the values of metrics that your algorithm emits. You pass these metrics to the `CreateHyperParameterTuningJob` operation in the `TrainingJobDefinition` parameter as the `MetricDefinitions` field of the `AlgorithmSpecification` field.

The following example defines 4 metrics:
Define Hyperparameter Ranges

Hyperparameter tuning finds the best hyperparameter values for your model by searching over a set of values that you specify for each of the hyperparameters that are tunable. Choosing hyperparameters and ranges significantly affects the performance of your tuning job. For guidance on choosing hyperparameters and ranges, see Best Practices for Hyperparameter Tuning (p. 2465).

To define hyperparameter ranges by using the low-level API, you specify the names of hyperparameters and ranges of values in the ParameterRanges field of the HyperParameterTuningJobConfig parameter that you pass to the CreateHyperParameterTuningJob operation. The ParameterRanges field has three subfields, one for each of the categorical, integer, and continuous hyperparameter ranges. You can define up to 20 hyperparameters to search over. Each value of a categorical hyperparameter range counts as a hyperparameter against the limit.

If you create a tuning job with a Grid strategy, you can only specify categorical values. In addition, you don't need to provide the MaxNumberOfTrainingJobs. This value is inferred from the total number of configurations that can be produced from your categorical parameters. If specified, the value of MaxNumberOfTrainingJobs should be equal to the total number of distinct categorical combinations possible.

Hyperparameter ranges have the following structure:

```python
=[
  { "Name": "loss",
    "Regex": "Loss = (.*?)\n",
  },
  { "Name": "ganloss",
    "Regex": "GAN_loss=(.*?);",
  },
  { "Name": "discloss",
    "Regex": "disc_train_loss=(.*?);",
  },
  { "Name": "disc-combined",
    "Regex": "disc-combined=(.*?);",
  },
]
```

The following is an example of the log that the algorithm writes:

```
GAN_loss=0.138318; Scaled_reg=2.654134; disc: [-0.017371, 0.102429] real 93.3% gen 0.0%
disc-combined=0.000000; disc_train_loss=1.374587; Loss = 16.020744; Iteration 0 took 0.704s; Elapsed=0s
```

Use the regular expression (regex) to match the algorithm's log output and capture the numeric values of metrics. For example, in the regex for the loss metric defined above, the first part of the regex finds the exact text "Loss = ", and the expression (.*)\n; captures zero or more of any character until the first semicolon character. In this expression, the parenthesis tell the regex to capture what is inside them, \ means any character, * means zero or more, and ? means capture only until the first instance of the ; character.

Choose one of the metrics that you define as the objective metric for the tuning job. If you are using the API, specify the value of the name key in the HyperParameterTuningJobObjective field of the HyperParameterTuningJobConfig parameter that you send to the CreateHyperParameterTuningJob operation.
"ParameterRanges": {
    "CategoricalParameterRanges": [
    {
        "Name": "tree_method",
        "Values": ["auto", "exact", "approx", "hist"]
    }
    ],
    "ContinuousParameterRanges": [
    {
        "Name": "eta",
        "MaxValue": "0.5",
        "MinValue": "0",
        "ScalingType": "Auto"
    }
    ],
    "IntegerParameterRanges": [
    {
        "Name": "max_depth",
        "MaxValue": "10",
        "MinValue": "1",
        "ScalingType": "Auto"
    }
    ]
}

**Hyperparameter Scaling**

For integer and continuous hyperparameter ranges, you can choose the scale you want hyperparameter tuning to use to search the range of values by specifying a value for the `ScalingType` field of the hyperparameter range. You can choose from the following scaling types:

**Auto**

SageMaker hyperparameter tuning chooses the best scale for the hyperparameter.

**Linear**

Hyperparameter tuning searches the values in the hyperparameter range by using a linear scale. Typically, you choose this if the range of all values from the lowest to the highest is relatively small (within one order of magnitude), because uniformly searching values from the range will give you a reasonable exploration of the entire range.

**Logarithmic**

Hyperparameter tuning searches the values in the hyperparameter range by using a logarithmic scale.

Logarithmic scaling works only for ranges that have only values greater than 0.

Choose logarithmic scaling when you are searching a range that spans several orders of magnitude. For example, if you are tuning a Tune a linear learner model (p. 2014) model, and you specify a range of values between .0001 and 1.0 for the `learning_rate` hyperparameter, searching uniformly on a logarithmic scale gives you a better sample of the entire range than searching on a linear scale would, because searching on a linear scale would, on average, devote 90 percent of your training budget to only the values between .1 and 1.0, leaving only 10 percent of your training budget for the values between .0001 and .1.

**ReverseLogarithmic**

Hyperparameter tuning searches the values in the hyperparameter range by using a reverse logarithmic scale. reverse logarithmic scaling is supported only for continuous hyperparameter ranges. It is not supported for integer hyperparameter ranges.
Reverse logarithmic scaling works only for ranges that are entirely within the range 0<=x<1.0.

Choose reverse logarithmic scaling when you are searching a range that is highly sensitive to small changes that are very close to 1.

For an example notebook that uses hyperparameter scaling, see https://github.com/awslabs/amazon-sagemaker-examples/blob/master/hyperparameter_tuning/xgboost_random_log/hpo_xgboost_random_log.ipynb.

Tune Multiple Algorithms with Hyperparameter Optimization to Find the Best Model

To create a new hyperparameter optimization (HPO) job with Amazon SageMaker that tunes multiple algorithms, you must provide job settings that apply to all of the algorithms to be tested and a training definition for each of these algorithms. You must also specify the resources you want to use for the tuning job.

- The **job settings** to configure include warm starting, early stopping, and the tuning strategy. Warm starting and early stopping are available only when tuning a single algorithm.
- The **training job definition** to specify the name, algorithm source, objective metric, and the range of values, when required, to configure the set of hyperparameter values for each training job. It configures the channels for data inputs, data output locations, and any checkpoint storage locations for each training job. The definition also configures the resources to deploy for each training job, including instance types and counts, managed spot training, and stopping conditions.
- The **tuning job resources** to deploy, including the maximum number of concurrent training jobs that a hyperparameter tuning job can run concurrently and the maximum number of training jobs that the hyperparameter tuning job can run.

Get Started

You can create a new hyperparameter tuning job, clone a job, add or edit tags to a job from the console. You can also use the search feature to find jobs by their name, creation time, or status. Alternatively, you can also hyperparameter tuning jobs with the SageMaker API.

- **In the console**: To create a new job, open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/, choose Hyperparameter tuning jobs from the Training menu, and then choose Create hyperparameter tuning job. Then following the configuration steps to create a training job for each algorithm that you want to use. These steps are documented in the Create a Hyperparameter Optimization Tuning Job for One or More Algorithms (Console) (p. 2443) topic.
  
  **Note**
  When you start the configuration steps, note that the warm start and early stopping features are not available to use with multi-algorithm HPO. If you want to use these features, you can only tune a single algorithm at a time.

- **With the API**: For instructions on using the SageMaker API to create a hyperparameter tuning job, see Example: Hyperparameter Tuning Job. When you call CreateHyperParameterTuningJob to tune multiple algorithms, you must provide a list of training definitions using TrainingJobDefinitions instead of specifying a single TrainingJobDefinition. You must choose just one of these definition types depending on the number of algorithms being tuned.

**Topics**

- Create a Hyperparameter Optimization Tuning Job for One or More Algorithms (Console) (p. 2443)
- Manage Hyperparameter Tuning and Training Jobs (p. 2446)
Create a Hyperparameter Optimization Tuning Job for One or More Algorithms (Console)

To create a new hyperparameter optimization (HPO) tuning job for one or more algorithms, you need to define the settings for the tuning job, create training job definitions for each algorithm being tuned, and configure the resources for the tuning job.

Topics
- Define job settings (p. 2443)
- Create Training Job Definitions (p. 2444)
- Configure Tuning Job Resources (p. 2446)
- Review and Create HPO Tuning Job (p. 2446)

Define job settings

Your tuning job settings are applied across all of the algorithms in the HPO tuning job. Warm start and early stopping are available only when tuning a single algorithm. After you define the job settings you will create individual training definitions for each algorithm or variation you want to tune.

Warm Start

If you cloned this job, you can choose to use the results from a previous tuning job to improve the performance of this new tuning job. This is the warm start feature and it is only available when tuning a single algorithm. When you choose this option, you can choose up to five previous hyperparameter tuning jobs to use. Alternatively, you can use transfer learning to add additional data to the parent tuning job. When you select this option, you choose one previous tuning job as the parent.

Note
Warm start is compatible only with tuning jobs created after October 1, 2018. For more information, see Run a warm start job.

Early Stopping

To reduce compute time and avoid overfitting your model, training jobs can be stopped early when they are unlikely to improve the current best objective metric of the hyperparameter tuning job. Like warm start, this feature is only available when tuning a single algorithm. This is an automatic feature without configuration options, and it's disabled by default. For more information on how early stopping works, the algorithms that support it, and how to use it with your own algorithms, see Stop Training Jobs Early.

Tuning Strategy

Tuning strategy can be either random, Bayesian or Hyperband. These selections specify how automatic tuning algorithms search over specified hyperparameter ranges (selected in a later step). Random search chooses random combinations of values from the specified ranges and can be run sequentially or in parallel. Bayesian optimization chooses values based on what is likely to get the best result given what is known about the history of previous selections. Hyperband uses a multi-fidelity strategy that dynamically allocates resources towards well-utilized jobs and automatically stops those that underperform. The new configuration that starts after stopping other configurations is chosen randomly. Hyperband can only be used with iterative algorithms. For more information search strategies, see How Hyperparameter Tuning Works.

Note
Hyperband uses an advanced internal mechanism to apply early stopping. Thus, the parameter TrainingJobEarlyStoppingType in the HyperParameterTuningJobConfig API must be set to OFF when using Hyperband's internal early stopping feature.

Tags
You enter tags as key-value pairs to assign metadata to tuning jobs to help you manage them. Values are not required. You can use just the key. To see the keys associated with a job, choose the Tags tab on the details page for tuning job. For more information about using tags for tuning jobs, see Manage Hyperparameter Tuning and Training Jobs (p. 2446)

**Create Training Job Definitions**

To create a training job definition, you need to configure the algorithm and parameters, define the data input and output, and configure resources. You must provide at least one TrainingJobDefinition for each HPO tuning job. Each training definition specifies the configuration for an algorithm. To create several definitions for your training job you can clone a job definition. Cloning a job can save time as it copies all of the job settings, including data channels, S3 storage locations for output artifacts. You can then edit the cloned job just for changes needed to configure the algorithm options.

**Topics**
- Configure algorithm and parameters (p. 2444)
- Define Data Input and Output (p. 2445)
- Configure Training Job Resources (p. 2445)
- Add or Clone a Training Job (p. 2445)

**Configure algorithm and parameters**

Each training job definition for a tuning job requires a name, permission to access services, and the specification of algorithm options, an objective metric, and the range of values, when required, to configure the set of hyperparameter values for each training job.

**Name**

Provide a unique name for the training definition.

**Permissions**

Amazon SageMaker requires permissions to call other services on your behalf. Choose an IAM role or let AWS create a role that has the AmazonSageMakerFullAccess IAM policy attached.

**Optional Security Settings**

The network isolation setting prevents the container from making any outbound network calls. This is required for AWS Marketplace machine learning offerings.

You can also choose to use a private VPC.

**Note**

Inter-container encryption is only available when creating job definitions from the API.

**Algorithm Options**

You can choose one of the built-in algorithms, your own algorithm, your own container with an algorithm, or you can subscribe to an algorithm from AWS Marketplace.

- If you choose a built-in algorithm, it has the ECR image information prepopulated.
- If you choose your own container, you must specify the ECR image information. You can select the input mode for the algorithm as file or pipe.
- If you plan to supply your data using a .CSV file from Amazon S3, you should select the file.

**Metrics**

When you choose a built-in algorithm, metrics are provided for you. If you choose your own algorithm, you need to define your metrics. You can define up to 20 metrics for your tuning job to monitor, one
of which must be chosen as the objective metric. For more information on how to define a metric for a
tuning job, see Define Metrics (p. 2439).

Objective Metric

To find the best training job, set an objective metric and whether to maximize or minimize it. After the
training job is complete, you can view the tuning job detail page for a summary of the best training job
found using this objective metric.

Hyperparameter Configuration

When you choose a built-in algorithm, the default values for its hyperparameters are set for you, using
ranges that are optimized for the algorithm being tuned. You can change these values as you see fit. For
example, instead of a range, you can set a fixed value for a hyperparameter by setting the parameter’s
type to static. Each algorithm has different required and optional parameters. For more information,
see Best Practices for Hyperparameter Tuning and Define Hyperparameter Ranges.

Define Data Input and Output

Each training job definition for a tuning job must configure the channels for data inputs, data output
locations, and optionally any checkpoint storage locations for each training job.

Input Data Configuration

Input data is defined by channels, each with their own source location (Amazon S3 or Amazon Elastic
File System), compression, and format options. You can define up to 20 channels of input sources. If the
algorithm you chose supports multiple input channels, you can specify those too. For example, when
using the XGBoost churn prediction notebook, you could add two channels: train and validation.

Checkpoint Configuration

Checkpoints are periodically generated during training. You must choose an Amazon S3 location for
the checkpoints to be saved. Checkpoints are used in metrics reporting, and are also used to resume
managed spot training jobs. For more information, see Use Checkpoints in Amazon SageMaker (p. 2696).

Output Data Configuration

You must define an Amazon S3 location for the artifacts of the training job to be stored. You have the
option of adding encryption to the output using an AWS Key Management Service (AWS KMS) key.

Configure Training Job Resources

Each training job definition for a tuning job must configure the resources to deploy, including instance
types and counts, managed spot training, and stopping conditions.

Resource Configuration

Each training definition can have a different resource configuration. You choose the instance type and
number of nodes.

Managed spot training

You can save computer costs for jobs if you have flexibility in start and end times by allowing SageMaker
to use spare capacity to run jobs. For more information, see Managed Spot Training in Amazon
SageMaker (p. 2695).

Stopping condition

The stopping condition specifies the maximum duration allowed per training job.

Add or Clone a Training Job

Once you have created a training job definition for a tuning job, you are returned to the Training
Job Definition(s) panel where you can create additional training job definitions to train additional
You can select the Add training job definition and work through the steps to define a training job again or choose Clone from the Action menu to replicate an existing training job definition and edit it for the new algorithm. The clone option can save time as it copies all of the job's settings, including the data channels, S3 storage locations. For more information on cloning, see Manage Hyperparameter Tuning and Training Jobs (p. 2446).

### Configure Tuning Job Resources

#### Resource Limits

You can specify the maximum number of concurrent training jobs that a hyperparameter tuning job can run concurrently (10 at most) and the maximum number of training jobs that the hyperparameter tuning job can run (500 at most). The number of parallel jobs should not exceed the number of nodes you have requested across all of your training definitions. The total number of jobs can't exceed the number of jobs that your definitions are expected to run.

#### Review and Create HPO Tuning Job

Review the job settings, the training job definition(s), and resource limits. Then select Create hyperparameter tuning job.

### Manage Hyperparameter Tuning and Training Jobs

A tuning job can contain many training jobs and creating and managing these jobs and their definitions can become a complex and onerous task. SageMaker provides tools to help facilitate the management of these jobs. Tuning jobs you have run can be accessed from the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/. Select Hyperparameter tuning job from the Training menu to see the list. This page is also where you start the procedure to create a new tuning job by selecting Create hyperparameter tuning job.

To see the training jobs run a part of a tuning job, select one of the hyperparameter tuning jobs from the list. The tabs on the tuning job page allow you to inspect the training jobs, their definitions, the tags and configuration used for the tuning job, and the best training job found during tuning. You can select the best training job or any of the other training jobs that belong to the tuning job to see all of their settings. From here you can create a model that uses the hyperparameter values found by a training job by selecting Create Model or you can clone the training job by selecting Clone.

#### Cloning

You can save time by cloning a training job that belongs to a hyperparameter tuning job. Cloning copies all of the job’s settings, including data channels, S3 storage locations for output artifacts. You can do this for training jobs you have already run from the tuning job page, as just described, or when you are creating additional training job definitions while creating a hyperparameter tuning job, as described in Add or Clone a Training Job (p. 2445) step of that procedure.

#### Tagging

Automatic Model Tuning launches multiple training jobs within a single parent tuning job to discover the ideal weighting of model hyperparameters. Tags can be added to the parent tuning job as described in the Define job settings (p. 2443) section and these tags are then propagated to the individual training jobs underneath. Customers can use these tags for purposes such as cost allocation or access control. To add tags using the SageMaker SDK, use AddTags API. For more information about using tagging for AWS resources, see Tagging AWS resources.

### Example: Hyperparameter Tuning Job

This example shows how to create a new notebook for configuring and launching a hyperparameter tuning job. The tuning job uses the XGBoost Algorithm (p. 2038) to train a model to predict whether a customer will enroll for a term deposit at a bank after being contacted by phone.
You use the low-level AWS SDK for Python (Boto) to configure and launch the hyperparameter tuning job, and the AWS Management Console to monitor the status of hyperparameter tuning jobs. You can also use the Amazon SageMaker high-level Amazon SageMaker Python SDK to configure, run, monitor, and analyze hyperparameter tuning jobs. For more information, see https://github.com/aws/sagemaker-python-sdk.

**Prerequisites**

To run the code in this example, you need

- An AWS account and an administrator user (p. 34)
- An Amazon S3 bucket for storing your training dataset and the model artifacts created during training
- A running SageMaker notebook instance (p. 74)

**Topics**

- Create a Notebook (p. 2447)
- Get the Amazon SageMaker Boto 3 Client (p. 2448)
- Get the SageMaker Execution Role (p. 2448)
- Specify a S3 Bucket to Upload Training Datasets and Store Output Data (p. 2448)
- Download, Prepare, and Upload Training Data (p. 2449)
- Configure and Launch a Hyperparameter Tuning Job (p. 2450)
- Monitor the Progress of a Hyperparameter Tuning Job (p. 2454)
- Clean up (p. 2457)

**Create a Notebook**

Create a Jupyter notebook that contains a pre-installed environment with the default Anaconda installation and Python3.

**To create a Jupyter notebook**

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Open a running notebook instance, by choosing Open next to its name. The Jupyter notebook server page appears:

   ![Jupyter Notebook Server Page](image)

3. To create a notebook, choose Files, New, and conda_python3.
4. Name the notebook.

**Next Step**

Get the Amazon SageMaker Boto 3 Client (p. 2448)
Get the Amazon SageMaker Boto 3 Client

Import Amazon SageMaker Python SDK, AWS SDK for Python (Boto3), and other Python libraries. In a new Jupyter notebook, paste the following code to the first cell:

```python
import sagemaker
import boto3
import numpy as np  # For performing matrix operations and numerical processing
import pandas as pd  # For manipulating tabular data
from time import gmtime, strftime
import os
region = boto3.Session().region_name
smclient = boto3.Session().client('sagemaker')
```

The preceding code cell defines `region` and `smclient` objects that you will use to call the built-in XGBoost algorithm and set the SageMaker hyperparameter tuning job.

Next Step

Get the SageMaker Execution Role (p. 2448)

Get the SageMaker Execution Role

Get the execution role for the notebook instance. This is the IAM role that you created for your notebook instance. You pass the role to the tuning job.

```python
from sagemaker import get_execution_role
role = get_execution_role()
print(role)
```

Next Step

Specify a S3 Bucket to Upload Training Datasets and Store Output Data (p. 2448)

Specify a S3 Bucket to Upload Training Datasets and Store Output Data

Set up a S3 bucket to upload training datasets and save training output data.

To use a default S3 bucket

Use the following code to specify the default S3 bucket allocated for your SageMaker session. `prefix` is the path within the bucket where SageMaker stores the data for the current training job.

```python
sess = sagemaker.Session()
bucket = sess.default_bucket()  # Set a default S3 bucket
prefix = 'DEMO-automatic-model-tuning-xgboost-dm'
```

(Optional) To use a specific S3 bucket

If you want to use a specific S3 bucket, use the following code and replace the strings to the exact name of the S3 bucket. The name of the bucket must contain `sagemaker`, and be globally unique. The bucket must be in the same AWS Region as the notebook instance that you use for this example.

---

2448
bucket = "sagemaker-your-preferred-s3-bucket"

**Note**
The name of the bucket doesn't need to contain **sagemaker** if the IAM role that you use to run the hyperparameter tuning job has a policy that gives the S3FullAccess permission.

**Next Step**

**Download, Prepare, and Upload Training Data** (p. 2449)

**Download, Prepare, and Upload Training Data**

For this example, you use a training dataset of information about bank customers that includes the customer's job, marital status, and how they were contacted during the bank's direct marketing campaign. To use a dataset for a hyperparameter tuning job, you download it, transform the data, and then upload it to an Amazon S3 bucket.

For more information about the dataset and the data transformation that the example performs, see the `hpo_xgboost_direct_marketing_sagemaker_APIs` notebook in the **Hyperparameter Tuning** section of the **SageMaker Examples** tab in your notebook instance.

**Download and Explore the Training Dataset**

To download and explore the dataset, run the following code in your notebook:

```bash
!unzip -o bank-additional.zip
data = pd.read_csv('./bank-additional/bank-additional-full.csv', sep=';')
pd.set_option('display.max_columns', 500)     # Make sure we can see all of the columns
pd.set_option('display.max_rows', 5)         # Keep the output on one page
data
```

**Prepare and Upload Data**

Before creating the hyperparameter tuning job, prepare the data and upload it to an S3 bucket where the hyperparameter tuning job can access it.

Run the following code in your notebook:

```python
data['no_previous_contact'] = np.where(data['pdays'] == 999, 1, 0)  # Indicator variable to capture when pdays takes a value of 999
data['not_working'] = np.where(np.in1d(data['job'], ['student', 'retired', 'unemployed']), 1, 0)  # Indicator for individuals not actively employed
model_data = pd.get_dummies(data)  # Convert categorical variables to sets of indicators
model_data = model_data.drop(['duration', 'emp.var.rate', 'cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed'], axis=1)
train_data, validation_data, test_data = np.split(model_data.sample(frac=1, random_state=1729), [int(0.7 * len(model_data)), int(0.9*len(model_data))])
pd.concat([train_data['y_yes'], train_data.drop(['y_no', 'y_yes'], axis=1)], axis=1).to_csv('train.csv', index=False, header=False)
pd.concat([validation_data['y_yes'], validation_data.drop(['y_no', 'y_yes'], axis=1)], axis=1).to_csv('validation.csv', index=False, header=False)
pd.concat([test_data['y_yes'], test_data.drop(['y_no', 'y_yes'], axis=1)], axis=1).to_csv('test.csv', index=False, header=False)
```
Example: Hyperparameter Tuning Job

```python
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'train/train.csv')).upload_file('train.csv')
boto3.Session().resource('s3').Bucket(bucket).Object(os.path.join(prefix, 'validation/validation.csv')).upload_file('validation.csv')```

Next Step

Configure and Launch a Hyperparameter Tuning Job (p. 2450)

**Configure and Launch a Hyperparameter Tuning Job**

To configure and launch a hyperparameter tuning job, complete the following steps.

**Topics**

- Specify the Hyperparameter Tuning Job Settings (p. 2450)
- Configure the Training Jobs (p. 2451)
- Name and Launch the Hyperparameter Tuning Job (p. 2453)
- Next Step (p. 2453)

**Specify the Hyperparameter Tuning Job Settings**

To specify settings for the hyperparameter tuning job, you define a JSON object. You pass the object as the value of the `HyperParameterTuningJobConfig` parameter to `CreateHyperParameterTuningJob` when you create the tuning job.

In this JSON object, you specify:

- The ranges of hyperparameters that you want to tune. For more information, see Define Hyperparameter Ranges (p. 2440)
- The limits of the resource that the hyperparameter tuning job can consume.
- The objective metric for the hyperparameter tuning job. An objective metric is the metric that the hyperparameter tuning job uses to evaluate the training job that it launches.

**Note**

To use your own algorithm for hyperparameter tuning, you need to define metrics for your algorithm. For information, see Define Metrics (p. 2439).

The hyperparameter tuning job defines ranges for the `eta`, `alpha`, `min_child_weight`, and `max_depth` hyperparameters of the XGBoost Algorithm (p. 2038) built-in algorithm. The objective metric for the hyperparameter tuning job maximizes the `validation:auc` metric that the algorithm sends to CloudWatch Logs.

```json
tuning_job_config = {
    "ParameterRanges": {
        "CategoricalParameterRanges": [],
        "ContinuousParameterRanges": [
            {
                "MaxValue": "1",
                "MinValue": "0",
                "Name": "eta"
            },
            {
                "MaxValue": "2",
                "MinValue": "0",
                "Name": "alpha"
            }
        ]
    }
}  
```
Configure the Training Jobs

To configure the training jobs that the tuning job launches, define a JSON object that you pass as the value of the `TrainingJobDefinition` parameter of the `CreateHyperParameterTuningJob` call.

In this JSON object, you specify:

- Optional—Metrics that the training jobs emit.

  **Note**
  Define metrics only when you use a custom training algorithm. Because this example uses a built-in algorithm, you don't specify metrics. For information about defining metrics, see Define Metrics (p. 2439).

- The container image that specifies the training algorithm.
- The input configuration for your training and test data.
- The storage location for the algorithm’s output. Specify the S3 bucket where you want to store the output of the training jobs.
- The values of algorithm hyperparameters that are not tuned in the tuning job.
- The type of instance to use for the training jobs.
- The stopping condition for the training jobs. This is the maximum duration for each training job.

In this example, we set static values for the `eval_metric`, `num_round`, `objective`, `rate_drop`, and `tweedie_variance_power` parameters of the XGBoost Algorithm (p. 2038) built-in algorithm.

SageMaker Python SDK v1

```python
from sagemaker.amazon.amazon_estimator import get_image_uri
training_image = get_image_uri(region, 'xgboost', repo_version='1.0-1')

s3_input_train = 's3://{}//train'.format(bucket, prefix)
s3_input_validation = 's3://{}//validation'.format(bucket, prefix)

training_job_definition = {
```
```python
```
"AlgorithmSpecification": {
    "TrainingImage": training_image,
    "TrainingInputMode": "File"
},
"InputDataConfig": [
    {
        "ChannelName": "train",
        "CompressionType": "None",
        "ContentType": "csv",
        "DataSource": {
            "S3DataSource": {
                "S3DataDistributionType": "FullyReplicated",
                "S3DataType": "S3Prefix",
                "S3Uri": s3_input_train
            }
        }
    },
    {
        "ChannelName": "validation",
        "CompressionType": "None",
        "ContentType": "csv",
        "DataSource": {
            "S3DataSource": {
                "S3DataDistributionType": "FullyReplicated",
                "S3DataType": "S3Prefix",
                "S3Uri": s3_input_validation
            }
        }
    }
],
"OutputDataConfig": {
    "S3OutputPath": "s3://{}//{}\output".format(bucket, prefix)
},
"ResourceConfig": {
    "InstanceCount": 2,
    "InstanceType": "ml.c4.2xlarge",
    "VolumeSizeInGB": 10
},
"RoleArn": role,
"StaticHyperParameters": {
    "eval_metric": "auc",
    "num_round": "100",
    "objective": "binary:logistic",
    "rate_drop": "0.3",
    "tweedie_variance_power": "1.4"
},
"StoppingCondition": {
    "MaxRuntimeInSeconds": 43200
}

SageMaker Python SDK v2

```
training_image = sagemaker.image_uris.retrieve('xgboost', region, '1.0-1')

s3_input_train = 's3://{}//{}\train'.format(bucket, prefix)
s3_input_validation = 's3://{}//{}\validation/'.format(bucket, prefix)

training_job_definition = {
    "AlgorithmSpecification": {
        "TrainingImage": training_image,
        "TrainingInputMode": "File"
    },
    "InputDataConfig": [
        {
```
"ChannelName": "train",
"CompressionType": "None",
"ContentType": "csv",
"DataSource": {
    "S3DataSource": {
        "S3DataDistributionType": "FullyReplicated",
        "S3DataType": "S3Prefix",
        "S3Uri": s3_input_train
    }
},
"ChannelName": "validation",
"CompressionType": "None",
"ContentType": "csv",
"DataSource": {
    "S3DataSource": {
        "S3DataDistributionType": "FullyReplicated",
        "S3DataType": "S3Prefix",
        "S3Uri": s3_input_validation
    }
}
],
"OutputDataConfig": {
    "S3OutputPath": "s3://{}/{}".format(bucket,prefix)
},
"ResourceConfig": {
    "InstanceCount": 2,
    "InstanceType": "ml.c4.2xlarge",
    "VolumeSizeInGB": 10
},
"RoleArn": role,
"StaticHyperParameters": {
    "eval_metric": "auc",
    "num_round": "100",
    "objective": "binary:logistic",
    "rate_drop": "0.3",
    "tweedie_variance_power": "1.4"
},
"StoppingCondition": {
    "MaxRuntimeInSeconds": 43200
}
}

Name and Launch the Hyperparameter Tuning Job

Now you can provide a name for the hyperparameter tuning job and then launch it by calling the CreateHyperParameterTuningJob API. Pass tuning_job_config, and training_job_definition that you created in previous steps as the values of the parameters.

tuning_job_name = "MyTuningJob"
smclient.create_hyper_parameter_tuning_job(HyperParameterTuningJobName = tuning_job_name, HyperParameterTuningJobConfig = tuning_job_config, TrainingJobDefinition = training_job_definition)

Next Step

Monitor the Progress of a Hyperparameter Tuning Job (p. 2454)
Monitor the Progress of a Hyperparameter Tuning Job

To monitor the progress of a hyperparameter tuning job and the training jobs that it launches, use the Amazon SageMaker console.

Topics

• View the Status of the Hyperparameter Tuning Job (p. 2454)
• View the Status of the Training Jobs (p. 2456)
• View the Best Training Job (p. 2457)

View the Status of the Hyperparameter Tuning Job

To view the status of the hyperparameter tuning job

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Choose Hyperparameter tuning jobs.
Example: Hyperparameter Tuning Job
3. In the list of hyperparameter tuning jobs, check the status of the hyperparameter tuning job you launched. A tuning job can be:
   - Completed—The hyperparameter tuning job successfully completed.
   - InProgress—The hyperparameter tuning job is in progress. One or more training jobs are still running.
   - Failed—The hyperparameter tuning job failed.
   - Stopped—The hyperparameter tuning job was manually stopped before it completed. All training jobs that the hyperparameter tuning job launched are stopped.
   - Stopping—The hyperparameter tuning job is in the process of stopping.

View the Status of the Training Jobs

To view the status of the training jobs that the hyperparameter tuning job launched

1. In the list of hyperparameter tuning jobs, choose the job that you launched.
2. Choose Training jobs.

A training job can be:
   - Completed—The training job successfully completed.
   - InProgress—The training job is in progress.
   - Stopped—The training job was manually stopped before it completed.
   - Failed (Retryable)—The training job failed, but can be retried. A failed training job can be retried only if it failed because an internal service error occurred.
   - Failed (Non-retryable)—The training job failed and can't be retried. A failed training job can't be retried when a client error occurs.
**Note**
Hyperparameter tuning jobs can be stopped and the underlying resources deleted, but the jobs themselves cannot be deleted.

**View the Best Training Job**

A hyperparameter tuning job uses the objective metric that each training job returns to evaluate training jobs. While the hyperparameter tuning job is in progress, the best training job is the one that has returned the best objective metric so far. After the hyperparameter tuning job is complete, the best training job is the one that returned the best objective metric.

To view the best training job, choose **Best training job**.

![Best training job screenshot](image)

To deploy the best training job as a model that you can host at a SageMaker endpoint, choose **Create model**.

**Next Step**

**Clean up (p. 2457)**

**Clean up**

To avoid incurring unnecessary charges, when you are done with the example, use the AWS Management Console to delete the resources that you created for it.

**Note**
If you plan to explore other examples, you might want to keep some of these resources, such as your notebook instance, S3 bucket, and IAM role.

2. Open the Amazon S3 console at [https://console.aws.amazon.com/s3/](https://console.aws.amazon.com/s3/) and delete the bucket that you created to store model artifacts and the training dataset.
3. Open the IAM console at https://console.aws.amazon.com/iam/ and delete the IAM role. If you created permission policies, you can delete them, too.

4. Open the Amazon CloudWatch console at https://console.aws.amazon.com/cloudwatch/ and delete all of the log groups that have names starting with /aws/sagemaker/.

**Stop Training Jobs Early**

Stop the training jobs that a hyperparameter tuning job launches early when they are not improving significantly as measured by the objective metric. Stopping training jobs early can help reduce compute time and helps you avoid overfitting your model. To configure a hyperparameter tuning job to stop training jobs early, do one of the following:

- If you are using the AWS SDK for Python (Boto 3), set the `TrainingJobEarlyStoppingType` field of the `HyperParameterTuningJobConfig` object that you use to configure the tuning job to `AUTO`.
- If you are using the Amazon SageMaker Python SDK, set the `early_stopping_type` parameter of the `HyperParameterTuner` object to `Auto`.
- In the Amazon SageMaker console, in the Create hyperparameter tuning job workflow, under Early stopping, choose `Auto`.

For a sample notebook that demonstrates how to use early stopping, see https://github.com/awslabs/amazon-sagemaker-examples/blob/master/hyperparameter_tuning/image_classification_early_stopping/hpo_image_classification_early_stopping.ipynb or open the hpo_image_classification_early_stopping.ipynb notebook in the Hyperparameter Tuning section of the SageMaker Examples in a notebook instance. For information about using sample notebooks in a notebook instance, see Example Notebooks (p. 306).

**How Early Stopping Works**

When you enable early stopping for a hyperparameter tuning job, SageMaker evaluates each training job the hyperparameter tuning job launches as follows:

- After each epoch of training, get the value of the objective metric.
- Compute the running average of the objective metric for all previous training jobs up to the same epoch, and then compute the median of all of the running averages.
- If the value of the objective metric for the current training job is worse (higher when minimizing or lower when maximizing the objective metric) than the median value of running averages of the objective metric for previous training jobs up to the same epoch, SageMaker stops the current training job.

**Algorithms That Support Early Stopping**

To support early stopping, an algorithm must emit objective metrics for each epoch. The following built-in SageMaker algorithms support early stopping:

- LightGBM (p. 2005)
- CatBoost (p. 1978)
- AutoGluon-Tabular (p. 1971)
- TabTransformer (p. 2031)
- Linear Learner Algorithm (p. 2014)—Supported only if you use `objective_loss` as the objective metric.
- XGBoost Algorithm (p. 2038)
Note
This list of built-in algorithms that support early stopping is current as of December 13, 2018. Other built-in algorithms might support early stopping in the future. If an algorithm emits a metric that can be used as an objective metric for a hyperparameter tuning job (preferably a validation metric), then it supports early stopping.

To use early stopping with your own algorithm, you must write your algorithms such that it emits the value of the objective metric after each epoch. The following list shows how you can do that in different frameworks:

TensorFlow
Use the `tf.keras.callbacks.ProgbarLogger` class. For information, see the `tf.keras.callbacks.ProgbarLogger API`.

MXNet
Use the `mxnet.callback.LogValidationMetricsCallback`. For information, see the `mxnet.callback APIs`.

Chainer
Extend chainer by using the `chainer.training.extensions.Evaluator` class. For information, see the `chainer.training.extensions.Evaluator API`.

PyTorch and Spark
There is no high-level support. You must explicitly write your training code so that it computes objective metrics and writes them to logs after each epoch.

Run a Warm Start Hyperparameter Tuning Job

Use warm start to start a hyperparameter tuning job using one or more previous tuning jobs as a starting point. The results of previous tuning jobs are used to inform which combinations of hyperparameters to search over in the new tuning job. Hyperparameter tuning uses either Bayesian or random search to choose combinations of hyperparameter values from ranges that you specify. For more information, see How Hyperparameter Tuning Works (p. 2437). Using information from previous hyperparameter tuning jobs can help increase the performance of the new hyperparameter tuning job by making the search for the best combination of hyperparameters more efficient.

Note
Warm start tuning jobs typically take longer to start than standard hyperparameter tuning jobs, because the results from the parent jobs have to be loaded before the job can start. The increased time depends on the total number of training jobs launched by the parent jobs.

Reasons you might want to consider warm start include:

• You want to gradually increase the number of training jobs over several tuning jobs based on the results you see after each iteration.
• You get new data, and want to tune a model using the new data.
Run a Warm Start Hyperparameter Tuning Job

- You want to change the ranges of hyperparameters that you used in a previous tuning job, change static hyperparameters to tunable, or change tunable hyperparameters to static values.
- You stopped a previous hyperparameter job early or it stopped unexpectedly.

Topics
- Types of Warm Start Tuning Jobs (p. 2460)
- Warm Start Tuning Restrictions (p. 2460)
- Warm Start Tuning Sample Notebook (p. 2461)
- Create a Warm Start Tuning Job (p. 2461)

Types of Warm Start Tuning Jobs

There are two different types of warm start tuning jobs:

IDENTICAL_DATA_AND_ALGORITHM

The new hyperparameter tuning job uses the same input data and training image as the parent tuning jobs. You can change the hyperparameter ranges to search and the maximum number of training jobs that the hyperparameter tuning job launches. You can also change hyperparameters from tunable to static, and from static to tunable, but the total number of static plus tunable hyperparameters must remain the same as it is in all parent jobs. You cannot use a new version of the training algorithm, unless the changes in the new version do not affect the algorithm itself. For example, changes that improve logging or adding support for a different data format are allowed.

Use identical data and algorithm when you use the same training data as you used in a previous hyperparameter tuning job, but you want to increase the total number of training jobs or change ranges or values of hyperparameters.

When you run an warm start tuning job of type IDENTICAL_DATA_AND_ALGORITHM, there is an additional field in the response to DescribeHyperParameterTuningJob named OverallBestTrainingJob. The value of this field is the TrainingJobSummary for the training job with the best objective metric value of all training jobs launched by this tuning job and all parent jobs specified for the warm start tuning job.

TRANSFER_LEARNING

The new hyperparameter tuning job can include input data, hyperparameter ranges, maximum number of concurrent training jobs, and maximum number of training jobs that are different than those of its parent hyperparameter tuning jobs. You can also change hyperparameters from tunable to static, and from static to tunable, but the total number of static plus tunable hyperparameters must remain the same as it is in all parent jobs. The training algorithm image can also be a different version from the version used in the parent hyperparameter tuning job. When you use transfer learning, changes in the dataset or the algorithm that significantly affect the value of the objective metric might reduce the usefulness of using warm start tuning.

Warm Start Tuning Restrictions

The following restrictions apply to all warm start tuning jobs:

- A tuning job can have a maximum of 5 parent jobs, and all parent jobs must be in a terminal state (Completed, Stopped, or Failed) before you start the new tuning job.
- The objective metric used in the new tuning job must be the same as the objective metric used in the parent jobs.
Run a Warm Start Hyperparameter Tuning Job

- The total number of static plus tunable hyperparameters must remain the same between parent jobs and the new tuning job. Because of this, if you think you might want to use a hyperparameter as tunable in a future warm start tuning job, you should add it as a static hyperparameter when you create a tuning job.

- The type of each hyperparameter (continuous, integer, categorical) must not change between parent jobs and the new tuning job.

- The number of total changes from tunable hyperparameters in the parent jobs to static hyperparameters in the new tuning job, plus the number of changes in the values of static hyperparameters cannot be more than 10. Each value in a categorical hyperparameter counts against this limit. For example, if the parent job has a tunable categorical hyperparameter with the possible values red and blue, you change that hyperparameter to static in the new tuning job, that counts as 2 changes against the allowed total of 10. If the same hyperparameter had a static value of red in the parent job, and you change the static value to blue in the new tuning job, it also counts as 2 changes.

- Warm start tuning is not recursive. For example, if you create MyTuningJob3 as a warm start tuning job with MyTuningJob2 as a parent job, and MyTuningJob2 is itself an warm start tuning job with a parent job MyTuningJob1, the information that was learned when running MyTuningJob1 is not used for MyTuningJob3. If you want to use the information from MyTuningJob1, you must explicitly add it as a parent for MyTuningJob3.

- The training jobs launched by every parent job in a warm start tuning job count against the 500 maximum training jobs for a tuning job.

- Hyperparameter tuning jobs created before October 1, 2018 cannot be used as parent jobs for warm start tuning jobs.

Warm Start Tuning Sample Notebook

For a sample notebook that shows how to use warm start tuning, see https://github.com/awslabs/amazon-sagemaker-examples/blob/master/hyperparameter_tuning/image_classification_warmstart/hpo_image_classification_warmstart.ipynb. For instructions how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see Example Notebooks (p. 306). Once you have created a notebook instance and opened it, select the SageMaker Examples tab to see a list of all the SageMaker samples. The warm start tuning example notebook is located in the Hyperparameter tuning section, and is named hpo_image_classification_warmstart.ipynb. To open a notebook, click on its Use tab and select Create copy.

Create a Warm Start Tuning Job

You can use either the low-level AWS SDK for Python (Boto 3) or the high-level SageMaker Python SDK to create a warm start tuning job.

Topics
- Create a Warm Start Tuning Job (Low-level SageMaker API for Python (Boto 3)) (p. 2461)
- Create a Warm Start Tuning Job (SageMaker Python SDK) (p. 2462)

Create a Warm Start Tuning Job (Low-level SageMaker API for Python (Boto 3))

To use warm start tuning, you specify the values of a HyperParameterTuningJobWarmStartConfig object, and pass that as the WarmStartConfig field in a call to CreateHyperParameterTuningJob.

The following code shows how to create a HyperParameterTuningJobWarmStartConfig object and pass it to CreateHyperParameterTuningJob job by using the low-level SageMaker API for Python (Boto 3).

Create the HyperParameterTuningJobWarmStartConfig object:
Create the warm start tuning job:

```
smclient = boto3.Session().client('sagemaker')
smclient.create_hyperparameter_tuning_job(HyperParameterTuningJobName = 'MyWarmStartTuningJob',
    HyperParameterTuningJobConfig = tuning_job_config, # See notebook for tuning configuration
    TrainingJobDefinition = training_job_definition, # See notebook for job definition
    WarmStartConfig = warm_start_config)
```

Create a Warm Start Tuning Job (SageMaker Python SDK)

To use the Amazon SageMaker Python SDK to run a warm start tuning job, you:

- Specify the parent jobs and the warm start type by using a WarmStartConfig object.
- Pass the WarmStartConfig object as the value of the warm_start_config argument of a HyperparameterTuner object.
- Call the fit method of the HyperparameterTuner object.

For more information about using the Amazon SageMaker Python SDK for hyperparameter tuning, see https://github.com/aws/sagemaker-python-sdk#sagemaker-automatic-model-tuning.

This example uses an estimator that uses the Image Classification - MXNet (p. 2172) algorithm for training. The following code sets the hyperparameter ranges that the warm start tuning job searches within to find the best combination of values. For information about setting hyperparameter ranges, see Define Hyperparameter Ranges (p. 2440).

```
hyperparameter_ranges = {'learning_rate': ContinuousParameter(0.0, 0.1),
                        'momentum': ContinuousParameter(0.0, 0.99))
```

The following code configures the warm start tuning job by creating a WarmStartConfig object.

```
from sagemaker.tuner import WarmStartConfig,WarmStartTypes
parent_tuning_job_name = "MyParentTuningJob"
warm_start_config = WarmStartConfig(warm_start_type=WarmStartTypes.IDENTICAL_DATA_AND_ALGORITHM,
                                      parents={parent_tuning_job_name})
```

Now set the values for static hyperparameters, which are hyperparameters that keep the same value for every training job that the warm start tuning job launches. In the following code, imageclassification is an estimator that was created previously.

```
imageclassification.set_hyperparameters(num_layers=18,
                                          image_shape='3,224,224',
                                          num_classes=257,
                                          num_training_samples=15420,
                                          mini_batch_size=128,
```

2462
epochs=30,
optimizer='sgd',
top_k='2',
precision_dtype='float32',
augmentation_type='crop')

Now create the `HyperparameterTuner` object and pass the `WarmStartConfig` object that you previously created as the `warm_start_config` argument.

```python
tuner_warm_start = HyperparameterTuner(imageclassification,
    'validation:accuracy',
    hyperparameter_ranges,
    objective_type='Maximize',
    max_jobs=10,
    max_parallel_jobs=2,
    base_tuning_job_name='warmstart',
    warm_start_config=warm_start_config)
```

Finally, call the `fit` method of the `HyperparameterTuner` object to launch the warm start tuning job.

```python
tuner_warm_start.fit(
    {'train': s3_input_train, 'validation': s3_input_validation},
    include_cls_metadata=False)
```

---

**Resource Limits for Automatic Model Tuning**

SageMaker sets the following default limits for resources used by automatic model tuning:

<table>
<thead>
<tr>
<th>Resource</th>
<th>Regions</th>
<th>Default limits</th>
<th>Can be increased to</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of parallel (concurrent) hyperparameter tuning jobs</td>
<td>All</td>
<td>100</td>
<td>N/A</td>
</tr>
<tr>
<td>Number of hyperparameters that can be searched *</td>
<td>All</td>
<td>30</td>
<td>N/A</td>
</tr>
<tr>
<td>Number of metrics defined per hyperparameter tuning job</td>
<td>All</td>
<td>20</td>
<td>N/A</td>
</tr>
<tr>
<td>Number of parallel training jobs per hyperparameter tuning job</td>
<td>All</td>
<td>10</td>
<td>100</td>
</tr>
<tr>
<td>[Bayesian optimization] Number of training jobs per hyperparameter tuning job</td>
<td>All</td>
<td>750</td>
<td>N/A</td>
</tr>
<tr>
<td>[Random search] Number of training jobs</td>
<td>All</td>
<td>750</td>
<td>10000</td>
</tr>
<tr>
<td>Resource</td>
<td>Regions</td>
<td>Default limits</td>
<td>Can be increased to</td>
</tr>
<tr>
<td>----------------------------------------------</td>
<td>-----------</td>
<td>----------------</td>
<td>---------------------</td>
</tr>
<tr>
<td>per hyperparameter tuning job</td>
<td>All</td>
<td>750</td>
<td>N/A</td>
</tr>
<tr>
<td>[Hyperband] Number of training jobs per hyperparameter tuning job</td>
<td>All</td>
<td>750</td>
<td>N/A</td>
</tr>
<tr>
<td>[Grid] Number of training jobs per hyperparameter tuning job, either specified explicitly or inferred from the search space</td>
<td>All</td>
<td>750</td>
<td>N/A</td>
</tr>
<tr>
<td>Maximum run time for a hyperparameter tuning job</td>
<td>All</td>
<td>30 days</td>
<td>N/A</td>
</tr>
</tbody>
</table>

* Every possible value in a categorical hyperparameter counts against this limit.

**Resource limit example**

When you plan hyperparameter tuning jobs, you also have to take into account the limits on training resources. For information about the default resource limits for SageMaker training jobs, see SageMaker Limits. Every concurrent training instance on which all of your hyperparameter tuning jobs run counts against the total number of training instances allowed. For example, if you run 10 concurrent hyperparameter tuning jobs, each of those hyperparameter tuning jobs runs 100 total training jobs and 20 concurrent training jobs. Each of those training jobs runs on one ml.m4.xlarge instance. The following limits apply:

- Number of concurrent hyperparameter tuning jobs: You don't need to increase the limit, because 10 tuning jobs is below the limit of 100.
- Number of training jobs per hyperparameter tuning job: You don't need to increase the limit, because 100 training jobs is below the limit of 750.
- Number of concurrent training jobs per hyperparameter tuning job: You need to request a limit increase to 20, because the default limit is 10.
- SageMaker training ml.m4.xlarge instances: You need to request a limit increase to 200, because you have 10 hyperparameter tuning jobs, each of which is running 20 concurrent training jobs. The default limit is 20 instances.
- SageMaker training total instance count: You need to request a limit increase to 200, because you have 10 hyperparameter tuning jobs, each of which is running 20 concurrent training jobs. The default limit is 20 instances.

**To request a quota increase:**

1. Open the AWS Support Center page, sign in if necessary, and then choose Create case.
2. On the Create case page, choose Service limit increase.
4. On the Requests panel for Request 1, select the Region, the resource Limit to increase and the New Limit value you are requesting. Select Add another request if you have additional requests for quota increases.
5. In the **Case description** panel, provide a description of your use case.

6. In the **Contact options** panel, select your preferred **Contact methods** *(Web, Chat or Phone)* and then choose **Submit**.

### Best Practices for Hyperparameter Tuning

Hyperparameter optimization is not a fully-automated process. To improve optimization, use the following guidelines when you create hyperparameters.

**Topics**
- Choosing a Strategy *(p. 2465)*
- Choosing the Number of Hyperparameters *(p. 2466)*
- Choosing Hyperparameter Ranges *(p. 2466)*
- Using Logarithmic Scales for Hyperparameters *(p. 2466)*
- Choosing the Best Number of Concurrent Training Jobs *(p. 2466)*
- Running Training Jobs on Multiple Instances *(p. 2466)*

**Choosing a Strategy**

For large jobs, using Hyperband can reduce computation time by utilizing its internal early stopping mechanism, reallocation of resources and ability to run parallel jobs. If runtime and resources are limited, use either random search or Bayesian optimization instead. Bayesian optimization uses information gathered from prior runs to make increasingly informed decisions about improving hyperparameter
configurations in the next run. Because of its sequential nature, Bayesian optimization cannot massively scale. Random search is able to run large numbers of parallel jobs. Consider using grid search if it is important to be able to reproduce results of a tuning job, or if simplicity and transparency of the optimization algorithm are important. Grid search is also a good option when it is important to explore the entire hyperparameter search space evenly.

**Choosing the Number of Hyperparameters**

The computational complexity of a hyperparameter tuning job depends primarily on the number of hyperparameters whose range of values Amazon SageMaker has to search through during optimization. Although you can simultaneously specify up to 20 hyperparameters to optimize for a tuning job, limiting your search to a much smaller number is likely to give you better results.

**Choosing Hyperparameter Ranges**

The range of values for hyperparameters that you choose to search can significantly affect the success of hyperparameter optimization. Although you might want to specify a very large range that covers every possible value for a hyperparameter, you get better results by limiting your search to a small range of values. If you know that you get the best metric values within a subset of the possible range, consider limiting the range to that subset.

**Using Logarithmic Scales for Hyperparameters**

During hyperparameter tuning, SageMaker attempts to figure out if your hyperparameters are log-scaled or linear-scaled. Initially, it assumes that hyperparameters are linear-scaled. If they are in fact log-scaled, it might take some time for SageMaker to discover that fact. If you know that a hyperparameter is log-scaled and can convert it yourself, doing so could improve hyperparameter optimization.

**Choosing the Best Number of Concurrent Training Jobs**

When setting the resource limit `MaxParallelTrainingJobs` for the maximum number of concurrent training jobs that a hyperparameter tuning job can launch, consider the following tradeoff. Running more hyperparameter tuning jobs concurrently gets more work done quickly, but a tuning job improves only through successive rounds of experiments. Typically, running one training job at a time achieves the best results with the least amount of compute time.

**Running Training Jobs on Multiple Instances**

When a training job runs on multiple instances, hyperparameter tuning uses the last-reported objective metric value from all instances of that training job as the value of the objective metric for that training job. Design distributed training jobs so that the objective metric reported is the one that you want.

**Amazon SageMaker Distributed Training Libraries**

SageMaker provides distributed training libraries for data parallelism and model parallelism. The libraries are optimized for the SageMaker training environment, help adapt your distributed training jobs to SageMaker, and improve training speed and throughput.

**Topics**

- Get Started with Distributed Training (p. 2467)
- Basic Distributed Training Concepts (p. 2467)
- Advanced Concepts (p. 2468)
- Strategies (p. 2469)
- Optimize Distributed Training (p. 2471)
Get Started with Distributed Training

If you're familiar with distributed training, follow one of the links to your preferred strategy or framework to get started. Otherwise, continue on to the next section to learn some distributed training concepts.

SageMaker distributed training libraries:

- SageMaker's Distributed Data Parallel Library (p. 2475)
- SageMaker's Distributed Model Parallel (p. 2507)

Note
The SageMaker distributed training libraries are available only through the AWS deep learning containers for the TensorFlow, PyTorch, and HuggingFace frameworks within the SageMaker training platform. To use the libraries, you must use the SageMaker Python SDK or the SageMaker APIs through SDK for Python (Boto3) or AWS Command Line Interface. Throughout the documentation, instructions and examples focus on how to use the distributed training libraries with the SageMaker Python SDK.

Basic Distributed Training Concepts

SageMaker's distributed training libraries use the following distributed training terms and features.

Datasets and Batches

- **Training Dataset**: All of the data you use to train the model.
- **Global batch size**: The number of records selected from the training dataset in each iteration to send to the GPUs in the cluster. This is the number of records over which the gradient is computed at each iteration. If data parallelism is used, it is equal to the total number of model replicas multiplied by the per-replica batch size: \( \text{global batch size} = (\text{the number of model replicas}) \times (\text{per-replica batch size}) \). A single batch of global batch size is often referred to as the mini-batch in machine learning literature.
- **Per-replica batch size**: When data parallelism is used, this is the number of records sent to each model replica. Each model replica performs a forward and backward pass with this batch to calculate weight updates. The resulting weight updates are synchronized (averaged) across all replicas before the next set of per-replica batches are processed.
- **Micro-batch**: A subset of the mini-batch or, if hybrid model and data parallelism is used, it is a subset of the per-replica sized batch. When you use SageMaker's distributed model parallelism library, each micro-batch is fed into the training pipeline one-by-one and follows an execution schedule defined by the library's runtime.

Training

- **Epoch**: One training cycle through the entire dataset. It is common to have multiple iterations per an epoch. The number of epochs you use in training is unique on your model and use case.
- **Iteration**: A single forward and backward pass performed using a global batch sized batch (a mini-batch) of training data. The number of iterations performed during training is determined by the
global batch size and the number of epochs used for training. For example, if a dataset includes 5,000 samples, and you use a global batch size of 500, it will take 10 iterations to complete a single epoch.

- **Learning rate**: A variable that influences the amount that weights are changed in response to the calculated error of the model. The learning rate plays an important role in the model's ability to converge as well as the speed and optimality of convergence.

### Instances and GPUs

- **Instances**: An AWS machine learning compute instance. These are also referred to as nodes.
- **Cluster size**: When using SageMaker's distributed training library, this is the number of instances multiplied by the number of GPUs in each instance. For example, if you use two ml.p3.8xlarge instances in a training job, which have 4 GPUs each, the cluster size is 8. While increasing cluster size can lead to faster training times, communication between instances must be optimized; Otherwise, communication between the nodes can add overhead and lead to slower training times. The SageMaker distributed training library is designed to optimize communication between AWS ML compute instances, leading to higher device utilization and faster training times.

### Distributed Training Solutions

- **Data parallelism**: A strategy in distributed training where a training dataset is split up across multiple processing nodes (such as AWS ML Instances), and each processing node contains a replica of the model. Each node receives different batches of training data, performs a forward and backward pass, and shares weight updates with the other nodes for synchronization before moving on to the next batch and ultimately another epoch.
- **Model parallelism**: A strategy in distributed training where the model partitioned across multiple processing nodes (such as AWS ML Instances). The model might be complex and have a large number of hidden layers and weights, making it unable to fit in the memory of a single node. Each node carries a subset of the model, through which the data flows and the transformations are shared and compiled. The efficiency of model parallelism, in terms of GPU utilization and training time, is heavily dependent on how the model is partitioned and the execution schedule used to perform forward and backward passes.
- **Pipeline Execution Schedule (Pipelining)**: The pipeline execution schedule determines the order in which computations (micro-batches) are made and data is processed across devices during model training. Pipelining is a technique to achieve true parallelization in model parallelism and overcome the performance loss due to sequential computation by having the GPUs compute simultaneously on different data samples. To learn more, see Pipeline Execution Schedule.

### Example

The following example demonstrates how these terms might be used to describe a training job that uses hybrid model and data parallelism:

A 2-way data parallelism and 4-way model parallelism training job is launched with a global batch size of 64 images. This training job requires a total of 8 GPUs. Each of the two model replicas processes a per-replica batch of size 32. During the forward and backward pass, a per-replica batch is further divided up into micro-batches. These micro-batches are processed in an interleaved fashion using a pipelined execution schedule.

The training dataset includes 640 images, and so a single epoch takes 10 iterations.

### Advanced Concepts

Machine Learning (ML) practitioners commonly face two scaling challenges when training models: *scaling model size* and *scaling training data*. While model size and complexity can result in better
accuracy, there is a limit to the model size you can fit into a single CPU or GPU. Furthermore, scaling model size may result in more computations and longer training times.

Not all models handle training data scaling equally well because they need to ingest all the training data in memory for training. They only scale vertically, and to bigger and bigger instance types. In most cases, scaling training data results in longer training times.

Deep Learning (DL) is a specific family of ML algorithms consisting of several layers of artificial neural networks. The most common training method is with mini-batch Stochastic Gradient Descent (SGD). In mini-batch SGD, the model is trained by conducting small iterative changes of its coefficients in the direction that reduces its error. Those iterations are conducted on equally sized subsamples of the training dataset called mini-batches. For each mini-batch, the model is run in each record of the mini-batch, its error measured and the gradient of the error estimated. Then the average gradient is measured across all the records of the mini-batch and provides an update direction for each model coefficient. One full pass over the training dataset is called an epoch. Model trainings commonly consist of dozens to hundreds of epochs. Mini-batch SGD has several benefits: First, its iterative design makes training time theoretically linear of dataset size. Second, in a given mini-batch each record is processed individually by the model without need for inter-record communication other than the final gradient average. The processing of a mini-batch is consequently particularly suitable for parallelization and distribution.

Parallelizing SGD training by distributing the records of a mini-batch over different computing devices is called data parallel distributed training, and is the most commonly used DL distribution paradigm. Data parallel training is a relevant distribution strategy to scale the mini-batch size and process each mini-batch faster. However, data parallel training comes with the extra complexity of having to compute the mini-batch gradient average with gradients coming from all the workers and communicating it to all the workers, a step called allreduce that can represent a growing overhead, as the training cluster is scaled, and that can also drastically penalize training time if improperly implemented or implemented over improper hardware subtracts.

Data parallel SGD still requires developers to be able to fit at least the model and a single record in a computing device, such as a single CPU or GPU. When training very large models such as large transformers in Natural Language Processing (NLP), or segmentation models over high-resolution images, there may be situations in which this is not feasible. An alternative way to break up the workload is to partition the model over multiple computing devices, an approach called model-parallel distributed training.

Distributed training is usually split by two approaches: data parallel and model parallel. Data parallel is the most common approach to distributed training: You have a lot of data, batch it up, and send blocks of data to multiple CPUs or GPUs (nodes) to be processed by the neural network or ML algorithm, then combine the results. The neural network is the same on each node. A model parallel approach is used with large models that won’t fit in a node’s memory in one piece; it breaks up the model and places different parts on different nodes. In this situation, you need to send your batches of data out to each node so that the data is processed on all parts of the model.

The terms network and model are often used interchangeably: A large model is really a large network with many layers and parameters. Training with a large network produces a large model, and loading the model back onto the network with all your pre-trained parameters and their weights loads a large model into memory. When you break apart a model to split it across nodes, you’re also breaking apart the underlying network. A network consists of layers, and to split up the network, you put layers on different compute devices.

A common pitfall of naively splitting layers across devices is severe GPU under-utilization. Training is inherently sequential in both forward and backward passes, and at a given time, only one GPU can actively compute, while the others wait on the activations to be sent. Modern model parallel libraries solve this problem by using pipeline execution schedules to improve device utilization. However, only the Amazon SageMaker’s distributed model parallel library includes automatic model splitting. The two
core features of the library, automatic model splitting and pipeline execution scheduling, simplifies the process of implementing model parallelism by making automated decisions that lead to efficient device utilization.

**Train with Data Parallel and Model Parallel**

If you are training with a large dataset, start with a data parallel approach. If you run out of memory during training, you may want to switch to a model parallel approach, or try hybrid model and data parallelism. You can also try the following to improve performance with data parallel:

- Change your model's hyperparameters.
- Reduce the batch size.
- Keep reducing the batch size until it fits. If you reduce batch size to 1, and still run out of memory, then you should try model-parallel training.

Try gradient compression (FP16, INT8):

- On NVIDIA TensorCore-equipped hardware, using mixed precision training creates both speed-up and memory consumption reduction.
- SageMaker's distributed data parallelism library supports Automatic Mixed Precision (AMP) out of the box. No extra action is needed to enable AMP other than the framework-level modifications to your training script. If gradients are in FP16, the SageMaker data parallelism library runs its `AllReduce` operation in FP16. For more information about implementing AMP APIs to your training script, see the following resources:
  - Frameworks - PyTorch in the NVIDIA Deep Learning Performance documentation
  - Frameworks - TensorFlow in the NVIDIA Deep Learning Performance documentation
  - Automatic Mixed Precision for Deep Learning in the NVIDIA Developer Docs
  - Introducing native PyTorch automatic mixed precision for faster training on NVIDIA GPUs in the PyTorch Blog
  - TensorFlow mixed precision APIs in the TensorFlow documentation

Try reducing the input size:

- Reduce the NLP sequence length if you increase the sequence link, need to adjust the batch size down, or adjust the GPUs up to spread the batch.
- Reduce image resolution.

Check if you use batch normalization, since this can impact convergence. When you use distributed training, your batch is split across GPUs and the effect of a much lower batch size can be a higher error rate thereby disrupting the model from converging. For example, if you prototyped your network on a single GPU with a batch size of 64, then scaled up to using four p3dn.24xlarge, you now have 32 GPUs and your per-GPU batch size drops from 64 to 2. This will likely break the convergence you saw with a single node.

Start with model-parallel training when:

- Your model does not fit on a single device.
- Due to your model size, you're facing limitations in choosing larger batch sizes, such as if your model weights take up most of your GPU memory and you are forced to choose a smaller, suboptimal batch size.

To learn more about the SageMaker distributed libraries, see the following:

- SageMaker's Distributed Data Parallel Library (p. 2475)
• SageMaker's Distributed Model Parallel (p. 2507)

Optimize Distributed Training

Customize hyperparameters for your use case and your data to get the best scaling efficiency. In the following discussion, we highlight some of the most impactful training variables and provide references to state-of-the-art implementations so you can learn more about your options. Also, we recommend that you refer to your preferred framework’s distributed training documentation.

- Apache MXNet distributed training
- PyTorch distributed training
- TensorFlow distributed training

Batch Size

SageMaker distributed toolkits generally allow you to train on bigger batches. For example, if a model fits within a single device but can only be trained with a small batch size, using either model-parallel training or data parallel training enables you to experiment with larger batch sizes.

Be aware that batch size directly influences model accuracy by controlling the amount of noise in the model update at each iteration. Increasing batch size reduces the amount of noise in the gradient estimation, which can be beneficial when increasing from very small batches sizes, but can result in degraded model accuracy as the batch size increases to large values.

Tip

Adjust your hyperparameters to ensure that your model trains to a satisfying convergence as you increase its batch size.

A number of techniques have been developed to maintain good model convergence when batch is increased.

Mini-Batch Size

In SGD, the mini-batch size quantifies the amount of noise present in the gradient estimation. A small mini-batch results in a very noisy mini-batch gradient, which is not representative of the true gradient over the dataset. A large mini-batch results in a mini-batch gradient close to the true gradient over the dataset and potentially not noisy enough—likely to stay locked in irrelevant minima.

To learn more about these techniques, see the following papers:

- Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour, Goya et al.
- PowerAI DDL, Cho et al.
- Scale Out for Large Minibatch SGD: Residual Network Training on ImageNet-1K with Improved Accuracy and Reduced Time to Train, Codreanu et al.
- ImageNet Training in Minutes, You et al.
- Large Batch Training of Convolutional Networks, You et al.
- Large Batch Optimization for Deep Learning: Training BERT in 76 Minutes, You et al.
- Accelerated Large Batch Optimization of BERT Pretraining in 54 minutes, Zheng et al.
- Deep Gradient Compression, Lin et al.

Scenarios

The following sections cover scenarios in which you may want to scale up training, and how you can do so using AWS resources.
Scaling from a Single GPU to Many GPUs

The amount of data or the size of the model used in machine learning can create situations in which the
time to train a model is longer that you are willing to wait. Sometimes, the training doesn’t work at all
because the model or the training data is too large. One solution is to increase the number of GPUs you
use for training. On an instance with multiple GPUs, like a p3.16xlarge that has eight GPUs, the data
and processing is split across the eight GPUs. When you use distributed training libraries, this can result
in a near-linear speedup in the time it takes to train your model. It takes slightly over 1/8 the time it
would have taken on p3.2xlarge with one GPU.

<table>
<thead>
<tr>
<th>Instance type</th>
<th>GPUs</th>
</tr>
</thead>
<tbody>
<tr>
<td>p3.2xlarge</td>
<td>1</td>
</tr>
<tr>
<td>p3.8xlarge</td>
<td>4</td>
</tr>
<tr>
<td>p3.16xlarge</td>
<td>8</td>
</tr>
<tr>
<td>p3dn.24xlarge</td>
<td>8</td>
</tr>
</tbody>
</table>

**Note**
The ml instance types used by SageMaker training have the same number of GPUs as the
corresponding p3 instance types. For example, ml.p3.8xlarge has the same number of GPUs
as p3.8xlarge - 4.

Scaling from a Single Instance to Multiple Instances

If you want to scale your training even further, you can use more instances. However, you should choose
a larger instance type before you add more instances. Review the previous table to see how many GPUs
are in each p3 instance type.

If you have made the jump from a single GPU on a p3.2xlarge to four GPUs on a p3.8xlarge, but
decide that you require more processing power, you may see better performance and incur lower costs
if you choose a p3.16xlarge before trying to increase instance count. Depending on the libraries you
use, when you keep your training on a single instance, performance is better and costs are lower than a
scenario where you use multiple instances.

When you are ready to scale the number of instances, you can do this with SageMaker Python
SDK estimator function by setting your instance_count. For example, you can set
instance_type = p3.16xlarge and instance_count = 2. Instead of the eight GPUs on a single p3.16xlarge,
you have 16 GPUs across two identical instances. The following chart shows scaling and throughput
starting with eight GPUs on a single instance and increasing to 64 instances for a total of 256 GPUs.
Availability Zones and Network Backplane

With multiple instances, it’s important to understand the network that connects the instances, how they read the training data, and how they share information between themselves (for example, communication between the nodes in the cluster when doing an AllReduce operation).

First, your instances need to be in the same Region and same Availability Zone. For example, instances in us-west-2 must all be in us-west-2a. When you use the SageMaker Python SDK, this is handled for you. If you use Amazon EC2 and orchestrate your own training clusters, you need to be aware of this, or your training speeds suffer.

Your training data should also be in the same Availability Zone. When you use a SageMaker estimator, you pass in the Region and the S3 bucket, and if the data is not in the Region you set, you get an error.

Optimized GPU, Network, and Storage

The p3dn.24xlarge instance type was designed for fast local storage and a fast network backplane with up to 100 gigabits, and we highly recommend it as the most performant option for distributed training. SageMaker supports streaming data modes from S3, referred to as pipe mode. For HPC loads like distributed training, we recommend Amazon FSx for your file storage.

Custom Training Scripts

While SageMaker makes it simple to deploy and scale the number of instances and GPUs, depending on your framework of choice, managing the data and results can be very challenging, which is why external supporting libraries are often used. This most basic form of distributed training requires modification of your training script to manage the data distribution.

SageMaker also supports Horovod and implementations of distributed training native to each major deep learning framework. If you choose to use examples from these frameworks, you can follow SageMaker’s container guide for Deep Learning Containers, and various example notebooks that demonstrate implementations.

SageMaker Distributed Training Features and Libraries

The SageMaker built-in algorithms consists of 18 popular machine learning algorithms: 17 ML algorithms and the Reinforcement Learning algorithm. Many of them are rewritten from scratch to be scalable and distributed out of the box.

If you want to use distributed training strategies for deep learning tasks such as computer vision and natural language processing, we recommend that you use Amazon SageMaker’s distributed training libraries. SageMaker’s distributed training libraries make it easier for you to write highly scalable and cost-effective custom data parallel and model parallel deep learning training jobs.

SageMaker distributed training libraries offer both data parallel and model parallel training strategies. It combines software and hardware technologies to improve inter-GPU and inter-node communications. It extends SageMaker’s training capabilities with built-in options that require only small code changes to your training scripts.

- SageMaker’s Distributed Data Parallel Library (p. 2475)
- SageMaker’s Distributed Model Parallel (p. 2507)

If you want to use open source distributed training frameworks such as Horovod and MPI, follow instructions in the following pages in the SageMaker Python SDK documentation:

- PyTorch Distributed Training and SageMaker PyTorch Estimator's distribution argument
SageMaker's Distributed Data Parallel Library

The SageMaker distributed data parallel library extends SageMaker training capabilities on deep learning models with near-linear scaling efficiency, achieving fast time-to-train with minimal code changes.

When training a model on a large amount of data, machine learning practitioners often turn to distributed training to reduce the time to train. In some cases, where time is of the essence, the business requirement is to finish training as quickly as possible or at least within a constrained time period. Then, distributed training is scaled to use a cluster of multiple nodes—not just multiple GPUs in a computing instance, but multiple instances with multiple GPUs. As the cluster size increases, so does the significant drop in performance. This drop in performance is primarily caused by the communications overhead between nodes in a cluster.

To resolve such overhead problems, SageMaker offers two distributed training options: SageMaker model parallel and SageMaker data parallel. This guide focuses on how to train models using the SageMaker data parallel library.

- The library optimizes your training job for AWS network infrastructure and Amazon EC2 instance topology.
- The library takes advantage of gradient updates to communicate between nodes with a custom AllReduce algorithm.

To track the latest updates of the library, see the SageMaker Distributed Data Parallel Release Notes in the SageMaker Python SDK documentation.

For more information about training with a model-parallel strategy, see SageMaker's Distributed Model Parallel (p. 2507).

Topics
- Introduction to SageMaker's Distributed Data Parallel Library (p. 2475)
- Supported Frameworks, AWS Regions, and Instances Types (p. 2478)
- Run a SageMaker Distributed Training Job with Data Parallelism (p. 2482)
- SageMaker Distributed Data Parallel Configuration Tips and Pitfalls (p. 2501)
- Amazon SageMaker Data Parallel Library FAQ (p. 2503)
- Data Parallel Troubleshooting (p. 2505)

Introduction to SageMaker's Distributed Data Parallel Library

Why Use SageMaker Distributed Data Parallel Library?

SageMaker's distributed data parallel library addresses communications overhead in two ways:

1. The library performs AllReduce, a key operation during distributed training that is responsible for a large portion of communication overhead.
2. The library performs optimized node-to-node communication by fully utilizing AWS's network infrastructure and Amazon EC2 instance topology.

Use this data parallel library to increase speed by up to 25% in training models such as BERT. While implementations like Horovod offer sub-linear performance at scale, this library offers near-linear performance at scale. This means that you get a faster training time and a lower cost to train a model.
Note
The SageMaker distributed training libraries are available only through the AWS deep learning containers for the TensorFlow, PyTorch, and HuggingFace frameworks within the SageMaker training platform. To use the libraries, you must use the SageMaker Python SDK or the SageMaker APIs through SDK for Python (Boto3) or AWS Command Line Interface. Throughout the documentation, instructions and examples focus on how to use the distributed training libraries with the SageMaker Python SDK.

Training Benchmarks

PyTorch with SageMaker's data parallel library

<table>
<thead>
<tr>
<th>Model</th>
<th>Setup</th>
<th>Throughput</th>
<th>Speed up</th>
<th>Scaling Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>PT-DDP</td>
<td>SageMaker</td>
<td>Speed up</td>
</tr>
<tr>
<td>BERT Large</td>
<td>2 node p3dn.24x1d</td>
<td>1752</td>
<td>2479</td>
<td>41%</td>
</tr>
<tr>
<td>(sampled)</td>
<td>4 node p3dn.24x1d</td>
<td>3017</td>
<td>4603</td>
<td>52%</td>
</tr>
<tr>
<td></td>
<td>8 node p3dn.24x1d</td>
<td>7409</td>
<td>8551</td>
<td>15%</td>
</tr>
<tr>
<td>MaskRCNN</td>
<td>2 node p3dn.24x1d</td>
<td>152</td>
<td>158</td>
<td>4%</td>
</tr>
<tr>
<td>(sampled)</td>
<td>4 node p3dn.24x1d</td>
<td>258</td>
<td>307</td>
<td>19%</td>
</tr>
<tr>
<td></td>
<td>8 node p3dn.24x1d</td>
<td>545</td>
<td>617</td>
<td>13%</td>
</tr>
</tbody>
</table>

Using instance type p3dn.24x1 and on 2, 4, and 8 node clusters:

- **BERT**: When used with PyTorch, the SageMaker library is 41%, 52%, and 13% faster than PyTorch-DDP.
- **MaskRCNN**: When used with PyTorch, the SageMaker library is 4%, 19%, and 15% faster than PyTorch-DDP.

These benchmarks were run on PyTorch v1.6 using ml.p3dn.24xlarge instances. You can find the training code on the SageMaker examples website. The examples website also has benchmark training code for these models using TensorFlow 2.3.

Optimal Bandwidth Use with Balanced Fusion Buffer

SageMaker's distributed data parallel library uses a communication pattern similar to parameter servers to reduce the amount of data transferred and the number of steps involved in averaging gradients from multiple GPUs. It also uses a new technique called balanced fusion buffers to make optimal use of the bandwidth available across all nodes in the cluster.

One key disadvantage of traditional parameter servers is their suboptimal use of available network bandwidth. Parameter servers treat variables as atomic units and place each variable on one server. Since gradients become available sequentially during the backward pass, at any given instant, there is imbalance in the volume of data being sent and received from different servers. Some servers are receiving and sending more data, some less, and some none. This problem becomes worse as the number of parameter servers increases.

The library addresses these problems by introducing **balanced fusion buffers**. A balanced fusion buffer is a buffer in the GPU that holds the gradients until the size of the buffer exceeds a threshold. In a setup with N parameter servers, when the buffer exceeds the threshold, the balanced fusion buffer is copied to CPU memory, sharded into N parts, and the ith part is sent to the ith parameter server. Each server receives
exactly the same number of bytes from a balanced fusion buffer. The ith server receives the ith partition of the balanced fusion buffer from all workers, sums them up, and sends the results back to all workers. Since all the servers participate equally in averaging each balanced fusion buffer, server bandwidth is efficiently utilized.

**Optimal GPU Usage with Efficient AllReduce Overlapping with a Backward Pass**

SageMaker's distributed data parallel library achieves optimal overlapping of the AllReduce operation with the backward pass, significantly improving the GPU utilization, and achieves near-linear scaling efficiency and faster time to train by optimizing tasks between CPUs and GPUs. The library performs AllReduce in parallel while GPU is computing gradients without taking away additional GPU cycles, which makes the library faster.

- **Leverages CPUs:** The library uses CPUs to AllReduce gradients, offloading this task from the GPUs.
- **Improved GPU usage:** The cluster's GPUs focus on computing gradients, improving their utilization throughout training.

**SageMaker Distributed Data Parallel Architecture**

The library supports larger compute instances that have 8 GPUs per node: `ml.p3.16xlarge`, `ml.p3dn.24xlarge`, and `ml.p4d.24xlarge`. The high-level workflow of the SageMaker distributed data parallel library is as following:

1. The library assigns ranks to GPUs (workers).
2. At each iteration, the library divides each global batch by the total number of workers (world size) and assigns small batches (batch shards) to the workers.
   - The size of the global batch is `(number of nodes in a cluster) * (number of GPUs per node) * (per batch shard)`.
   - A batch shard (small batch) is a subset of dataset assigned to each GPU (worker) per iteration.
3. The library launches a training script on each worker.
4. The library manages copies of model weights and gradients from the workers at the end of every iteration.
5. The library synchronizes model weights and gradients across the workers to aggregate a single trained model.

The following architecture diagram shows an example of how the library sets up data parallelism for a cluster of 3 nodes.
To start using the SageMaker distributed data parallel library, see Step 2: Launch a SageMaker Distributed Training Job Using the SageMaker Python SDK (p. 2490) to set up a SageMaker estimator through Amazon SageMaker Python SDK, and Run a SageMaker Distributed Training Job with Data Parallelism (p. 2482) to adapt your training script using the SageMaker distributed data parallel library.

Supported Frameworks, AWS Regions, and Instances Types

Before using the SageMaker data parallel library, check what are the supported ML frameworks and instance types and if there are enough quotas in your AWS account and AWS Region.

Supported Frameworks

The following tables show the deep learning frameworks and their versions that SageMaker and the SageMaker distributed data parallel library support. The SageMaker data parallel library is available in AWS Deep Learning Containers (DLC) or downloadable as a binary file.

Topics

- PyTorch (p. 2479)
- PyTorch Lightning (p. 2480)
- TensorFlow (p. 2481)
- Hugging Face Transformers (p. 2481)
### PyTorch

<table>
<thead>
<tr>
<th>PyTorch versions</th>
<th>SageMaker distributed data parallel library versions</th>
<th>smdistributed-datatparallel integrated image URI</th>
<th>URL of the binary file**</th>
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</tr>
</tbody>
</table>
The SageMaker distributed data parallelism library v1.4.0 and later works as a backend of PyTorch distributed. In accordance with the change, the following `smdistributed APIs` for the PyTorch distributed package are deprecated.

- `smdistributed.dataparallel.torch.distributed` is deprecated. Use the `torch.distributed` package instead.
- `smdistributed.dataparallel.torch.parallel.DistributedDataParallel` is deprecated. Use the `torch.nn.parallel.DistributedDataParallel` API instead.

If you need to use the previous versions of the library (v1.3.0 or before), see the archived SageMaker distributed data parallel library documentation in the `SageMaker Python SDK documentation`.

** The URLs of the binary files are for installing the SageMaker distributed data parallelism library in custom containers. For more information, see Create Your Own Docker Container with the SageMaker Distributed Data Parallel Library (p. 2493).

### PyTorch Lightning

<table>
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<th>PyTorch Lightning versions</th>
<th>PyTorch versions</th>
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<td>1.5.10</td>
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</tbody>
</table>

Note

PyTorch Lightning and its utility libraries such as Lightning Bolts are not preinstalled in the PyTorch DLCs. When you construct a SageMaker PyTorch estimator and submit a training job request in Step 2, you need to provide `requirements.txt` to install `pytorch-lightning` and `lightning-bolts` in the SageMaker PyTorch training container.

```python
# requirements.txt
pytorch-lightning
lightning-bolts
```

For more information about specifying the source directory to place the `requirements.txt` file along with your training script and a job submission, see Using third-party libraries in the `Amazon SageMaker Python SDK documentation`.
## TensorFlow

<table>
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</tr>
</tbody>
</table>

## Hugging Face Transformers

The AWS Deep Learning Containers for Hugging Face use the SageMaker Training Containers for PyTorch and TensorFlow as their base images. To look up the Hugging Face Transformers library versions and paired PyTorch and TensorFlow versions, see the latest Hugging Face Containers and the Prior Hugging Face Container Versions.

## AWS Regions

The SageMaker data parallel library is available in all of the AWS Regions where the AWS Deep Learning Containers for SageMaker are in service. For more information, see Available Deep Learning Containers Images.

## Supported Instance Types

The SageMaker data parallel library requires one of the following ML instance types.

<table>
<thead>
<tr>
<th>Instance type</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
</tbody>
</table>

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Run a SageMaker Distributed Training Job with Data Parallelism

SageMaker's distributed data parallel library APIs are designed for ease of use and to provide seamless integration with existing distributed training toolkits.

• **SageMaker Python SDK with the library API** – In most cases, all you have to change in your training script is the data parallel library import statements. Swap these out with the SageMaker data parallel library equivalents.

• **Focus on your model training without infrastructure management** – When training a deep learning model with the library on SageMaker, you can focus on writing your training script and model training. You can run a training job using estimator classes provided by the SageMaker Python SDK. The estimator classes help prepare ML instances, load datasets from specified data resources, submit the training job using your training script, and shut down the instances after the training job is completed.

To begin, you need to adapt TensorFlow or PyTorch training scripts to use the library. The following topics provide instructions on how to modify your training script.

**Topics**

• **Step 1: Modify Your Own Training Script** (p. 2482)

• **Step 2: Launch a SageMaker Distributed Training Job Using the SageMaker Python SDK** (p. 2490)

**Step 1: Modify Your Own Training Script**

Use this section to learn how to customize your training script to use the core features of the Amazon SageMaker distributed data parallel library. To use the library-specific API functions and parameters, we recommend you use this documentation alongside the SageMaker data parallel library APIs in the SageMaker Python SDK documentation.

The training script examples provided in these sections are simplified and designed to highlight the required changes you must make to use the library. For end-to-end, runnable notebook examples that demonstrate how to use a TensorFlow or PyTorch training script with the SageMaker distributed data parallel library, see Amazon SageMaker Distributed Training Notebook Examples (p. 2572).

**Topics**

• **Modify a TensorFlow Training Script** (p. 2483)

• **Modify a PyTorch Training Script** (p. 2485)
• Modify a PyTorch Lightning Script (p. 2488)

Modify a TensorFlow Training Script

The following steps show you how to modify a TensorFlow training script to utilize SageMaker's distributed data parallel library.

The library APIs are designed to be similar to Horovod APIs. For additional details on each API that the library offers for TensorFlow, see the SageMaker distributed data parallel TensorFlow API documentation.

Note
SageMaker distributed data parallel is adaptable to TensorFlow training scripts composed of tf core modules except tf.keras modules. SageMaker distributed data parallel does not support TensorFlow with Keras implementation.

Note
SageMaker's distributed data parallelism library supports Automatic Mixed Precision (AMP) out of the box. No extra action is needed to enable AMP other than the framework-level modifications to your training script. If gradients are in FP16, the SageMaker data parallelism library runs its AllReduce operation in FP16. For more information about implementing AMP APIs to your training script, see the following resources:

- Frameworks - TensorFlow in the NVIDIA Deep Learning Performance documentation
- Automatic Mixed Precision for Deep Learning in the NVIDIA Developer Docs
- TensorFlow mixed precision APIs in the TensorFlow documentation

1. Import the library's TensorFlow client and initialize it.

```python
import smdistributed.dataparallel.tensorflow as sdp
sdp.init()
```

2. Pin each GPU to a single `smdistributed.dataparallel` process with `local_rank`—this refers to the relative rank of the process within a given node. The `sdp.tensorflow.local_rank()` API provides you the local rank of the device. The leader node is rank 0, and the worker nodes are rank 1, 2, 3, and so on. This is invoked in the following code block as `sdp.local_rank()`.

   `set_memory_growth` is not directly related to SageMaker distributed, but must be set for distributed training with TensorFlow.

   ```python
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
    tf.config.experimental.set_memory_growth(gpu, True)
if gpus:
    tf.config.experimental.set_visible_devices(gpus[sdp.local_rank()], 'GPU')
```

3. Scale the learning rate by the number of workers. The `sdp.tensorflow.size()` API provides you the number of workers in the cluster. This is invoked in the following code block as `sdp.size()`.

   ```python
   learning_rate = learning_rate * sdp.size()
   ```

4. Use the library's `DistributedGradientTape` to optimize AllReduce operations during training. This wraps `tf.GradientTape`.

   ```python
   with tf.GradientTape() as tape:
       output = model(input)
       loss_value = loss(label, output)  ```
5. Broadcast the initial model variables from the leader node (rank 0) to all the worker nodes (ranks 1 through n). This is needed to ensure a consistent initialization across all the worker ranks. Use the sdp.tensorflow.broadcast_variables API after the model and optimizer variables are initialized. This is invoked in the following code block as sdp.broadcast_variables().

```python
sdp.broadcast_variables(model.variables, root_rank=0)
sdp.broadcast_variables(opt.variables(), root_rank=0)
```

6. Finally, modify your script to save checkpoints only on the leader node. The leader node has a synchronized model. This also avoids worker nodes overwriting the checkpoints and possibly corrupting the checkpoints.

```python
if sdp.rank() == 0:
    checkpoint.save(checkpoint_dir)
```

The following is an example TensorFlow training script for distributed training with the library.

```python
import tensorflow as tf
# SageMaker data parallel: Import the library TF API
import smdistributed.dataparallel.tensorflow as sdp
# SageMaker data parallel: Initialize the library
sdp.init()
gpus = tf.config.experimental.list_physical_devices('GPU')
for gpu in gpus:
tf.config.experimental.set_memory_growth(gpu, True)
if gpus:
    # SageMaker data parallel: Pin GPUs to a single library process
tf.config.experimental.set_visible_devices(gpus[sdp.local_rank()], 'GPU')

# Prepare Dataset
dataset = tf.data.Dataset.from_tensor_slices(...)

# Define Model
mnist_model = tf.keras.Sequential(...)
loss = tf.losses.SparseCategoricalCrossentropy()

# SageMaker data parallel: Scale Learning Rate
# LR for 8 node run : 0.000125
# LR for single node run : 0.001
opt = tf.optimizers.Adam(0.000125 * sdp.size())

@tf.function
def training_step(images, labels, first_batch):
    with tf.GradientTape() as tape:
        probs = mnist_model(images, training=True)
        loss_value = loss(labels, probs)

        # SageMaker data parallel: Wrap tf.GradientTape with the library's
        # DistributedGradientTape
        tape = sdp.DistributedGradientTape(tape)

        grads = tape.gradient(loss_value, mnist_model.trainable_variables)
        opt.apply_gradients(zip(grads, mnist_model.trainable_variables))
```
if first_batch:
    # SageMaker data parallel: Broadcast model and optimizer variables
    sdp.broadcast_variables(mnist_model.variables, root_rank=0)
    sdp.broadcast_variables(opt.variables(), root_rank=0)

    return loss_value
...

# SageMaker data parallel: Save checkpoints only from master node.
if sdp.rank() == 0:
    checkpoint.save(checkpoint_dir)

After you have completed adapting your training script, move on to Step 2: Launch a SageMaker Distributed Training Job Using the SageMaker Python SDK (p. 2490).

Modify a PyTorch Training Script

In the SageMaker data parallel library v1.4.0 and later, the library is available as a backend option for the PyTorch distributed package. You only need to import the library once at the top of your training script and set it as the PyTorch distributed backend during initialization. With the single line of backend specification, you can keep your PyTorch training script unchanged and directly use the PyTorch distributed modules. To find the latest API documentation for the library, see the SageMaker distributed data parallel APIs for PyTorch in the SageMaker Python SDK documentation. To learn more about the PyTorch distributed package and backend options, see Distributed communication package - torch.distributed.

Important
Because the SageMaker distributed data parallelism library v1.4.0 and later works as a backend of PyTorch distributed, the following smdistributed APIs for the PyTorch distributed package are deprecated.

- smdistributed.dataparallel.torch.distributed is deprecated. Use the torch.distributed package instead.
- smdistributed.dataparallel.torch.parallel.DistributedDataParallel is deprecated. Use the torch.nn.parallel.DistributedDataParallel API instead.

If you need to use the previous versions of the library (v1.3.0 or before), see the archived SageMaker distributed data parallel library documentation in the SageMaker Python SDK documentation.

Use the SageMaker Distributed Data Parallel Library as the Backend of torch.distributed

To use the SageMaker distributed data parallel library, the only thing you need to do is to import the SageMaker distributed data parallel library's PyTorch client (smdistributed.dataparallel.torch.torch_smdp). The client registers smddp as a backend for PyTorch. When you initialize the PyTorch distributed process group using the torch.distributed.init_process_group API, make sure you specify 'smddp' to the backend argument.

```python
import smdistributed.dataparallel.torch.torch_smdp
import torch.distributed as dist

dist.init_process_group(backend='smddp')
```

Note
The smddp backend currently does not support creating subprocess groups with the torch.distributed.new_group() API. You cannot use the smddp backend concurrently with other process group backends such as NCCL and Gloo.
If you already have a working PyTorch script and only need to add the backend specification, you can proceed to Using the SageMaker Framework Estimators For PyTorch and TensorFlow (p. 2490) in the Step 2: Launch a SageMaker Distributed Training Job Using the SageMaker Python SDK (p. 2490) topic.

If you still need to modify your training script to properly use the PyTorch distributed package, follow the rest of the procedures on this page.

Preparing a PyTorch Training Script for Distributed Training

The following steps provide additional tips on how to prepare your training script to successfully run a distributed training job using PyTorch.

**Note**

In v1.4.0, the SageMaker distributed data parallel library supports the following collective primitive data types of the torch.distributed interface: all_reduce, broadcast, reduce, all_gather, and barrier.

1. Import the PyTorch distributed modules.

   ```python
   import torch
   import torch.distributed as dist
   from torch.nn.parallel import DistributedDataParallel as DDP
   ```

2. After parsing arguments and defining a batch size parameter (for example, `batch_size=args.batch_size`), add two lines of code to resize the batch size per worker (GPU). PyTorch's DataLoader operation does not automatically handle the batch resizing for distributed training.

   ```python
   batch_size //= dist.get_world_size()
   batch_size = max(batch_size, 1)
   ```

3. Pin each GPU to a single SageMaker data parallel library process with `local_rank`—this refers to the relative rank of the process within a given node.

   You can retrieve the rank of the process from the LOCAL_RANK environment variable.

   ```python
   import os
   local_rank = os.environ["LOCAL_RANK"]
   torch.cuda.set_device(local_rank)
   ```

4. After defining a model, wrap it with the PyTorch DistributedDataParallel API.

   ```python
   model = ...
   # Wrap the model with the PyTorch DistributedDataParallel API
   model = DDP(model)
   ```

5. When you call the torch.utils.data.distributed.DistributedSampler API, specify the total number of processes (GPUs) participating in training across all the nodes in the cluster. This is called `world_size`, and you can retrieve the number from the torch.distributed.get_world_size() API. Also, specify the rank of each process among all processes using the torch.distributed.get_rank() API.

   ```python
   from torch.utils.data.distributed import DistributedSampler
   train_sampler = DistributedSampler(  
       train_dataset,  
       num_replicas = dist.get_world_size(),  
       rank = dist.get_rank())
   ```
6. Modify your script to save checkpoints only on the leader process (rank 0). The leader process has a synchronized model. This also avoids other processes overwriting the checkpoints and possibly corrupting the checkpoints.

```python
if dist.get_rank() == 0:
    torch.save(...)
```

The following example code shows the structure of a PyTorch training script with smddp as the backend.

```python
import os
import torch

# SageMaker data parallel: Import the library PyTorch API
import smdistributed.dataparallel.torch.torch_smddp

# SageMaker data parallel: Import PyTorch's distributed API
import torch.distributed as dist
from torch.nn.parallel import DistributedDataParallel as DDP

# SageMaker data parallel: Initialize the process group
dist.init_process_group(backend='smddp')

class Net(nn.Module):
    ...
    # Define model
def train(...):
        ...
        # Model training
def test(...):
            ...
            # Model evaluation
def main():

        # SageMaker data parallel: Scale batch size by world size
        batch_size //= dist.get_world_size()
        batch_size = max(batch_size, 1)

        # Prepare dataset
        train_dataset = torchvision.datasets.MNIST(...)

        # SageMaker data parallel: Set num_replicas and rank in DistributedSampler
        train_sampler = torch.utils.data.distributed.DistributedSampler(
            train_dataset,
            num_replicas=dist.get_world_size(),
            rank=dist.get_rank())

        train_loader = torch.utils.data.DataLoader(...)  

        # SageMaker data parallel: Wrap the PyTorch model with the library's DDP
        model = DDP(Net().to(device))

        # SageMaker data parallel: Pin each GPU to a single library process.
        local_rank = os.environ["LOCAL_RANK"]
        torch.cuda.set_device(local_rank)
        model.cuda(local_rank)

        # Train
```
After you have completed adapting your training script, proceed to Step 2: Launch a SageMaker Distributed Training Job Using the SageMaker Python SDK (p. 2490).

Modify a PyTorch Lightning Script

If you want to bring your PyTorch Lightning training script and run a distributed data parallel training job in SageMaker, you can run the script with minimal changes in your training script. The necessary changes include the following: import the smdistributed.dataparallel library's PyTorch modules, set up the environment variables for PyTorch Lightning to accept the SageMaker environment variables that are preset by the SageMaker training toolkit, and activate the SageMaker data parallel library by setting the process group backend to "smddp". To learn more, walk through the following instructions that break down the steps with code examples.

Note
The PyTorch Lightning support is available in the SageMaker data parallel library v1.5.0 and later.

1. Import the pytorch_lightning library and the smdistributed.dataparallel.torch modules.

```python
import pytorch_lightning as pl
import smdistributed.dataparallel.torch.torch_smddp
```

2. Set the world size and the rank for the LightningEnvironment class object. When launching a training job in SageMaker, the SageMaker training toolkit sets up the environment variables "RANK", "LOCAL_RANK", and "WORLD_SIZE". These environment variables represent the processes' global ranks, their local ranks, and the world size, respectively. Use these SageMaker environment variables to configure the LightningEnvironment.

```python
import os
from pytorch_lightning.plugins.environments.lightning_environment \ import LightningEnvironment

env = LightningEnvironment()
env.world_size = lambda: int(os.environ["WORLD_SIZE"])
env.global_rank = lambda: int(os.environ["RANK"])
```

3. Set distributed training strategy using the PyTorch Lightning DDPStrategy module, create a PyTorch Lightning Trainer object, and adapt them to use the SageMaker data parallel library.

(Recommended) For PyTorch Lightning v1.6.0 and later

Create an object (ddp in the following code example) of the DDPStrategy class, and specify "smddp" to the process_group_backend parameter. When configuring a PyTorch Lightning Trainer object, use the SageMaker environment variables to specify the scale of the GPU cluster and the ddp object to set up the distributed training strategy.
Note
We recommend that you check the versions of PyTorch Lightning tested for compatibility with the SageMaker data parallel library in the the section called “Supported Frameworks and AWS Regions” (p. 2516) page.

```python
from pytorch_lightning.strategies import DDPStra tegy

ddp = DDPStrategy(
    cluster_environment=env,
    process_group_backend="smddp",
    accelerator="gpu"
)

world_size = int(os.environ["WORLD_SIZE"])
num_gpus = int(os.environ["SM_NUM_GPUS"])
num_nodes = int(world_size/num_gpus)

trainer = pl.Trainer(
    devices=num_gpus,
    num_nodes=num_nodes,
    max_epochs=10,
    strategy=ddp
)
```

(Optional) For PyTorch Lightning v1.5.10

If you are using DDPPlugin, which is a deprecated functionality, set the distributed strategy as shown in the following code example.

```python
from pytorch_lightning.plugins.training_type.ddp import DDPPlugin

os.environ["PL_TORCH_DISTRIBUTED_BACKEND"] = "smddp"

ddp = DDPPlugin(
    parallel_devices=[torch.device("cuda", d) for d in range(num_gpus)],
    cluster_environment=env
)

world_size = int(os.environ["WORLD_SIZE"])
num_gpus = int(os.environ["SM_NUM_GPUS"])
num_nodes = int(world_size/num_gpus)

trainer = pl.Trainer(
    gpus=num_gpus,
    num_nodes=num_nodes,
    max_epochs=10,
    strategy=ddp
)
```

4. Run `trainer.fit` to start the training job of a PyTorch model. The following code example shows a PyTorch model object wrapped by the PyTorch Lightning Trainer's fit method with the PyTorch Lightning MNIST data module.

```python
from pl_bolts.datamodules import MNISTDataModule

trainer.fit(model, datamodule=MNISTDataModule(batch_size=32))
```

After you have completed adapting your training script, proceed to Step 2: Launch a SageMaker Distributed Training Job Using the SageMaker Python SDK (p. 2490).
Note
When you construct a SageMaker PyTorch estimator and submit a training job request in Step 2, you need to provide requirements.txt to install pytorch-lightning and lightning-bolts in the SageMaker PyTorch training container.

```bash
# requirements.txt
pytorch-lightning
lightning-bolts
```

For more information about specifying the source directory to place the requirements.txt file along with your training script and a job submission, see Using third-party libraries in the Amazon SageMaker Python SDK documentation.

**Step 2: Launch a SageMaker Distributed Training Job Using the SageMaker Python SDK**

To run your adapted script in Step 1: Modify Your Own Training Script (p. 2482), start with creating a SageMaker framework or generic estimator object with the prepared training script and the distributed training configuration parameter. You can use the library in any kind of SageMaker environment and web IDEs, such as SageMaker notebook instance and SageMaker Studio.

Use the high-level SageMaker Python SDK to do one of the following:

- If you want to achieve a quick adoption of your distributed training job in SageMaker, configure a SageMaker PyTorch or TensorFlow framework estimator class. The framework estimator picks up your training script and automatically matches the right image URI of the pre-built PyTorch or TensorFlow Deep Learning Containers (DLC), given the value specified to the framework_version parameter.
- If you want to extend one of the pre-built containers or build a custom container to create your own ML environment with SageMaker, use the SageMaker generic Estimator class and specify the image URI of the custom Docker container hosted in your Amazon Elastic Container Registry (Amazon ECR).

Your training datasets should be stored in Amazon S3 or Amazon FSx for Lustre in the AWS Region in which you are launching your training job. If you use Jupyter notebooks, you should have a SageMaker notebook instance or a SageMaker Studio app running in the same AWS Region. For more information about storing your training data, see the SageMaker Python SDK data inputs documentation.

**Tip**
We highly recommend that you use Amazon FSx for Lustre instead of Amazon S3 to increase training performance. Amazon FSx has higher throughput and lower latency than Amazon S3.

Choose one of the following topics for instructions on how to run your TensorFlow or PyTorch training scripts. After you launch a training job, you can monitor system utilization and model performance using Debug and Profile Training Jobs Using Amazon SageMaker Debugger (p. 2258) or Amazon CloudWatch.

While you follow instructions in the following topics to learn more about technical details, we also recommend that you try the Amazon SageMaker Distributed Training Notebook Examples (p. 2572) to get started.

**Topics**
- Using the SageMaker Framework Estimators For PyTorch and TensorFlow (p. 2490)
- Using the SageMaker Generic Estimator to Extend Prebuilt Containers (p. 2492)
- Create Your Own Docker Container with the SageMaker Distributed Data Parallel Library (p. 2493)

**Using the SageMaker Framework Estimators For PyTorch and TensorFlow**

You can activate the SageMaker distributed data parallel library by specifying it as the distribution strategy in the SageMaker framework estimator class.
SageMaker PyTorch

from sagemaker.pytorch import PyTorch

pt_estimator = PyTorch(
    base_job_name="training_job_name_prefix",
    source_dir="sub-folder-for-your-code",
    entry_point="adapted-training-script.py",
    role="SageMakerRole",
    py_version="py38",
    framework_version="1.12.0",

    # For running a multi-node distributed training job, specify a value greater than 1
    # Example: 2,3,4,...8
    instance_count=2,

    # Instance types supported by the SageMaker data parallel library:
    # ml.p4d.24xlarge, ml.p5dn.24xlarge, and ml.p3.16xlarge
    instance_type="ml.p3.16xlarge",

    # Training using the SageMaker data parallel distributed training strategy
    distribution={ "smdistributed": { "dataparallel": { "enabled": True } } }
)

pt_estimator.fit("s3://bucket/path/to/training/data")

Note
PyTorch Lightning and its utility libraries such as Lightning Bolts are not preinstalled in the SageMaker PyTorch DLCs. Create the following requirements.txt file and save in the source directory where you save the training script.

# requirements.txt
pytorch-lightning
lightning-bolts

For example, the tree-structured directory should look like the following.

### pytorch_training_launcher_jupyter_notebook.ipynb
### sub-folder-for-your-code
### adapted-training-script.py
### requirements.txt

For more information about specifying the source directory to place the requirements.txt file along with your training script and a job submission, see Using third-party libraries in the Amazon SageMaker Python SDK documentation.

SageMaker TensorFlow

from sagemaker.tensorflow import TensorFlow

tf_estimator = TensorFlow(
    base_job_name="training_job_name_prefix",
    entry_point="adapted-training-script.py",
    role="SageMakerRole",
    framework_version="2.9.1",
    py_version="py38",

    # For running a multi-node distributed training job, specify a value greater than 1
    # Example: 2,3,4,...8
    instance_count=2,
# Instance types supported by the SageMaker data parallel library:
# ml.p4d.24xlarge, ml.p3dn.24xlarge, and ml.p3.16xlarge
instance_type="ml.p3.16xlarge",

# Training using the SageMaker data parallel distributed training strategy
distribution={ "smdistributed": { "dataparallel": { "enabled": True } } }
}

tf_estimator.fit("s3://bucket/path/to/training/data")

The following two parameters of the SageMaker framework estimator are required to activate the SageMaker data parallelism.

distribution (dict): A dictionary with information on how to run distributed training (default: None).

- To use smdistributed.dataparallel as a distribution strategy, configure a dictionary as shown in the following code:

```python
distribution = { "smdistributed": { "dataparallel": { "enabled": True } } }
```

- custom_mpi_options (str)(optional): Custom MPI options. The following is an example of how you can use this parameter when defining distribution. To learn more, see Custom MPI Options (p. 2502).

```python
distribution = {
    "smdistributed": {
        "dataparallel": {
            "enabled": True,
            "custom_mpi_options": "-verbose -x NCCL_DEBUG=VERSION"
        }
    }
}
```

instance_type (str): A type of Amazon EC2 instance to use.

- If using the smdistributed with dataparallel distribution strategy, you must use one of the following instance types: ml.p4d.24xlarge, ml.p3dn.24xlarge, and ml.p3.16xlarge. For best performance, we recommend that you use an EFA-enabled instance, which are ml.p3dn.24xlarge and ml.p4d.24xlarge.

Using the SageMaker Generic Estimator to Extend Prebuilt Containers

You can customize SageMaker prebuilt containers or extend them to handle any additional functional requirements for your algorithm or model that the prebuilt SageMaker Docker image doesn't support. For an example of how you can extend a pre-built container, see Extend a Prebuilt Container.

To extend a prebuilt container or adapt your own container to use the library, you must use one of the images listed in Supported Frameworks (p. 2478).

Important

From TensorFlow 2.4.1 and PyTorch 1.8.1, the framework DLCs supports EFA-enabled instance types (ml.p3dn.24xlarge, ml.p4d.24xlarge). We recommend that you use the DLC images that contain TensorFlow 2.4.1 or later and PyTorch 1.8.1 or later.

For example, if you use PyTorch, your Dockerfile should contain a FROM statement similar to the following:
# SageMaker PyTorch image
FROM 763104351884.dkr.ecr.<aws-region>.amazonaws.com/pytorch-training:<image-tag>

ENV PATH="/opt/ml/code:${PATH}"

# this environment variable is used by the SageMaker PyTorch container to determine our user code directory.
ENV SAGEMAKER_SUBMIT_DIRECTORY /opt/ml/code

# /opt/ml and all subdirectories are utilized by SageMaker, use the /code subdirectory to store your user code.
COPY cifar10.py /opt/ml/code/cifar10.py

# Defines cifar10.py as script entrypoint
ENV SAGEMAKER_PROGRAM cifar10.py

You can further customize your own Docker container to work with SageMaker using the SageMaker Training toolkit and the binary file of the SageMaker distributed data parallel library. To learn more, see the instructions in the following section.

Create Your Own Docker Container with the SageMaker Distributed Data Parallel Library

To build your own Docker container for training and use the SageMaker data parallel library, you must include the correct dependencies and the binary files of the SageMaker distributed parallel libraries in your Dockerfile. This section provides instructions on how to create a complete Dockerfile with the minimum set of dependencies for distributed training in SageMaker using the data parallel library.

**Note**
This custom Docker option with the SageMaker data parallel library as a binary is available only for PyTorch.

**To create a Dockerfile with the SageMaker training toolkit and the data parallel library**

1. Start with a Docker image from NVIDIA CUDA. Use the cuDNN developer versions that contain CUDA runtime and development tools (headers and libraries) to build from the PyTorch source code.

   FROM nvidia/cuda:11.3.1-cudnn8-devel-ubuntu20.04

   **Tip**
   The official AWS Deep Learning Container (DLC) images are built from the NVIDIA CUDA base images. If you want to use the prebuilt DLC images as references while following the rest of the instructions, see the AWS Deep Learning Containers for PyTorch Dockerfiles.

2. Add the following arguments to specify versions of PyTorch and other packages. Also, indicate the Amazon S3 bucket paths to the SageMaker data parallel library and other software to use AWS resources, such as the Amazon S3 plug-in.

   To use versions of the third party libraries other than the ones provided in the following code example, we recommend you look into the official Dockerfiles of AWS Deep Learning Container for PyTorch to find versions that are tested, compatible, and suitable for your application.

   To find URLs for the SMDATAPARALLEL_BINARY argument, see the look up tables at Supported Frameworks (p. 2478).

   ARG PYTORCH_VERSION=1.10.2
   ARG PYTHON_SHORT_VERSION=3.8
   ARG EFA_VERSION=1.14.1
   ARG SMDATAPARALLEL_BINARY=https://smdataparallel.s3.amazonaws.com/binary/pytorch/${PYTORCH_VERSION}/cu113/2022-02-18/smdistributed_dataparallel-1.4.0-cp38-cp38-linux_x86_64.whl
3. Set the following environment variables to properly build SageMaker training components and run the data parallel library. You use these variables for the components in the subsequent steps.

```bash
# Set ENV variables required to build PyTorch
ENV TORCH_CUDA_ARCH_LIST="7.0+PTX 8.0"
ENV TORCH_NVCC_FLAGS="-Xfatbin -compress-all"
ENV NCCL_VERSION=2.10.3

# Add OpenMPI to the path.
ENV PATH /opt/amazon/openmpi/bin:$PATH

# Add Conda to path
ENV PATH $CONDA_PREFIX/bin:$PATH

# Set this environment variable for SageMaker to launch SMDDP correctly.
ENV SAGEMAKER_TRAINING_MODULE=sagemaker_pytorch_container.training:main

# Add environment variable for processes to be able to call fork()
ENV RDMAV_FORK_SAFE=1

# Indicate the container type
ENV DLC_CONTAINER_TYPE=training

# Add EFA and SMDDP to LD library path
ENV LD_LIBRARY_PATH="/opt/conda/lib/python${PYTHON_SHORT_VERSION}/site-packages/smdistributed/dataparallel/lib:$LD_LIBRARY_PATH"
ENV LD_LIBRARY_PATH=/opt/amazon/efa/lib/:$LD_LIBRARY_PATH
```

4. Install or update `curl`, `wget`, and `git` to download and build packages in the subsequent steps.

```bash
RUN --mount=type=cache,id=apt-final,target=/var/cache/apt
    apt-get update && apt-get install -y --no-install-recommends
curl
    wget
    git
    && rm -rf /var/lib/apt/lists/*
```

5. Install Elastic Fabric Adapter (EFA) software for Amazon EC2 network communication.

```bash
RUN DEBIAN_FRONTEND=noninteractive apt-get update
RUN mkdir /tmp/efa
    && cd /tmp/efa
    && tar -xf aws-efa-installer-$(EFA_VERSION).tar.gz
    && cd aws-efa-installer
    && ./efa_installer.sh -y --skip-kmod -g
    && rm -rf /tmp/efa
```

6. Install Conda to handle package management.

```bash
RUN curl -fsSl -v -o ~/miniconda.sh -o https://repo.anaconda.com/miniconda/Miniconda3-latest-Linux-x86_64.sh &&
    chmod +x ~/miniconda.sh &&
    ~/miniconda.sh -b -p $CONDA_PREFIX &&
    rm ~/miniconda.sh &&
    $CONDA_PREFIX/bin/conda install -y python=$(PYTHON_SHORT_VERSION) conda-build pyyaml
    numpy ipython &&
```

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7. Get, build, and install PyTorch and its dependencies. We build PyTorch from the source code because we need to have control of the NCCL version to guarantee compatibility with the AWS OFI NCCL plug-in.

a. Following the steps in the PyTorch official dockerfile, install build dependencies and set up ccache to speed up recompilation.

```
RUN DEBIAN_FRONTEND=noninteractive \
    apt-get install -y --no-install-recommends \
    build-essential \
    ca-certificates \
    ccache \
    cmake \
    git \
    libjpeg-dev \
    libpng-dev \
    && rm -rf /var/lib/apt/lists/*
# Setup ccache
RUN /usr/sbin/update-ccache-symlinks
RUN mkdir /opt/ccache && ccache --set-config=cache_dir=/opt/ccache
```

b. Install PyTorch's common and Linux dependencies.

```
# Common dependencies for PyTorch
RUN conda install astunparse numpy ninja pyyaml mkl mkl-include setuptools cmake cffi 
    typing_extensions future six requests dataclasses
# Linux specific dependency for PyTorch
RUN conda install -c pytorch magma-cuda113
```

c. Clone the PyTorch GitHub repository.

```
RUN --mount=type=cache,target=/opt/ccache \
    cd / \
    && git clone --recursive https://github.com/pytorch/pytorch -b v${PYTORCH_VERSION}
```

d. Install and build a specific NCCL version. To do this, replace the content in the PyTorch's default NCCL folder (/pytorch/third_party/nccl) with the specific NCCL version from the NVIDIA repository. The NCCL version was set in the step 3 of this guide.

```
RUN cd /pytorch/third_party/nccl \
    && rm -rf nccl \
    && git clone https://github.com/NVIDIA/nccl.git -b v${NCCL_VERSION}-1 \
    && cd nccl \
    && make -j64 src.build CUDA_HOME=/usr/local/cuda NVCC_GENCODE="- 
        gencode=arch=compute_70,code=sm_70 -gencode=arch=compute_80,code=sm_80" \
        && make pkg.txz.build \
    && tar -xvf build/pkg/txz/nccl_*_txz -C $CONDA_PREFIX --strip-components=1
```

e. Build and install PyTorch. This process usually takes slightly more than one hour to complete. It is built using the NCCL version downloaded in a previous step.

```
RUN cd /pytorch \
    && CMAKE_PREFIX_PATH="$(dirname $(which conda))/../" \
    python setup.py install \n    && rm -rf /pytorch
```

8. Build and install AWS OFI NCCL plugin. This enables libfabric support for the SageMaker data parallel library.
RUN DEBIAN_FRONTEND=noninteractive apt-get update \
   && apt-get install -y --no-install-recommends \
   autoconf \ 
   automake \ 
   libtool \
RUN mkdir /tmp/efa-ofi-nccl \
   && cd /tmp/efa-ofi-nccl \
   && git clone https://github.com/aws/aws-ofi-nccl.git -b v${BRANCH_OFI} \
   && cd aws-ofi-nccl \
   && ./autogen.sh \
   && ./configure --with-libfabric=/opt/amazon/efa \
   --with-mpi=/opt/amazon/openmpi \
   --with-cuda=/usr/local/cuda \
   --with-nccl=$CONDA_PREFIX \ 
   && make \ 
   && make install \ 
   && rm -rf /tmp/efa-ofi-nccl


RUN pip install --no-cache-dir -U \
   packaging \
   mpi4py==3.0.3 \
RUN cd /tmp \
   && git clone https://github.com/pytorch/vision.git -b v0.9.1 \
   && cd vision \
   && BUILD_VERSION="0.9.1+cu111" python setup.py install \
   && cd /tmp \
   && rm -rf vision

10. Install and configure OpenSSH. OpenSSH is required for MPI to communicate between containers. Allow OpenSSH to talk to containers without asking for confirmation.

RUN apt-get update \
   && apt-get install -y --allow-downgrades --allow-change-held-packages --no-install-recommends \ 
   && apt-get install -y --no-install-recommends openssh-client openssh-server \ 
   && mkdir -p /var/run/sshhd \ 
   && cat /etc/ssh/ssh_config | grep -v StrictHostKeyChecking > /etc/ssh/ssh_config.new \ 
   && echo "  StrictHostKeyChecking no" >> /etc/ssh/ssh_config.new \ 
   && mv /etc/ssh/ssh_config.new /etc/ssh/ssh_config \ 
   && rm -rf /var/lib/apt/lists/*

# Configure OpenSSH so that nodes can communicate with each other
RUN mkdir -p /var/run/sshhd && \
   sed 's@session\$=required\$=pam_loginuid.so\$session optional pam_loginuid.so\$@g' -i /etc/pam.d/sshhd 
RUN rm -rf /root/.ssh/ && \
   ssh-keygen -q -t rsa -N '' -f /root/.ssh/id_rsa && \
   cp /root/.ssh/id_rsa.pub /root/.ssh/authorized_keys \
   && printf "Host *\n  StrictHostKeyChecking no\n" >> /root/.ssh/config

11. Install the PT S3 plug-in to efficiently access datasets in Amazon S3.

RUN pip install --no-cache-dir -U ${PT_S3_WHL_GPU} 
RUN mkdir -p /etc/pki/tls/certs && cp /etc/ssl/certs/ca-certificates.crt /etc/pki/tls/certs/ca-bundle.crt

12. Install the libboost library. This package is needed for networking the asynchronous IO functionality of the SageMaker data parallel library.
13. Install the following SageMaker tools for PyTorch training.

```bash
WORKDIR /root
RUN pip install --no-cache-dir -U \
    smclarify \
    "sagemaker>=2,<3" \
    sagemaker-experiments==0.* \
    sagemaker-pytorch-training
```

14. Finally, install the SageMaker data parallel binary and the remaining dependencies.

```bash
RUN --mount=type=cache,id=apt-final,target=/var/cache/apt \
    apt-get update && apt-get install -y --no-install-recommends \
    jq \
    libhwloc-dev \
    libnuma1 \
    libnuma-dev \
    libssl1.1 \
    libtool \
    hwloc \
    && rm -rf /var/lib/apt/lists/*
RUN SMDATAPARALLEL_PT=1 pip install --no-cache-dir ${SMDATAPARALLEL_BINARY}
```

15. After you finish creating the Dockerfile, see Adapting Your Own Training Container to learn how to build the Docker container, host it in Amazon ECR, and run a training job using the SageMaker Python SDK.

The following example code shows a complete Dockerfile after combining all the previous code blocks.

```bash
FROM nvidia/cuda:11.3.1-cudnn8-devel-ubuntu20.04

# Set appropriate versions and location for components
ARG PYTORCH_VERSION=1.10.2
ARG PYTHON_SHORT_VERSION=3.8
ARG EFA_VERSION=1.14.1
ARG SMDATAPARALLEL_BINARY=https://smdataparallel.s3.amazonaws.com/binary/pytorch/
    ${PYTORCH_VERSION}/cu113/2022-02-18/smdistributed_dataparallel-1.4.0-cp38-cp38-
    linux_x86_64.whl
ARG PT_S3_WHL_GPU=https://aws-s3-plugin.s3.us-west-2.amazonaws.com/binaries/0.0.1/1c3e69e/
    awsio-0.0.1-cp38-cp38-manylinux1_x86_64.whl
ARG CONDA_PREFIX="/opt/conda"
ARG BRANCH_OFI=1.1.3-aws

# Set ENV variables required to build PyTorch
ENV TORCH_CUDA_ARCH_LIST="3.7 5.0 7.0+PTX 8.0"
```

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ENV TORCH_NVCC_FLAGS="-Xfatbin -compress-all"
ENV NCCL_VERSION=2.10.3

# Add OpenMPI to the path.
ENV PATH /opt/amazon/openmpi/bin:$PATH

# Add Conda to path
ENV PATH $CONDA_PREFIX/bin:$PATH

# Set this environment variable for SageMaker to launch SMDDP correctly.
ENV SAGEMAKER_TRAINING_MODULE=sagemaker_pytorch_container.training:main

# Add environment variable for processes to be able to call fork()
ENV RDMAV_FORK_SAFE=1

# Indicate the container type
ENV DLC_CONTAINER_TYPE=training

# Add EFA and SMDDP to LD library path
ENV LD_LIBRARY_PATH="/opt/conda/lib/python${PYTHON_SHORT_VERSION}/site-packages/smdistributed/dataparallel/lib:$LD_LIBRARY_PATH"
ENV LD_LIBRARY_PATH=/opt/amazon/efa/lib/:$LD_LIBRARY_PATH

# Install basic dependencies to download and build other dependencies
RUN --mount=type=cache,id=apt-final,target=/var/cache/apt 
apt-get update && apt-get install -y --no-install-recommends 
curl 
wget 
git 
&& rm -rf /var/lib/apt/lists/*

# Install EFA.
# This is required for SMDDP backend communication
RUN DEBIAN_FRONTEND=noninteractive apt-get update
RUN mkdir /tmp/efa 
  && cd /tmp/efa 
  && curl --silent -O https://efa-installer.amazonaws.com/aws-efa-installer-${EFA_VERSION}.tar.gz 
  && tar -xf aws-efa-installer-${EFA_VERSION}.tar.gz 
  && cd aws-efa-installer 
  && ./efa_installer.sh -y --skip-kmod -g 
  && rm -rf /tmp/efa

# Install Conda
RUN curl -fsSL -v -o ~/miniconda.sh -O https://repo.anaconda.com/miniconda/Miniconda3-latest-Linux-x86_64.sh && 
  chmod +x ~/miniconda.sh && 
  ~/miniconda.sh -b -p $CONDA_PREFIX && 
  rm ~/miniconda.sh && 
  $CONDA_PREFIX/bin/conda install -y python=${PYTHON_SHORT_VERSION} conda-build pyyaml numpy ipython && 
  $CONDA_PREFIX/bin/conda clean -ya

# Install PyTorch.
# Start with dependencies listed in official PyTorch dockerfile
# https://github.com/pytorch/pytorch/blob/master/Dockerfile
RUN DEBIAN_FRONTEND=noninteractive 
  apt-get install -y --no-install-recommends 
  build-essential 
  ca-certificates 
  ccache 
  cmake 
  git 
  libjpeg-dev 
  libpng-dev && 
  rm -rf /var/lib/apt/lists/*
# Setup ccache
RUN /usr/sbin/update-ccache-symlinks
RUN mkdir /opt/ccache && ccache --set-config=cache_dir=/opt/ccache

# Common dependencies for PyTorch
RUN conda install astunparse numpy ninja pyyaml mkl mkl-include setuptools cmake cffi
typing_extensions future six requests dataclasses

# Linux specific dependency for PyTorch
RUN conda install -c pytorch magma-cuda113

# Clone PyTorch
RUN --mount=type=cache,target=/opt/ccache
  cd / 
  && git clone --recursive https://github.com/pytorch/pytorch -b v${PYTORCH_VERSION}

# Note that we need to use the same NCCL version for PyTorch and OFI plugin.
# To enforce that, install NCCL from source before building PT and OFI plugin.

# Install NCCL.
# Required for building OFI plugin (OFI requires NCCL's header files and library)
RUN cd /pytorch/third_party/nccl 
  && rm -rf nccl 
  && git clone https://github.com/NVIDIA/nccl.git -b v${NCCL_VERSION}-1 
  && cd nccl 
  && make -j64 src.build CUDA_HOME=/usr/local/cuda NVCC_GENCODE="-gencode=arch=compute_70,code=sm_70 -gencode=arch=compute_80,code=sm_80" 
  && make pkg.txz.build 
  && tar -xvf build/pkg/txz/nccl_*.txz -C $CONDA_PREFIX --strip-components=1

# Build and install PyTorch.
RUN cd /pytorch 
  && CMAKE_PREFIX_PATH="$(dirname $(which conda))/../" python setup.py install 
  && rm -rf /pytorch

RUN ccache -C

# Build and install OFI plugin. 
# It is required to use libFabric.
RUN DEBIAN_FRONTEND=noninteractive apt-get update 
  && apt-get install -y --no-install-recommends 
      autoconf 
      automake 
      libtool
RUN mkdir /tmp/efa-ofi-nccl 
  && cd /tmp/efa-ofi-nccl 
  && git clone https://github.com/aws/aws-ofi-nccl.git -b v${BRANCH_OFI} 
  && cd aws-ofi-nccl 
  && ./autogen.sh 
  && ./configure --with-libfabric=/opt/amazon/efa 
      --with-mpi=/opt/amazon/openmpi 
      --with-cuda=/usr/local/cuda 
      --with-nccl=$CONDA_PREFIX 
  && make 
  && make install 
  && rm -rf /tmp/efa-ofi-nccl

# Build and install Torchvision
RUN pip install --no-cache-dir -U 
  packaging 
  mpi4py==3.0.3
RUN cd /tmp 
  && git clone https://github.com/pytorch/vision.git -b v0.9.1 
  && cd vision 
  && BUILD_VERSION="0.9.1+cu111" python setup.py install 

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&& cd /tmp \
&& rm -rf vision
# Install OpenSSH.
# Required for MPI to communicate between containers, allow OpenSSH to talk to containers
without asking for confirmation
RUN apt-get update \
&& apt-get install -y --allow-downgrades --allow-change-held-packages --no-installrecommends \
&& apt-get install -y --no-install-recommends openssh-client openssh-server \
&& mkdir -p /var/run/sshd \
&& cat /etc/ssh/ssh_config | grep -v StrictHostKeyChecking > /etc/ssh/ssh_config.new \
&& echo "
StrictHostKeyChecking no" >> /etc/ssh/ssh_config.new \
&& mv /etc/ssh/ssh_config.new /etc/ssh/ssh_config \
&& rm -rf /var/lib/apt/lists/*
# Configure OpenSSH so that nodes can communicate with each other
RUN mkdir -p /var/run/sshd && \
sed 's@session\s*required\s*pam_loginuid.so@session optional pam_loginuid.so@g' -i /
etc/pam.d/sshd
RUN rm -rf /root/.ssh/ && \
mkdir -p /root/.ssh/ && \
ssh-keygen -q -t rsa -N '' -f /root/.ssh/id_rsa && \
cp /root/.ssh/id_rsa.pub /root/.ssh/authorized_keys \
&& printf "Host *\n StrictHostKeyChecking no\n" >> /root/.ssh/config
# Install PT S3 plugin.
# Required to efficiently access datasets in Amazon S3
RUN pip install --no-cache-dir -U ${PT_S3_WHL_GPU}
RUN mkdir -p /etc/pki/tls/certs && cp /etc/ssl/certs/ca-certificates.crt /etc/pki/tls/
certs/ca-bundle.crt
# Install libboost from source.
# This package is needed for smdataparallel functionality (for networking asynchronous IO).
WORKDIR /
RUN wget https://sourceforge.net/projects/boost/files/boost/1.73.0/boost_1_73_0.tar.gz/
download -O boost_1_73_0.tar.gz \
&& tar -xzf boost_1_73_0.tar.gz \
&& cd boost_1_73_0 \
&& ./bootstrap.sh \
&& ./b2 threading=multi --prefix=${CONDA_PREFIX} -j 64 cxxflags=-fPIC cflags=-fPIC
install || true \
&& cd .. \
&& rm -rf boost_1_73_0.tar.gz \
&& rm -rf boost_1_73_0 \
&& cd ${CONDA_PREFIX}/include/boost
# Install SageMaker PyTorch training.
WORKDIR /root
RUN pip install --no-cache-dir -U \
smclarify \
"sagemaker>=2,<3" \
sagemaker-experiments==0.* \
sagemaker-pytorch-training
# Install SageMaker data parallel binary (SMDDP)
# Start with dependencies
RUN --mount=type=cache,id=apt-final,target=/var/cache/apt \
apt-get update && apt-get install -y --no-install-recommends \
jq \
libhwloc-dev \
libnuma1 \
libnuma-dev \
libssl1.1 \
libtool \
hwloc \
&& rm -rf /var/lib/apt/lists/*

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Tip
For more general information about creating a custom Dockerfile for training in SageMaker, see Use Your Own Training Algorithms.

Tip
If you want to extend the custom Dockerfile to incorporate the SageMaker model parallel library, see Create Your Own Docker Container with the SageMaker Distributed Model Parallel Library (p. 2538).

SageMaker Distributed Data Parallel Configuration Tips and Pitfalls

Review the following tips and pitfalls before using SageMaker's distributed data parallel library. This list includes tips that are applicable across frameworks.

Topics
- Data Preprocessing (p. 2501)
- Single Versus Multiple Nodes (p. 2501)
- Debug Scaling Efficiency with Debugger (p. 2501)
- Batch Size (p. 2502)
- Custom MPI Options (p. 2502)
- Use Amazon FSx and set up an optimal storage and throughput capacity (p. 2502)

Data Preprocessing

If you preprocess data during training using an external library that utilizes the CPU, you may run into a CPU bottleneck because SageMaker distributed data parallel uses the CPU for AllReduce operations. You may be able to improve training time by moving preprocessing steps to a library that uses GPUs or by completing all preprocessing before training.

Single Versus Multiple Nodes

We recommend that you use this library with multiple nodes. The library can be used with a single-host, multi-device setup (for example, a single ML compute instance with multiple GPUs); however, when you use two or more nodes, the library’s AllReduce operation gives you significant performance improvement. Also, on a single host, NVLink already contributes to in-node AllReduce efficiency.

Debug Scaling Efficiency with Debugger

You can use Amazon SageMaker Debugger to monitor and visualize CPU and GPU utilization and other metrics of interest during training. You can use Debugger built-in rules to monitor computational performance issues, such as CPU Bottleneck, Load Balancing, and Low GPU Utilization. You can specify these rules with Debugger configurations when you define an Amazon SageMaker Python SDK estimator. If you use AWS CLI and AWS Boto3 for training on SageMaker, you can enable Debugger as shown in Configure Debugger Using Amazon SageMaker API.

To see an example using Debugger in a SageMaker training job, you can reference one of the notebook examples in the SageMaker Notebook Examples GitHub repository. To learn more about Debugger, see Amazon SageMaker Debugger.
### Batch Size

In distributed training, as more nodes are added, batch sizes should increase proportionally. To improve convergence speed as you add more nodes to your training job and increase the global batch size, increase the learning rate.

One way to achieve this is by using a gradual learning rate warmup where the learning rate is ramped up from a small to a large value as the training job progresses. This ramp avoids a sudden increase of the learning rate, allowing healthy convergence at the start of training. For example, you can use a *Linear Scaling Rule* where each time the mini-batch size is multiplied by k, the learning rate is also multiplied by k. To learn more about this technique, see the research paper, *Accurate, Large Minibatch SGD: Training ImageNet in 1 Hour*, Sections 2 and 3.

### Custom MPI Options

The SageMaker distributed data parallel library employs Message Passing Interface (MPI), a popular standard for managing communication between nodes in a high-performance cluster, and uses NVIDIA's NCCL library for GPU-level communication. When you use the data parallel library with a TensorFlow or Pytorch Estimator, the respective container sets up the MPI environment and executes the `mpirun` command to start jobs on the cluster nodes.

You can set custom MPI operations using the `custom_mpi_options` parameter in the Estimator. Any `mpirun` flags passed in this field are added to the `mpirun` command and executed by SageMaker for training. For example, you may define the distribution parameter of an Estimator using the following to use the `NCCL_DEBUG` variable to print the NCCL version at the start of the program:

```python
distribution = {'smdistributed': {'dataparallel': {'enabled': True, "custom_mpi_options": "-verbose -x NCCL_DEBUG=VERSION"}}}
```

### Use Amazon FSx and set up an optimal storage and throughput capacity

When training a model on multiple nodes with distributed data parallelism, it is highly recommended to use **FSx for Lustre**. Amazon FSx is a scalable and high-performance storage service that supports shared file storage with a faster throughput. Using Amazon FSx storage at scale, you can achieve a faster data loading speed across the compute nodes.

Typically, with distributed data parallelism, you would expect that the total training throughput scales near-linearly with the number of GPUs. However, if you use suboptimal Amazon FSx storage, the training performance might slow down due to a low Amazon FSx throughput.

For example, if you use the **SCRATCH_2 deployment type of Amazon FSx file system** with the minimum 1.2 TiB storage capacity, the I/O throughput capacity is 240 MB/s. Amazon FSx storage works in a way that you can assign physical storage devices, and the more devices assigned, the larger throughput you get. The smallest storage increment for the SRATCH_2 type is 1.2 TiB, and the corresponding throughput gain is 240 MB/s.

Assume that you have a model to train on a 4-node cluster over a 100 GB data set. With a given batch size that's optimized to the cluster, assume that the model can complete one epoch in about 30 seconds. In this case, the minimum required I/O speed is approximately 3 GB/s (100 GB / 30 s). This is apparently a much higher throughput requirement than 240 MB/s. With such a limited Amazon FSx capacity, scaling your distributed training job up to larger clusters might aggravate I/O bottleneck problems; model training throughput might improve in later epochs as cache builds up, but Amazon FSx throughput can still be a bottleneck.

To alleviate such I/O bottleneck problems, you should increase the Amazon FSx storage size to obtain a higher throughput capacity. Typically, to find an optimal I/O throughput, you may experiment with different Amazon FSx throughput capacities, assigning an equal to or slightly lower throughput than your estimate, until you find that it is sufficient to resolve the I/O bottleneck problems. In case of the aforementioned example, Amazon FSx storage with 2.4 GB/s throughput and 67 GB RAM cache would
be sufficient. If the file system has an optimal throughput, the model training throughput should reach maximum either immediately or after the first epoch as cache has built up.

To learn more about how to increase Amazon FSx storage and deployment types, see the following pages in the Amazon FSx for Lustre documentation:

- How to increase storage capacity
- Aggregate file system performance

### Amazon SageMaker Data Parallel Library FAQ

Use the following to find answers to commonly asked questions about SageMaker's data parallelism library.

**Q: When using the library, how are the allreduce-supporting CPU instances managed? Do I have to create heterogeneous CPU-GPU clusters, or does the SageMaker service create extra C5s for jobs that use the library?**

The library uses the CPUs available with GPU instances. No additional C5 or CPU instances are launched; if your SageMaker training job is 8-node `ml.p3dn.24xlarge` clusters, only 8 `ml.p3dn.24xlarge` instances are used. No additional instances are provisioned.

**Q: I have a training job taking 5 days on a single `ml.p3.24xlarge` instance with a set of hyperparameters H1 (learning rate, batch size, optimizer, etc). Is using SageMaker's data parallelism library and a five-time bigger cluster enough to achieve an approximate five-time speedup? Or do I have to revisit its training hyperparameters after activating the library?**

The library changes the overall batch size. The new overall batch size is scaled linearly with the number of training instances used. As a result of this, hyperparameters, such as learning rate, have to be changed to ensure convergence.

**Q: Does the library support Spot?**

Yes. You can use managed spot training. You specify the path to the checkpoint file in the SageMaker training job. You save and restore checkpoints in their training script as mentioned in the last steps of the section called "TensorFlow" (p. 2483) and the section called "PyTorch" (p. 2485).

**Q: Is the library relevant in a single-host, multi-device setup?**

The library can be used in single-host multi-device training but the library offers performance improvements only in multi-host training.

**Q: Can the library be used with PyTorch Lightning?**

No. However, with the library's DDP for PyTorch, you can write custom DDP to achieve the functionality.

**Q: Where should the training dataset be stored?**

The training dataset can be stored in an Amazon S3 bucket or on an Amazon FSx drive. See this document for various supported input file systems for a training job.

**Q: When using the library, is it mandatory to have training data in FSx for Lustre? Can Amazon EFS and Amazon S3 be used?**

We generally recommend you use Amazon FSx because of its lower latency and higher throughput. If you prefer, you can use Amazon EFS or Amazon S3.

**Q: Can the library be used with CPU nodes?**

No. The library supports `ml.p3.16xlarge`, `ml.p3dn.24xlarge`, and `ml.p4d.24xlarge` instances at this time.
Q: What frameworks and framework versions are currently supported by the library at launch?

The library currently supports PyTorch v1.6.0 or later and TensorFlow v2.3.0 or later. It doesn't support TensorFlow 1.x. For more information about which version of the library is packaged within AWS deep learning containers, see Release Notes for Deep Learning Containers.

Q: Does the library support AMP?

Yes, SageMaker's distributed data parallelism library supports Automatic Mixed Precision (AMP) out of the box. No extra action is needed to use AMP other than the framework-level modifications to your training script. If gradients are in FP16, the SageMaker data parallelism library runs its AllReduce operation in FP16. For more information about implementing AMP APIs to your training script, see the following resources:

- Frameworks - PyTorch in the NVIDIA Deep Learning Performance documentation
- Frameworks - TensorFlow in the NVIDIA Deep Learning Performance documentation
- Automatic Mixed Precision for Deep Learning in the NVIDIA Developer Docs
- Introducing native PyTorch automatic mixed precision for faster training on NVIDIA GPUs in the PyTorch Blog
- TensorFlow mixed precision APIs in the TensorFlow documentation

Q: How do I identify if my distributed training job is slowed down due to I/O bottleneck?

With a larger cluster, the training job requires more I/O throughput, and therefore the training throughput might take longer (more epochs) to ramp up to the maximum performance. This indicates that I/O is being bottlenecked and cache is harder to build up as you scale nodes up (higher throughput requirement and more complex network topology). For more information about monitoring the Amazon FSx throughput on CloudWatch, see Monitoring FSx for Lustre in the FSx for Lustre User Guide.

Q: How do I resolve I/O bottlenecks when running a distributed training job with data parallelism?

We highly recommend that you use Amazon FSx as your data channel if you are using Amazon S3. If you are already using Amazon FSx but still having I/O bottleneck problems, you might have set up your Amazon FSx file system with a low I/O throughput and a small storage capacity. For more information about how to estimate and choose the right size of I/O throughput capacity, see Use Amazon FSx and set up an optimal storage and throughput capacity (p. 2502).

Q: (For the library v1.4.0 or later) How do I resolve the Invalid backend error while initializing process group.

If you encounter the error message ValueError: Invalid backend: 'smddp' when calling init_process_group, this is due to the breaking change in the library v1.4.0 and later. You must import the PyTorch client of the library, smdistributed.dataparallel.torch.torch_smddp, which registers smddp as a backend for PyTorch. To learn more, see Use the SageMaker Distributed Data Parallel Library as the Backend of torch.distributed (p. 2485).

Q: (For the library v1.4.0 or later) I would like to call the collective primitives of the torch.distributed interface. Which primitives does the smddp backend support?

In v1.4.0, the library supports all_reduce, broadcast, reduce, all_gather, and barrier.

Q: (For the library v1.4.0 or later) Does this new API work with other custom DDP classes or libraries like Apex DDP?

The SageMaker data parallel library is tested with other third-party distributed data parallel libraries and framework implementations that use the torch.distributed modules. Using the SageMaker data parallel library with custom DDP classes works as long as the collectives used by the custom DDP classes are supported by the library. See the preceding question for a list of supported collectives. If you have these use cases and need further support, reach out to the SageMaker team through the AWS Support Center or AWS Developer Forums for Amazon SageMaker.
Q: Does the library support the bring-your-own-container (BYOC) option? If so, how do I install the library and run a distributed training job by writing a custom Dockerfile?

If you want to integrate the SageMaker data parallel library and its minimum dependencies in your own Docker container, BYOC is the right approach. You can build your own container using the binary file of the library. The recommended process is to write a custom Dockerfile with the library and its dependencies, build the Docker container, host it in Amazon ECR, and use the ECR image URI to launch a training job using the SageMaker generic estimator class. For more instructions on how to prepare a custom Dockerfile for distributed training in SageMaker with the SageMaker data parallel library, see Create Your Own Docker Container with the SageMaker Distributed Data Parallel Library (p. 2493).

Data Parallel Troubleshooting

If you have problems in running a training job when you use the library, use the following list to try to troubleshoot. If you need further support, reach out to the SageMaker team through AWS Support Center or AWS Developer Forums for Amazon SageMaker.

Topics

- Using SageMaker Distributed Data Parallel with Amazon SageMaker Debugger and Checkpoints (p. 2505)
- An Unexpected Prefix Attached to Model Parameter Keys (p. 2506)
- SageMaker Distributed Training Job Stalling During Initialization (p. 2506)
- SageMaker Distributed Training Job Stalling at the End of Training (p. 2507)
- Observing Scaling Efficiency Degradation Due to Amazon FSx Throughput Bottlenecks (p. 2507)
- SageMaker Distributed Training Job with PyTorch Returns Deprecation Warnings (p. 2507)

Using SageMaker Distributed Data Parallel with Amazon SageMaker Debugger and Checkpoints

To monitor system bottlenecks, profile framework operations, and debug model output tensors for training jobs with SageMaker distributed data parallel, use Amazon SageMaker Debugger.

However, when you use SageMaker Debugger, SageMaker distributed data parallel, and SageMaker checkpoints, you might see an error that looks like the following example.

| SMDebug Does Not Currently Support Distributed Training Jobs With Checkpointing Enabled |

This is due to an internal error between Debugger and checkpoints, which occurs when you enable SageMaker distributed data parallel.

- If you enable all three features, SageMaker Python SDK automatically turns off Debugger by passing `debugger_hook_config=False`, which is equivalent to the following framework example.

```python
bucket=sagemaker.Session().default_bucket()
base_job_name="sagemaker-checkpoint-test"
checkpoint_in_bucket="checkpoints"

# The S3 URI to store the checkpoints
checkpoint_s3_bucket="s3://{}/{}/{}".format(bucket, base_job_name, checkpoint_in_bucket)

estimator = TensorFlow(...
    distribution={"smdistributed": {"dataparallel": { "enabled": True }},
    checkpoint_s3_uri=checkpoint_s3_bucket,
```

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If you want to keep using both SageMaker distributed data parallel and SageMaker Debugger, a workaround is manually adding checkpointing functions to your training script instead of specifying the `checkpoint_s3_uri` and `checkpoint_local_path` parameters from the estimator. For more information about setting up manual checkpointing in a training script, see Saving Checkpoints (p. 2569).

**An Unexpected Prefix Attached to Model Parameter Keys**

For PyTorch distributed training jobs, an unexpected prefix (model for example) might be attached to `state_dict` keys (model parameters). The SageMaker data parallel library does not directly alter or prepend any model parameter names when PyTorch training jobs save model artifacts. The PyTorch's distributed training changes the names in the `state_dict` to go over the network, prepending the prefix. If you encounter any model failure problem due to different parameter names while you are using the SageMaker data parallel library and checkpointing for PyTorch training, adapt the following example code to remove the prefix at the step you load checkpoints in your training script.

```python
state_dict = {k.partition('model.')[2]: state_dict[k] for k in state_dict.keys()}
```

This takes each `state_dict` key as a string value, separates the string at the first occurrence of 'model. ', and takes the third list item (with index 2) of the partitioned string.

For more information about the prefix issue, see a discussion thread at Prefix parameter names in saved model if trained by multi-GPU? in the PyTorch discussion forum.

For more information about the PyTorch methods for saving and loading models, see Saving & Loading Model Across Devices in the PyTorch documentation.

**SageMaker Distributed Training Job Stalling During Initialization**

If your SageMaker distributed data parallel training job stalls during initialization when using EFA-enabled instances (ml.p3dn.24xlarge and ml.p4d.24xlarge), this might be due to a misconfiguration in the security group of the VPC subnet that's used for the training job. EFA requires a proper security group configuration to enable traffic between the nodes.

**To configure inbound and outbound rules for the security group**

1. Sign in to the AWS Management Console and open the Amazon VPC console at https://console.aws.amazon.com/vpc/.
2. Choose **Security Groups** in the left navigation pane.
3. Select the security group that's tied to the VPC subnet you use for training.
4. In the **Details** section, copy the **Security group ID**.
5. On the **Inbound rules** tab, choose **Edit inbound rules**.
6. On the **Edit inbound rules** page, do the following:
   a. Choose **Add rule**.
   b. For **Type**, choose **All traffic**.
   c. For **Source**, choose **Custom**, paste the security group ID into the search box, and select the security group that pops up.
7. Choose **Save rules** to finish configuring the inbound rule for the security group.
8. On the **Outbound rules** tab, choose **Edit outbound rules**.
9. Repeat the step 6 and 7 to add the same rule as an outbound rule.
After you complete the preceding steps for configuring the security group with the inbound and outbound rules, rerun the training job and verify if the stalling issue is resolved.

For more information about configuring security groups for VPC and EFA, see Security groups for your VPC and Elastic Fabric Adapter.

**SageMaker Distributed Training Job Stalling at the End of Training**

One of the root causes of stalling issues at the end of training is a mismatch in the number of batches that are processed per epoch across different ranks. All workers (GPUs) synchronize their local gradients in the backward pass to ensure they all have the same copy of the model at the end of the batch iteration. If the batch sizes are unevenly assigned to different worker groups during the final epoch of training, the training job stalls. For example, while a group of workers (group A) finishes processing all batches and exits the training loop, another group of workers (group B) starts processing another batch and still expects communication from group A to synchronize the gradients. This causes group B to wait for group A, which already completed training and does not have any gradients to synchronize.

Therefore, when setting up your training dataset, it is important that each worker gets the same number of data samples so that each worker goes through the same number of batches while training. Make sure each rank gets the same number of batches to avoid this stalling issue.

**Observing Scaling Efficiency Degradation Due to Amazon FSx Throughput Bottlenecks**

One potential cause of lowered scaling efficiency is the FSx throughput limit. If you observe a sudden drop in scaling efficiency when you switch to a larger training cluster, try using a larger FSx for Lustre file system with a higher throughput limit. For more information, see Aggregate file system performance and Managing storage and throughput capacity in the Amazon FSx for Lustre User Guide.

**SageMaker Distributed Training Job with PyTorch Returns Deprecation Warnings**

Since v1.4.0, the SageMaker distributed data parallelism library works as a backend of PyTorch distributed. Because of the breaking change of using the library with PyTorch, you might encounter a warning message that the smdistributed APIs for the PyTorch distributed package are deprecated. The warning message should be similar to the following:

```
smdistributed.dataparallel.torch.dist is deprecated in the SageMaker distributed data parallel library v1.4.0+.
Please use torch.distributed and specify 'smddp' as a backend when initializing process group as follows:
torch.distributed.init_process_group(backend='smddp')
For more information, see the library's API documentation at
```

In v1.4.0 and later, the library only needs to be imported once at the top of your training script and set as the backend during the PyTorch distributed initialization. With the single line of backend specification, you can keep your PyTorch training script unchanged and directly use the PyTorch distributed modules. See Modify a PyTorch Training Script (p. 2485) to learn about the breaking changes and the new way to use the library with PyTorch.

**SageMaker's Distributed Model Parallel**

Use Amazon SageMaker's distributed model parallel library to train large deep learning (DL) models that are difficult to train due to GPU memory limitations. The library automatically and efficiently splits a model across multiple GPUs and instances. Using the library, you can achieve a target prediction accuracy faster by efficiently training larger DL models with billions or trillions of parameters.
You can use the library to automatically partition your own TensorFlow and PyTorch models across multiple GPUs and multiple nodes with minimal code changes. You can access the library's API through the SageMaker Python SDK.

Use the following sections to learn more about model parallelism and the SageMaker model parallel library. This library's API documentation is located at Distributed Training APIs in the SageMaker Python SDK documentation.

To track the latest updates of the library, see the SageMaker Distributed Model Parallel Release Notes in the SageMaker Python SDK documentation.

Topics
- Introduction to Model Parallelism (p. 2508)
- Supported Frameworks and AWS Regions (p. 2516)
- Core Features of the SageMaker Model Parallel Library (p. 2518)
- Run a SageMaker Distributed Training Job with Model Parallelism (p. 2522)
- Extended Features of the SageMaker Model Parallel Library for PyTorch (p. 2540)
- SageMaker Distributed Model Parallel Best Practices (p. 2563)
- SageMaker Distributed Model Parallel Configuration Tips and Pitfalls (p. 2566)
- Model Parallel Troubleshooting (p. 2569)

Introduction to Model Parallelism

Model parallelism is a distributed training method in which the deep learning model is partitioned across multiple devices, within or across instances. This introduction page provides a high-level overview about model parallelism, a description of how it can help overcome issues that arise when training DL models that are typically very large in size, and examples of what the SageMaker model parallel library offers to help manage model parallel strategies as well as memory consumption.

What is Model Parallelism?

Increasing the size of deep learning models (layers and parameters) yields better accuracy for complex tasks such as computer vision and natural language processing. However, there is a limit to the maximum model size you can fit in the memory of a single GPU. When training DL models, GPU memory limitations can be bottlenecks in the following ways:

- They limit the size of the model you can train, since the memory footprint of a model scales proportionally to the number of parameters.
- They limit the per-GPU batch size during training, driving down GPU utilization and training efficiency.

To overcome the limitations associated with training a model on a single GPU, SageMaker provides the model parallel library to help distribute and train DL models efficiently on multiple compute nodes. Furthermore, with the library, you can achieve most optimized distributed training using EFA-supported devices, which enhance the performance of inter-node communication with low latency, high throughput, and OS bypass.

Estimate Memory Requirements Before Using Model Parallelism

Before you use the SageMaker model parallel library, consider the following to get a sense of the memory requirements of training large DL models.

For a training job that uses AMP (FP16) and Adam optimizers, the required GPU memory per parameter is about 20 bytes, which we can break down as follows:

- An FP16 parameter ~ 2 bytes
• An FP16 gradient ~ 2 bytes
• An FP32 optimizer state ~ 8 bytes based on the Adam optimizers
• An FP32 copy of parameter ~ 4 bytes (needed for the optimizer apply (OA) operation)
• An FP32 copy of gradient ~ 4 bytes (needed for the OA operation)

Even for a relatively small DL model with 10 billion parameters, it can require at least 200GB of memory, which is much larger than the typical GPU memory (for example, NVIDIA A100 with 40GB/80GB memory and V100 with 16/32 GB) available on a single GPU. Note that on top of the memory requirements for model and optimizer states, there are other memory consumers such as activations generated in the forward pass. The memory required can be a lot greater than 200GB.

For distributed training, we recommend that you use Amazon EC2 P3 and P4 instances that have NVIDIA A100 or V100 Tensor Core GPUs. For more details about specifications such as CPU cores, RAM, attached storage volume, and network bandwidth, see the Accelerated Computing section in the Amazon EC2 Instance Types page.

Even with the accelerated computing instances, it is obvious that models with about 10 billion parameters such as Megatron-LM and T5 and even larger models with hundreds of billions of parameters such as GPT-3 cannot fit model replicas in each GPU device.

How the Library Employs Model Parallelism and Memory Saving Techniques

The library consists of two types of model parallelism features, pipeline parallelism and tensor parallelism, as well as other memory-saving features such as optimizer state sharding, activation checkpointing, and activation offloading. All these techniques can be combined to efficiently train large models, such as GPT-2, consisting of hundreds of billions of parameters.

Topics

• Pipeline parallelism (p. 2509)
• Tensor parallelism (available for PyTorch) (p. 2512)
• Optimizer state sharding (available for PyTorch) (p. 2514)
• Activation offloading and checkpointing (available for PyTorch) (p. 2516)
• Choosing the right techniques for your model (p. 2516)

Pipeline parallelism

Pipeline parallelism partitions the set of layers or operations across the set of devices, leaving each operation intact. When you specify a value for the number of model partitions (pipeline_parallel_degree), the total number of GPUs (processes_per_host) must be divisible by the number of the model partitions. To set this up properly, you have to specify the correct values for the pipeline_parallel_degree and processes_per_host parameters. The simple math is as follows:

(pipeline_parallel_degree) x (data_parallel_degree) = processes_per_host

The library takes care of calculating the number of model replicas (also called data_parallel_degree) given the two input parameters you provide.

For example, if you set "pipeline_parallel_degree": 2 and "processes_per_host": 8 to use an ML instance with eight GPU workers such as ml.p3.16xlarge, the library automatically sets up the distributed model across the GPUs and four-way data parallelism. The following image illustrates how a model is distributed across the eight GPUs achieving four-way data parallelism and two-way pipeline parallelism. Each model replica, where we define it as a pipeline parallel group and label it as PP_GROUP, is partitioned across two GPUs. Each partition of the model is assigned to four GPUs, where the four
partition replicas are in a *data parallel group* and labeled as DP_GROUP. Without tensor parallelism, the pipeline parallel group is essentially the model parallel group.
To dive deep into pipeline parallelism, see Core Features of the SageMaker Model Parallel Library (p. 2518).

To get started with running your model using pipeline parallelism, see Run a SageMaker Distributed Training Job with the SageMaker Model Parallel Library.

Tensor parallelism (available for PyTorch)

Tensor parallelism splits individual layers, or `nn.Module`s, across devices, to be run in parallel. The following figure shows the simplest example of how the library splits a model with four layers to achieve two-way tensor parallelism (`"tensor_parallel_degree": 2`). The layers of each model replica are bisected and distributed into two GPUs. In this example case, the model parallel configuration also includes "pipeline_parallel_degree": 1 and "ddp": True (uses PyTorch DistributedDataParallel package in the background), so the degree of data parallelism becomes eight. The library manages communication across the tensor-distributed model replicas.
The usefulness of this feature is in the fact that you can select specific layers or a subset of layers to apply tensor parallelism. To dive deep into tensor parallelism and other memory-saving features for PyTorch, and to learn how to set a combination of pipeline and tensor parallelism, see *Extended Features of the SageMaker Model Parallel Library for PyTorch* (p. 2540).
Optimizer state sharding (available for PyTorch)

To understand how the library performs optimizer state sharding, consider a simple example model with four layers. The key idea in optimizing state sharding is you don't need to replicate your optimizer state in all of your GPUs. Instead, a single replica of the optimizer state is sharded across data-parallel ranks, with no redundancy across devices. For example, GPU 0 holds the optimizer state for layer one, the next GPU 1 holds the optimizer state for L2, and so on. The following animated figure shows a backward propagation with the optimizer state sharding technique. At the end of the backward propagation, there's compute and network time for the `optimizer.apply` (OA) operation to update optimizer states and the `all-gather` (AG) operation to update the model parameters for the next iteration. Most importantly, the `reduce` operation can overlap with the compute on GPU 0, resulting in a more memory-efficient and faster backward propagation. In the current implementation, AG and OA operations do not overlap with compute. It can result in an extended computation during the AG operation, so there might be a tradeoff.
Sample model with four layers

Optimizer State for L1

GPU 0

Optimizer State for L2

GPU 1

Optimizer State for L3

GPU 2

Optimizer State for L4

GPU 3
For more information about how to use this feature, see Optimizer State Sharding.

**Activation offloading and checkpointing (available for PyTorch)**

To save GPU memory, the library supports activation checkpointing to avoid storing internal activations in the GPU memory for user-specified modules during the forward pass. The library recomputes these activations during the backward pass. In addition, the activation offloading feature offloads the stored activations to CPU memory and fetches back to GPU during the backward pass to further reduce activation memory footprint. For more information about how to use these features, see Activation Checkpointing and Activation Offloading.

**Choosing the right techniques for your model**

For more information about choosing the right techniques and configurations, see SageMaker Distributed Model Parallel Best Practices and Configuration Tips and Pitfalls.

**Supported Frameworks and AWS Regions**

Before using the SageMaker model parallel library, check the supported frameworks and instance types, and determine if there are enough quotas in your AWS account and AWS Region.

**Supported Frameworks**

The SageMaker model parallel library supports the following deep learning frameworks and is available in AWS Deep Learning Containers (DLC) or downloadable as a binary file.

**PyTorch versions supported by SageMaker and the SageMaker distributed model parallel library**

<table>
<thead>
<tr>
<th>PyTorch version</th>
<th>SageMaker distributed model parallel library version</th>
<th>smdistributed-modelparallel integrated DLC image URI</th>
<th>URL of the binary file**</th>
</tr>
</thead>
<tbody>
<tr>
<td>v1.11.0*</td>
<td>smdistributed-modelparallel==v1.10.0</td>
<td>763104351884.dkr.ecr.&lt;region&gt;.amazonaws.com/pytorch-training:1.11.0-gpu-py38-cu113-ubuntu20.04-sagemaker</td>
<td><a href="https://sagemaker-distributed-model-parallel.s3.us-west-2.amazonaws.com/pytorch-1.11.0/build-artifacts/2022-07-11-19-23/smdistributed_modelparallel-1.10.0-cp38-cp38-linux_x86_64.whl">link</a></td>
</tr>
</tbody>
</table>
PyTorch version | SageMaker distributed model parallel library version | smdistributed-modelparallel integrated DLC image URI | URL of the binary file**
--- | --- | --- | ---
| | | | ubuntu20.04-sagemaker
v1.10.0 | smdistributed-modelparallel==v1.5.0 | 763104351884.dkr.ecr.<region>.amazonaws.com/pytorch-training:1.10.0-gpu-py38-cu113-ubuntu20.04-sagemaker
v1.9.1 | smdistributed-modelparallel==v1.4.0 | 763104351884.dkr.ecr.<region>.amazonaws.com/pytorch-training:1.9.1-gpu-py38-cu111-ubuntu20.04

* The SageMaker distributed model parallel library v1.6.0 and later provides extended features for PyTorch. For more information, see [Extended Features of the SageMaker Model Parallel Library for PyTorch](p. 2540).

** The URLs of the binary files are for installing the SageMaker distributed model parallelism library in custom containers. For more information, see the section called “Create Your Own Docker Container with the Library” (p. 2538).

**TensorFlow versions supported by SageMaker and the SageMaker distributed model parallel library**

<table>
<thead>
<tr>
<th>TensorFlow version</th>
<th>SageMaker distributed model parallel library version</th>
<th>smdistributed-modelparallel integrated DLC image URI</th>
</tr>
</thead>
<tbody>
<tr>
<td>v2.6.0</td>
<td>smdistributed-modelparallel==v1.4.0</td>
<td>763104351884.dkr.ecr.&lt;region&gt;.amazonaws.com/tensorflow-training:2.6.0-gpu-py38-cu112-ubuntu20.04</td>
</tr>
<tr>
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<td>smdistributed-modelparallel==v1.4.0</td>
<td>763104351884.dkr.ecr.&lt;region&gt;.amazonaws.com/tensorflow-training:2.5.1-gpu-py37-cu112-ubuntu18.04</td>
</tr>
</tbody>
</table>

**Hugging Face Transformers versions supported by SageMaker and the SageMaker distributed data parallel library**

The AWS Deep Learning Containers for Hugging Face use the SageMaker Training Containers for PyTorch and TensorFlow as their base images. To look up the Hugging Face Transformers library versions and
paired PyTorch and TensorFlow versions, see the latest Hugging Face Containers and the Prior Hugging Face Container Versions.

**Note**
To check the latest updates and release history of the library, see the SageMaker Distributed Model Parallel Release Notes in the SageMaker Python SDK documentation.

### AWS Regions

The SageMaker data parallel library is available in all of the AWS Regions where the AWS Deep Learning Containers for SageMaker are in service. For more information, see Available Deep Learning Containers Images.

### Core Features of the SageMaker Model Parallel Library

Amazon SageMaker's model parallel library makes model parallelism more accessible by providing automated model splitting and sophisticated pipeline execution scheduling. The model splitting algorithms can optimize for speed or memory consumption. The library also supports manual partitioning. When you use the library, training is executed in a pipelined fashion over microbatches to maximize GPU usage.

You can configure these features using a few lines of code when you create your training script and define your SageMaker PyTorch or TensorFlow estimators. Use the following sections to learn more about these core features of the library.

**Note**
The SageMaker distributed training libraries are available only through the AWS deep learning containers for the TensorFlow, PyTorch, and HuggingFace frameworks within the SageMaker training platform. To use the libraries, you must use the SageMaker Python SDK or the SageMaker APIs through SDK for Python (Boto3) or AWS Command Line Interface. Throughout the documentation, instructions and examples focus on how to use the distributed training libraries with the SageMaker Python SDK.

#### Automated Model Splitting

When you use SageMaker's model parallel library, you can take advantage of *automated model splitting*, also referred to as *automated model partitioning*. The library uses a partitioning algorithm that balances memory, minimizes communication between devices, and optimizes performance. You can configure the automated partitioning algorithm to optimize for speed or memory.

Alternatively, you can use manual model splitting. We recommend automated model splitting, unless you are very familiar with the model architecture and have a good idea of how to efficiently partition your model.

**How It Works**

Auto-partitioning occurs during the first training step, when the `smp.step`-decorated function is first called. During this call, the library first constructs a version of the model on the CPU RAM (to avoid GPU memory limitations), and then analyzes the model graph and makes a partitioning decision. Based on this decision, each model partition is loaded on a GPU, and only then the first step is executed. Because of these analysis and partitioning steps, the first training step might take longer.

In either framework, the library manages the communication between devices through its own backend, which is optimized for AWS infrastructure.

The auto-partition design adapts to the characteristics of the framework, and the library does the partitioning at the granularity level that is more natural in each framework. For instance, in TensorFlow, each specific operation can be assigned to a different device, whereas in PyTorch, the assignment is done at the module level, where each module consists of multiple operations. The follow section reviews the specifics of the design in each framework.
Automated Model Splitting with PyTorch

During the first training step, the model parallel library internally runs a tracing step that is meant to construct the model graph and determine the tensor and parameter shapes. After this tracing step, the library constructs a tree, which consists of the nested `nn.Module` objects in the model, as well as additional data gathered from tracing, such as the amount of stored `nn.Parameters`, and execution time for each `nn.Module`.

Next, the library traverses this tree from the root and runs a partitioning algorithm that assigns each `nn.Module` to a device, which balances computational load (measured by module execution time) and memory use (measured by the total stored `nn.Parameter` size and activations). If multiple `nn.Modules` share the same `nn.Parameter`, then these modules are placed on the same device to avoid maintaining multiple versions of the same parameter. Once the partitioning decision is made, the assigned modules and weights are loaded to their devices.

Automated Model Splitting with TensorFlow

The model parallel library analyzes the sizes of the trainable variables and the graph structure, and internally uses a graph partitioning algorithm. This algorithm comes up with a device assignment for each operation, with the objective of minimizing the amount of communication needed across devices, subject to two constraints:

- Balancing the number of variables stored in each device
- Balancing the number of operations executed in each device

If you specify `speed` for `optimize` (in the model parallel parameters in the Python SDK), the library tries to balance the number of operations and `tf.Variable` objects in each device. Otherwise, it tries to balance the total size of `tf.Variables`.

Once the partitioning decision is made, the library creates a serialized representation of the subgraph that each device needs to execute and imports them onto each device. While partitioning, the library places operations that consume the same `tf.Variable` and operations that are part of the same Keras layer onto the same device. It also respects the colocation constraints imposed by TensorFlow. This means that, for example, if there are two Keras layers that share a `tf.Variable`, then all operations that are part of these layers are placed on a single device.

Comparison of Automated Model Splitting Between Frameworks

In TensorFlow, the fundamental unit of computation is a `tf.Operation`, and TensorFlow represents the model as a directed acyclic graph (DAG) of `tf.Operations`, and therefore model parallel library partitions this DAG so that each node goes to one device. Crucially, `tf.Operation` objects are sufficiently rich with customizable attributes, and they are universal in the sense that every model is guaranteed to consist of a graph of such objects.

PyTorch on the other hand, does not have an equivalent notion of operation that is sufficiently rich and universal. The closest unit of computation in PyTorch that has these characteristics is an `nn.Module`, which is at a much higher granularity level, and this is why the library does partitioning at this level in PyTorch.

Manual Model Splitting

If you want to manually specify how your model is partitioned across devices, you can use manual model splitting by using `smp.partition` context managers.

To use this option, set `auto_partition` to `False`, and define a `default_partition` in the SageMaker Python SDK. Any operation that is not explicitly placed on a partition through the `smp.partition` context manager is executed on the `default_partition`. In this case, the automated splitting logic is bypassed, and each operation is placed based on your specification. Based on the resulting graph structure, the model parallel library creates a pipelined execution schedule automatically.
Pipeline Execution Schedule

A core feature of SageMaker’s distributed model parallel library is *pipelined execution*, which determines the order in which computations are made and data is processed across devices during model training. Pipelining is a technique to achieve true parallelization in model parallelism, by having the GPUs compute simultaneously on different data samples, and to overcome the performance loss due to sequential computation.

Pipelining is based on splitting a mini-batch into microbatches, which are fed into the training pipeline one-by-one and follow an execution schedule defined by the library runtime. A *microbatch* is a smaller subset of a given training mini-batch. The pipeline schedule determines which microbatch is executed by which device for every time slot.

For example, depending on the pipeline schedule and the model partition, GPU $i$ might perform (forward or backward) computation on microbatch $b$ while GPU $i+1$ performs computation on microbatch $b+1$, thereby keeping both GPUs active at the same time. During a single forward or backward pass, execution flow for a single microbatch might visit the same device multiple times, depending on the partitioning decision. For instance, an operation that is at the beginning of the model might be placed on the same device as an operation at the end of the model, while the operations in between are on different devices, which means this device is visited twice.

The library offers two different pipeline schedules, *simple* and *interleaved*, which can be configured using the pipeline parameter in the SageMaker Python SDK. In most cases, interleaved pipeline can achieve better performance by utilizing the GPUs more efficiently.

**Interleaved Pipeline**

In an interleaved pipeline, backward execution of the microbatches is prioritized whenever possible. This allows quicker release of the memory used for activations, using memory more efficiently. It also allows for scaling the number of microbatches higher, reducing the idle time of the GPUs. At steady-state, each device alternates between running forward and backward passes. This means that the backward pass of one microbatch may run before the forward pass of another microbatch finishes.

![Interleaved Pipeline Example](image)

The preceding figure illustrates an example execution schedule for the interleaved pipeline over 2 GPUs. In the figure, F0 represents the forward pass for microbatch 0, and B1 represents the backward pass for microbatch 1. **Update** represents the optimizer update of the parameters. GPU0 always prioritizes backward passes whenever possible (for instance, executes B0 before F2), which allows for clearing of the memory used for activations earlier.

**Simple Pipeline**

A simple pipeline, by contrast, finishes running the forward pass for each microbatch before starting the backward pass. This means that it only pipelines the forward pass and backward pass stages within themselves. The following figure illustrates an example of how this works, over 2 GPUs.

![Simple Pipeline Example](image)

**Pipelining Execution in Specific Frameworks**

Use the following sections to learn about the framework-specific pipeline scheduling decisions SageMaker’s distributed model parallel library makes for Tensorflow and PyTorch.
Pipeline Execution with TensorFlow

The following image is an example of a TensorFlow graph partitioned by the model parallel library, using automated model splitting. When a graph is split, each resulting subgraph is replicated $B$ times (except for the variables), where $B$ is the number of microbatches. In this figure, each subgraph is replicated 2 times ($B=2$). An SMPInput operation is inserted at each input of a subgraph, and an SMPOutput operation is inserted at each output. These operations communicate with the library backend to transfer tensors to and from each other.

The following image is an example of 2 subgraphs split with $B=2$ with gradient operations added. The gradient of a SMPInput op is a SMPOutput op, and vice versa. This enables the gradients to flow backwards during back-propagation.

This GIF demonstrates an example interleaved pipeline execution schedule with $B=2$ microbatches and 2 subgraphs. Each device sequentially executes one of the subgraph replicas to improve GPU utilization. As $B$ grows larger, the fraction of idle time slots goes to zero. Whenever it is time to do (forward or backward) computation on a specific subgraph replica, the pipeline layer signals to the corresponding blue SMPInput operations to start executing.
Once the gradients from all microbatches in a single mini-batch are computed, the library combines the gradients across microbatches, which can then be applied to the parameters.

**Pipeline Execution with PyTorch**

Conceptually, pipelining follows a similar idea in PyTorch. However, since PyTorch does not involve static graphs and so the model parallel library's PyTorch feature uses a more dynamic pipelining paradigm.

As in TensorFlow, each batch is split into a number of microbatches, which are executed one at a time on each device. However, the execution schedule is handled via execution servers launched on each device. Whenever the output of a submodule that is placed on another device is needed on the current device, an execution request is sent to the execution server of the remote device along with the input tensors to the submodule. The server then executes this module with the given inputs and returns the response to the current device.

Since the current device is idle during the remote submodule execution, the local execution for the current microbatch pauses, and the library runtime switches execution to another microbatch which the current device can actively work on. The prioritization of microbatches is determined by the chosen pipeline schedule. For an interleaved pipeline schedule, microbatches that are in the backward stage of the computation are prioritized whenever possible.

**Run a SageMaker Distributed Training Job with Model Parallelism**

Learn how to run a distributed model parallel training job using the SageMaker Python SDK with your own training script and SageMaker's distributed model parallel library.

There are three use-case scenarios for running a SageMaker training job:

1. You can use one of the prebuilt AWS Deep Learning Container for TensorFlow and PyTorch. This option is recommended if it is the first time for you to use the model parallel library. To find a tutorial for how to run a SageMaker model parallel training job, see [MNIST with PyTorch 1.6 and Amazon SageMaker's distributed model parallel library](#).
2. You can extend the prebuilt containers to handle any additional functional requirements for your algorithm or model that the prebuilt SageMaker Docker image doesn't support. To find an example of how you can extend a pre-built container, see [Extend a Prebuilt Container](#).
3. You can adapt your own Docker container to work with SageMaker using the SageMaker Training toolkit. For an example, see [Adapting Your Own Training Container](#).

For options 2 and 3 in the preceding list, refer to [Extend a Prebuilt Docker Container that Contains SageMaker's Distributed Model Parallel Library](#) to learn how to install the model parallel library in an extended or customized Docker container.

In all cases, you launch your training job configuring a SageMaker TensorFlow or PyTorch estimator to initialize the library. To learn more, see the following topics.

**Topics**

- **Step 1: Modify Your Own Training Script Using SageMaker's Distributed Model Parallel Library** (p. 2522)
- **Step 2: Launch a Training Job Using the SageMaker Python SDK** (p. 2534)

**Step 1: Modify Your Own Training Script Using SageMaker's Distributed Model Parallel Library**

Use this section to learn how to customize your training script to use the core features of the Amazon SageMaker distributed model parallel library. To use the library-specific API functions and parameters,
we recommend you use this documentation alongside the SageMaker model parallel library APIs in the SageMaker Python SDK documentation.

The training script examples provided in these sections are simplified and designed to highlight the required changes you must make to use the library. For end-to-end, runnable notebook examples that demonstrate how to use a TensorFlow or PyTorch training script with the SageMaker distributed model parallel library, see Amazon SageMaker Distributed Training Notebook Examples (p. 2572).

**Topics**
- Modify a TensorFlow Training Script (p. 2523)
- Modify a PyTorch Training Script (p. 2528)

**Modify a TensorFlow Training Script**

In this section, you learn how to modify TensorFlow training scripts to configure the SageMaker distributed model parallel library for auto-partitioning and manual partitioning. This selection of examples also includes an example integrated with Horovod for hybrid model and data parallelism.

**Note**
To find which TensorFlow versions are supported by the library, see the section called “Supported Frameworks and AWS Regions” (p. 2516).

The required modifications you must make to your training script to use the library are listed in TensorFlow (p. 2523).

To learn how to modify your training script to use hybrid model and data parallelism with Horovod, see TensorFlow with Horovod for Hybrid Model and Data Parallelism (p. 2525).

If you want to use manual partitioning, also review Manual partitioning with TensorFlow (p. 2527).

**Tip**
For end-to-end notebook examples that demonstrate how to use a TensorFlow training script with the SageMaker distributed model parallel library, see TensorFlow Examples (p. 2573).

The following topics show examples of training scripts that you can use to configure SageMaker's model parallel library for auto-partitioning and manual partitioning TensorFlow models.

**Note**
Auto-partitioning is enabled by default. Unless otherwise specified, the example scripts use auto-partitioning.

**Topics**
- TensorFlow (p. 2523)
- TensorFlow with Horovod for Hybrid Model and Data Parallelism (p. 2525)
- Manual partitioning with TensorFlow (p. 2527)
- Unsupported Framework Features (p. 2528)

**TensorFlow**

The following training script changes are required to run a TensorFlow model with SageMaker's distributed model parallel library:

1. Import and initialize the library with `smp.init()`.  
2. Define a Keras model by inheriting from `smp.DistributedModel` instead of the Keras Model class. Return the model outputs from the call method of the `smp.DistributedModel` object. Be mindful that any tensors returned from the call method will be broadcast across model-parallel devices,
incurring communication overhead, so any tensors that are not needed outside the call method (such as intermediate activations) should not be returned.

3. Set `drop_remainder=True` in `tf.Dataset.batch()` method. This is to ensure that the batch size is always divisible by the number of microbatches.

4. Seed the random operations in the data pipeline using `smp.dp_rank()`, e.g., `shuffle(ds, seed=smp.dp_rank())` to ensure consistency of data samples across GPUs that hold different model partitions.

5. Put the forward and backward logic in a step function and decorate it with `smp.step`.

6. Perform post-processing on the outputs across microbatches using `StepOutput` methods such as `reduce_mean`. The `smp.step` function must have a return value that depends on the output of `smp.DistributedModel`.

7. If there is an evaluation step, similarly place the forward logic inside an `smp.step-decorated function` and post-process the outputs using `StepOutput API`.

To learn more about the SageMaker's distributed model parallel library API, refer to the API documentation.

The following Python script is an example of a training script after the changes are made.

```python
import tensorflow as tf
# smdistributed: Import TF2.x API
import smdistributed.modelparallel.tensorflow as smp

# smdistributed: Initialize
smp.init()

# Download and load MNIST dataset.
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data(
    "MNIST-data-%d" % smp.rank())
x_train, x_test = x_train / 255.0, x_test / 255.0

# Add a channels dimension
x_train = x_train[..., tf.newaxis]
x_test = x_test[..., tf.newaxis]

# smdistributed: If needed, seed the shuffle with smp.dp_rank(), and drop_remainder # in batching to make sure batch size is always divisible by number of microbatches
train_ds = (tf.data.Dataset.from_tensor_slices((x_train, y_train))
    .shuffle(10000, seed=smp.dp_rank())
    .batch(256, drop_remainder=True)
)

# smdistributed: Define smp.DistributedModel the same way as Keras sub-classing API
class MyModel(smp.DistributedModel):
    def __init__(self):
        super(MyModel, self).__init__()
        # define layers

    def call(self, x, training=None):
        # define forward pass and return the model output

model = MyModel()

loss_object = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
optimizer = tf.keras.optimizers.Adam()
train_accuracy = tf.keras.metrics.SparseCategoricalAccuracy(name="train_accuracy")
```
# smdistributed: Define smp.step. Return any tensors needed outside
@smp.step
def get_grads(images, labels):
    predictions = model(images, training=True)
    loss = loss_object(labels, predictions)
    grads = optimizer.get_gradients(loss, model.trainable_variables)
    return grads, loss, predictions

@tf.function
def train_step(images, labels):
    gradients, loss, predictions = get_grads(images, labels)

    # smdistributed: Accumulate the gradients across microbatches
    gradients = [g.accumulate() for g in gradients]
    optimizer.apply_gradients(zip(gradients, model.trainable_variables))

    # smdistributed: Merge predictions and average losses across microbatches
    train_accuracy(labels, predictions.merge())
    return loss.reduce_mean()

for epoch in range(5):
    # Reset the metrics at the start of the next epoch
    train_accuracy.reset_states()
    for images, labels in train_ds:
        loss = train_step(images, labels)
        accuracy = train_accuracy.result()
allows the library to internally initialize Horovod based on the device assignments of model partitions. Calling hvd.init() directly in your training script can cause problems.

**Note**
Using the hvd.DistributedOptimizer API directly in your training script might result in a poor training performance and speed, because the API implicitly places the AllReduce operation inside smp.step. We recommend you to use the model parallel library with Horovod by directly calling hvd.allreduce after calling accumulate() or reduce_mean() on the gradients returned from smp.step, as will be shown in the following example.

To learn more about the SageMaker's distributed model parallel library API, refer to the API documentation.

```python
import tensorflow as tf
import horovod.tensorflow as hvd

# Download and load MNIST dataset.
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data(
    "MNIST-data-%d" % hvd.rank())
x_train, x_test = x_train / 255.0, x_test / 255.0

# Add a channels dimension
x_train = x_train[..., tf.newaxis]
x_test = x_test[..., tf.newaxis]

# Define smp.DistributedModel the same way as Keras sub-classing API
class MyModel(smp.DistributedModel):
    def __init__(self):
        super(MyModel, self).__init__()
        # define layers
        def call(self, x, training=None):
            # define forward pass and return model outputs

model = MyModel()

loss_object = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
optimizer = tf.keras.optimizers.Adam()
train_accuracy = tf.keras.metrics.SparseCategoricalAccuracy(name="train_accuracy")

# Define smp.step. Return any tensors needed outside
@smp.step
def get_grads(images, labels):
    predictions = model(images, training=True)
    loss = loss_object(labels, predictions)
    grads = optimizer.get_gradients(loss, model.trainable_variables)
    return grads, loss, predictions
```
@tf.function
def train_step(images, labels, first_batch):
    gradients, loss, predictions = get_grads(images, labels)

    # smdistributed: Accumulate the gradients across microbatches
    # Horovod: Allreduce the accumulated gradients
    gradients = [hvd.allreduce(g.accumulate()) for g in gradients]
    optimizer.apply_gradients(zip(gradients, model.trainable_variables))

    # Horovod: Broadcast the variables after first batch
    if first_batch:
        hvd.broadcast_variables(model.variables, root_rank=0)
        hvd.broadcast_variables(optimizer.variables(), root_rank=0)

    # smdistributed: Merge predictions across microbatches
    train_accuracy(labels, predictions.merge())
    return loss.reduce_mean()

for epoch in range(5):
    # Reset the metrics at the start of the next epoch
    train_accuracy.reset_states()

    for batch, (images, labels) in enumerate(train_ds):
        loss = train_step(images, labels, tf.constant(batch == 0))

Manual partitioning with TensorFlow

Use smp.partition context managers to place operations in specific partition. Any operation not
placed in any smp.partition contexts is placed in the default_partition. To learn more about the
SageMaker's distributed model parallel library API, refer to the API documentation.

import tensorflow as tf

# smdistributed: Import TF2.x API.
import smdistributed.modelparallel.tensorflow as smp

# smdistributed: Initialize
smp.init()

# Download and load MNIST dataset.
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data(
    "MNIST-data-%d" % smp.rank())
x_train, x_test = x_train / 255.0, x_test / 255.0

# Add a channels dimension
x_train = x_train[..., tf.newaxis]
x_test = x_test[..., tf.newaxis]

# smdistributed: If needed, seed the shuffle with smp.dp_rank(), and drop_remainder
# in batching to make sure batch size is always divisible by number of microbatches.
train_ds = (tf.data.Dataset.from_tensor_slices((x_train, y_train))
    .shuffle(10000, seed=smp.dp_rank())
    .batch(256, drop_remainder=True)
)

# smdistributed: Define smp.DistributedModel the same way as Keras sub-classing API.
class MyModel(smp.DistributedModel):
    def __init__(self):
        # define layers
def call(self, x):
    with smp.partition(0):
        x = self.layer0(x)
    with smp.partition(1):
        return self.layer1(x)

model = MyModel()

loss_object = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
optimizer = tf.keras.optimizers.Adam()
train_accuracy = tf.keras.metrics.SparseCategoricalAccuracy(name="train_accuracy")

# smdistributed: Define smp.step. Return any tensors needed outside
@smp.step
def get_grads(images, labels):
    predictions = model(images, training=True)
    loss = loss_object(labels, predictions)

    grads = optimizer.get_gradients(loss, model.trainable_variables)
    return grads, loss, predictions

@tf.function
def train_step(images, labels):
    gradients, loss, predictions = get_grads(images, labels)

    # smdistributed: Accumulate the gradients across microbatches
    gradients = [g.accumulate() for g in gradients]
    optimizer.apply_gradients(zip(gradients, model.trainable_variables))

    # smdistributed: Merge predictions and average losses across microbatches
    train_accuracy(labels, predictions.merge())
    return loss.reduce_mean()

for epoch in range(5):
    # Reset the metrics at the start of the next epoch
    train_accuracy.reset_states()
    for images, labels in train_ds:
        loss = train_step(images, labels)
        accuracy = train_accuracy.result()
Tip
For end-to-end notebook examples that demonstrate how to use a PyTorch training script with the SageMaker distributed model parallel library, see PyTorch Examples (p. 2573).

Note that auto-partitioning is enabled by default. Unless otherwise specified, the following scripts use auto-partitioning.

Topics
- PyTorch (p. 2529)
- Manual Partitioning with PyTorch (p. 2531)
- Important Considerations (p. 2532)
- Unsupported Framework Features (p. 2534)

PyTorch

The following training script changes are required to run a PyTorch training script with SageMaker's distributed model parallel library:

1. Import and initialize the library with `smdistributed.modelparallel.torch.init()`.
2. Wrap the model with `smdistributed.modelparallel.torch.DistributedModel`. Be mindful that any tensors returned from the forward method of the underlying `nn.Module` object will be broadcast across model-parallel devices, incurring communication overhead, so any tensors that are not needed outside the call method (such as intermediate activations) should not be returned.

   Note
   For FP16 training, you need to use the `smdistributed.modelparallel.torch.model_creation()` context manager to wrap the model. For more information, see FP16 Training with Model Parallelism (p. 2556).

3. Wrap the optimizer with `smdistributed.modelparallel.torch.DistributedOptimizer`.

   Note
   For FP16 training, you need to set up static or dynamic loss scaling. For more information, see FP16 Training with Model Parallelism (p. 2556).

4. Use the returned `DistributedModel` object instead of a user model.
5. Put the forward and backward logic in a step function and decorate it with `smdistributed.modelparallel.torch.step`.
6. Restrict each process to its own device through `torch.cuda.set_device(smp.local_rank())`.
7. Move the input tensors to the GPU using the `.to()` API before the `smp.step` call (see example below).
9. Perform post-processing on the outputs across microbatches using `StepOutput` methods such as `reduce_mean`.
10. If there is an evaluation step, similarly place the forward logic inside an `smp.step`-decorated function and post-process the outputs using `StepOutput API`.
11. Set `drop_last=True` in `DataLoader`. Alternatively, manually skip a batch in the training loop if the batch size is not divisible by the number of microbatches.

To learn more about the SageMaker's distributed model parallel library API, refer to the API documentation.

```python
import torch
import torch.nn as nn
```
import torch.nn.functional as F
import torch.optim as optim
from torchtext.dataset import SplitDataset
from torchvision import datasets
import smdistributed.modelparallel.torch as smp

class GroupedNet(nn.Module):
    def __init__(self):
        super(GroupedNet, self).__init__()
        # define layers

    def forward(self, x):
        # define forward pass and return model outputs

        @smp.step
        def train_step(model, data, target):
            output = model(data)
            loss = F.nll_loss(output, target, reduction="mean")
            model.backward(loss)
            return output, loss

    def train(model, device, train_loader, optimizer):
        model.train()
        for batch_idx, (data, target) in enumerate(train_loader):
            # smdistributed: Move input tensors to the GPU ID used by the current process,
            # based on the set_device call.
            data, target = data.to(device), target.to(device)
            optimizer.zero_grad()
            # Return value, loss_mb is a StepOutput object
            _, loss_mb = train_step(model, data, target)
            # smdistributed: Average the loss across microbatches.
            loss = loss_mb.reduce_mean()
            optimizer.step()

        # smdistributed: initialize the backend
        smp.init()

        # smdistributed: Set the device to the GPU ID used by the current process.
        # Input tensors should be transferred to this device.
        torch.cuda.set_device(smp.local_rank())
        device = torch.device("cuda")

        # smdistributed: Download only on a single process per instance.
        # When this is not present, the file is corrupted by multiple processes trying
        # to download and extract at the same time
        dataset = datasets.MNIST("../data", train=True, download=False)

        # smdistributed: Shard the dataset based on data-parallel ranks
        if smp.dp_size() > 1:
            partitions_dict = {f"{i}" : 1 / smp.dp_size() for i in range(smp.dp_size())}
            dataset = SplitDataset(dataset, partitions=partitions_dict)
            dataset.select(f"{smp.dp_rank()}")

        # smdistributed: Set drop_last=True to ensure that batch size is always divisible
        # by the number of microbatches
        train_loader = torch.utils.data.DataLoader(dataset, batch_size=64, drop_last=True)

        model = GroupedNet()
        optimizer = optim.Adadelta(model.parameters(), lr=4.0)
# smdistributed: Use the DistributedModel container to provide the model to be partitioned across different ranks. For the rest of the script, the returned DistributedModel object should be used in place of the model provided for DistributedModel class instantiation.

```python
def train(model, device, train_loader, optimizer):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        # smdistributed: Move input tensors to the GPU ID used by the current process, based on the set_device call.
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        out, loss_mb = train_step(model, data, target)
        # smdistributed: Average the loss across microbatches.
        loss = loss_mb.reduce_mean()
        optimizer.step()
```

## Manual Partitioning with PyTorch

Use `smp.partition` context managers to place modules in specific devices. Any module not placed in any `smp.partition` contexts is placed in the `default_partition`. The `default_partition` needs to be provided if `auto_partition` is set to `False`. The modules that are created within a specific `smp.partition` context are placed on the corresponding partition.

To learn more about the SageMaker's distributed model parallel library API, refer to the API documentation.

```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchtext.dataset import SplitDataset
from torchvision import datasets
import smdistributed.modelparallel.torch as smp
class GroupedNet(nn.Module):
    def __init__(self):
        super(GroupedNet, self).__init__()
        with smp.partition(0):
            # define child modules on device 0
            with smp.partition(1):
                # define child modules on device 1
                def forward(self, x):
                    # define forward pass and return model outputs

        # smdistributed: Define smp.step. Return any tensors needed outside.
        @smp.step
def train_step(model, data, target):
    output = model(data)
    loss = F.nll_loss(output, target, reduction="mean")
    model.backward(loss)
    return output, loss

def train(model, device, train_loader, optimizer):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        # smdistributed: Move input tensors to the GPU ID used by the current process, based on the set_device call.
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        out, loss_mb = train_step(model, data, target)
        # smdistributed: Average the loss across microbatches.
        loss = loss_mb.reduce_mean()
        optimizer.step()```
# smdistributed: initialize the backend
smp.init()

# smdistributed: Set the device to the GPU ID used by the current process.
# Input tensors should be transferred to this device.
torch.cuda.set_device(smp.local_rank())
device = torch.device("cuda")

# smdistributed: Download only on a single process per instance.
# When this is not present, the file is corrupted by multiple processes trying
# to download and extract at the same time
dataset = datasets.MNIST("../data", train=True, download=False)

# smdistributed: Shard the dataset based on data-parallel ranks
if smp.dp_size() > 1:
    partitions_dict = {f"{i}": 1 / smp.dp_size() for i in range(smp.dp_size())}
dataset = SplitDataset(dataset, partitions=partitions_dict)
dataset.select(f"{smp.dp_rank()}")

# smdistributed: Set drop_last=True to ensure that batch size is always divisible
# by the number of microbatches
train_loader = torch.utils.data.DataLoader(dataset, batch_size=64, drop_last=True)

model = GroupedNet()
optimizer = optim.Adadelta(model.parameters(), lr=4.0)

# smdistributed: Use the DistributedModel container to provide the model
# to be partitioned across different ranks. For the rest of the script,
# the returned DistributedModel object should be used in place of
# the model provided for DistributedModel class instantiation.
model = smp.DistributedModel(model)
optimizer = smp.DistributedOptimizer(optimizer)

train(model, device, train_loader, optimizer)

Important Considerations

When you configure a PyTorch training script using SageMaker's distributed model parallel library, you should be aware of the following:

- If you are using an optimization technique that relies on global gradient norms, for example gradient norm from the entire model, such as some variants of LAMB optimizer or global gradient clipping, you need to gather all the norms across the model partitions for correctness. You can use the library's communication basic data types to do this.

- All torch.Tensor arguments to the forward methods of the nn.Modules in your model must be used in the computation of the module output. In other words, the library does not support the case where there is a torch.Tensor argument to a module on which the module output does not depend.

- The argument to the smp.DistributedModel.backward() call must depend on all model outputs. In other words, there cannot be an output from the smp.DistributedModel.forward call that is not used in the computation of the tensor that is fed into the smp.DistributedModel.backward call.

- If there are torch.cuda.synchronize() calls in your code, you might need to call torch.cuda.set_device(smp.local_rank()) immediately before the synchronize call. Otherwise unnecessary CUDA contexts might be created in device 0, which will needlessly consume memory.

- Since the library places nn.Modules on different devices, the modules in the model must not depend on any global state that is modified inside smp.step. Any state that remains fixed throughout training, or that is modified outside smp.step in a way that is visible to all processes, is allowed.

- You don't need to move the model to GPU (for example, using model.to(device)) when using the library. If you try to move the model to GPU before the model is partitioned (before the first
smp.step call), the move call is ignored. The library automatically moves the part of the model assigned to a rank to its GPU. Once training with the library starts, don’t move the model to CPU and use it, as it won’t have correct parameters for modules not assigned to the partition held by the process. If you want to retrain a model or use it for inference without the library after it was trained using the model parallel library, the recommended way is to save the full model using our checkpointing API and load it back to a regular PyTorch Module.

- If you have a list of modules such that output of one feeds into another, replacing that list with nn.Sequential can significantly improve performance.

- The weight update (optimizer.step()) needs to happen outside of smp.step because that is when the entire backward pass is done and gradients are ready. When using a hybrid model with model and data parallelism, at this point, Allreduce of gradients is also guaranteed to finish.

- When using the library in combination with data parallelism, make sure that the number of batches on all data parallel ranks is the same so that Allreduce does not hang waiting for a rank which is not participating in the step.

- If you launch a training job using an ml.p4d instance type (such as ml.p4d.24xlarge), you must set the data loader variable num_workers=0. For example, you may define your DataLoader as follows:

```python
dataloader = torch.utils.data.DataLoader(
    data,
    batch_size=batch_size,
    num_workers=0,
    pin_memory=True,
    drop_last=True,
    shuffle=False,
)
```

- The inputs to smp.step must be the model inputs generated by DataLoader. This is because smp.step internally splits the input tensors along the batch dimension and pipelines them. This means that passing DataLoader itself to the smp.step function to generate the model inputs inside does not work.

For example, if you define a DataLoader as follows:

```python
train_loader = torch.utils.data.DataLoader(dataset, batch_size=64, drop_last=True)
```

You should access the model inputs generated by train_loader and pass those to an smp.step decorated function. Do not pass train_loader directly to the smp.step function.

```python
def train(model, device, train_loader, optimizer):
    model.train()
    for batch_idx, (data, target) in enumerate(train_loader):
        ...
        _, loss_mb = train_step(model, data, target)
        ...

    @smp.step
    def train_step(model, data, target):
        ...
        return output, loss
```

- The input tensors to smp.step must be moved to the current device using .to() API, which must take place after the torch.cuda.set_device(local_rank()) call.

For example, you may define the train function as follows. This function adds data and target to the current device using .to() API before using those input tensors to call train_step.

```python
def train(model, device, train_loader, optimizer):
    model.train()
```
for batch_idx, (data, target) in enumerate(train_loader):
    # smdistributed: Move input tensors to the GPU ID used by the current process,
    # based on the set_device call.
    data, target = data.to(device), target.to(device)
    optimizer.zero_grad()
    # Return value, loss_mb is a StepOutput object
    _, loss_mb = train_step(model, data, target)
    # smdistributed: Average the loss across microbatches.
    loss = loss_mb.reduce_mean()
    optimizer.step()

The input tensors to this smp.set decorated function have been moved to the current device in
the train function above. The model does not need to be moved to the current device. The library
automatically moves the part of the model assigned to a rank to its GPU.

@SMP.step
def train_step(model, data, target):
    output = model(data)
    loss = F.nll_loss(output, target, reduction="mean")
    model.backward(loss)
    return output, loss

Unsupported Framework Features

The following PyTorch features are unsupported by SageMaker's distributed model parallel library:

- If you use data parallelism with the native PyTorch DDP, the
  torch.nn.parallel.DistributedDataParallel wrapper module is not supported by the library.
  The library internally manages integrating with PyTorch DDP, including parameter broadcast and
  gradient AllReduce. When using the library, module buffers are only broadcast once at the start of
  training. If your model has module buffers that need to be synchronized across data parallel groups at
  each step, you can do so through the torch.distributed API, using the process group that can be
  obtained via smp.get_dp_process_group().
- For mixed precision training, the apex.amp module is not supported. The recommended way to use
  the library with automatic mixed-precision is to use torch.cuda.amp, with the exception of using
  smp.amp.GradScaler instead of the implementation in torch.
- torch.jit.ScriptModules or ScriptFunctions are not supported by smp.DistributedModel.
- apex: FusedLayerNorm, FusedAdam, FusedLAMB, and FusedNovoGrad from apex are not
  supported. You can use the library implementations of these through smp.optimizers and smp.nn
  APIs instead.

Step 2: Launch a Training Job Using the SageMaker Python SDK

The SageMaker Python SDK supports managed training of models with ML frameworks such as
TensorFlow and PyTorch. To launch a training job using one of these frameworks, you define a
SageMaker TensorFlow estimator, a SageMaker PyTorch estimator, or a SageMaker generic Estimator to
use the modified training script and model parallelism configuration.

Topics

- Using the SageMaker TensorFlow and PyTorch Estimators (p. 2535)
- Extend a Prebuilt Docker Container that Contains SageMaker's Distributed Model Parallel
  Library (p. 2537)
- Create Your Own Docker Container with the SageMaker Distributed Model Parallel Library (p. 2538)
Using the SageMaker TensorFlow and PyTorch Estimators

The TensorFlow and PyTorch estimator classes contain the `distribution` parameter, which you can use to specify configuration parameters for using distributed training frameworks. The SageMaker model parallel library internally uses MPI for hybrid data and model parallelism, so you must use the MPI option with the library.

The following template of a TensorFlow or PyTorch estimator shows how to configure the `distribution` parameter for using the SageMaker model parallel library with MPI.

Using the SageMaker TensorFlow estimator

```python
import sagemaker
from sagemaker.tensorflow import TensorFlow

smp_options = {
    "enabled": True,  # Required
    "parameters": {
        "partitions": 2,  # Required
        "microbatches": 4,
        "placement_strategy": "spread",
        "pipeline": "interleaved",
        "optimize": "speed",
        "horovod": True,  # Use this for hybrid model and data parallelism
    }
}

mpi_options = {
    "enabled": True,  # Required
    "processes_per_host": 8,  # Required
    # "custom_mpi_options" : "--mca btl_vader_single_copy_mechanism none"
}

smd_mp_estimator = TensorFlow(
    entry_point="your_training_script.py",  # Specify your train script
    source_dir="location_to_your_script",
    role=sagemaker.get_execution_role(),
    instance_count=1,
    instance_type='ml.p3.16xlarge',
    framework_version='2.6.3',
    py_version='py38',
    distribution={
        "smdistributed": {"modelparallel": smp_options},
        "mpi": mpi_options
    },
    base_job_name="SMD-MP-demo",
)

smd_mp_estimator.fit('s3://my_bucket/my_training_data/')
```

Using the SageMaker PyTorch estimator

```python
import sagemaker
from sagemaker.pytorch import PyTorch

smp_options = {
    "enabled": True,  # Required
    "parameters": {
        "pipeline_parallel_degree": 2,  # Required
        "microbatches": 4,
        "placement_strategy": "spread",
        "pipeline": "interleaved",
        "optimize": "speed",
    }
}

smd_mp_estimator = PyTorch(
    entry_point="your_training_script.py",  # Specify your train script
    source_dir="location_to_your_script",
    role=sagemaker.get_execution_role(),
    instance_count=1,
    instance_type='ml.p3.16xlarge',
    framework_version='2.6.3',
    py_version='py38',
    distribution={
        "smdistributed": {"modelparallel": smp_options},
        "mpi": mpi_options
    },
    base_job_name="SMD-MP-demo",
)

smd_mp_estimator.fit('s3://my_bucket/my_training_data/)
```
To enable the library, you need to pass configuration dictionaries to the "smdistributed" and "mpi" keys through the distribution argument of the SageMaker estimator constructors.

**Configuration parameters for SageMaker model parallelism**

- For the "smdistributed" key, pass a dictionary with the "modelparallel" key and the following inner dictionaries.

  **Note**
  Using "modelparallel" and "dataparallel" in one training job is not supported.

  - "enabled" – Required. To enable model parallelism, set "enabled": True.
  - "parameters" – Required. Specify a set of parameters for SageMaker model parallelism.
    - For a complete list of common parameters, see Parameters for smdistributed in the SageMaker Python SDK documentation.

    For TensorFlow, see TensorFlow-specific Parameters.

    For PyTorch, see PyTorch-specific Parameters.

  - "pipeline_parallel_degree" (or "partitions" in smdistributed-modelparallel<1.6.0) – Required. Among the parameters for smdistributed, this parameter is required to specify how many model partitions you want to split into.

  **Important**
  There is a breaking change in the parameter name. The "pipeline_parallel_degree" parameter replaces the "partitions" since smdistributed-modelparallel v1.6.0. For more information, see Common Parameters for SageMaker model parallelism configuration and SageMaker Distributed Model Parallel Release Notes in the SageMaker Python SDK documentation.

- For the "mpi" key, pass a dictionary that contains the following:
  - "enabled" – Required. Set True to launch the distributed training job with MPI.
  - "processes_per_host" – Required. Specify the number of processes MPI should launch on each host. In SageMaker a host is a single Amazon EC2 ML instance. The SageMaker Python SDK
maintains a one-to-one mapping between processes and GPUs across model and data parallelism. This means that SageMaker schedules each process on a single, separate GPU and no GPU contains more than one process. If you are using PyTorch, you must restrict each process to its own device through torch.cuda.set_device(smp.local_rank()). To learn more, see PyTorch (p. 2529).

Important
process_per_host must not be greater than the number of GPUs per instance and typically will be equal to the number of GPUs per instance.

- "custom_mpi_options" (optional) – Use this key to pass any custom MPI options you might need. If you do not pass any MPI custom options to the key, the MPI option is set by default to the following flag.

```bash
--mca btl_vader_single_copy_mechanism none
```

Note
You do not need to explicitly specify this default flag to the key. If you explicitly specify it, your distributed model parallel training job might fail with the following error:

The following MCA parameter has been listed multiple times on the command line:
MCA param: btl_vader_single_copy_mechanism MCA parameters can only be listed once on a command line to ensure there is no ambiguity as to its value.
Please correct the situation and try again.

Tip
If you launch a training job using an EFA-enabled instance type, such as ml.p4d.24xlarge and ml.p3dn.24xlarge, use the following flag for best performance:

```bash
-x FI_EFA_USE_DEVICE_RDMA=1 -x FI_PROVIDER=efa -x RDMAV_FORK_SAFE=1
```

To launch the training job using the estimator and your SageMaker model parallel configured training script, run the `estimator.fit()` function.

Use the following resources to learn more about using the model parallelism features in the SageMaker Python SDK:

- Use TensorFlow with the SageMaker Python SDK
- Use PyTorch with the SageMaker Python SDK

We recommend you use a SageMaker notebook instance if you are new users. To see an example of how you can launch a training job using a SageMaker notebook instance, see Amazon SageMaker Distributed Training Notebook Examples (p. 2572).

You can also submit a distributed training job from your machine using AWS CLI. To set up AWS CLI on your machine, see set up your AWS credentials and Region for development.

**Extend a Prebuilt Docker Container that Contains SageMaker's Distributed Model Parallel Library**

To extend a prebuilt container and use SageMaker's distributed model parallel library, you must use one of the available AWS Deep Learning Containers (DLC) images for PyTorch or TensorFlow. The SageMaker distributed model parallel library is included in the TensorFlow (2.3.0 and later) and PyTorch (1.6.0 and later) DLC images with CUDA (cuxyz). For a complete list of DLC images, see Available Deep Learning Containers Images in the AWS Deep Learning Containers GitHub repository.
Tip
We recommend that you use the image that contains the latest version of TensorFlow or PyTorch to access the most up-to-date version of the SageMaker distributed model parallel library.

For example, your Dockerfile should contain a FROM statement similar to the following:

```
# Use the SageMaker DLC image URI for TensorFlow or PyTorch
FROM aws-dlc-account-id.dkr.ecr.aws-region.amazonaws.com/framework-training:{framework-version-tag}

# Add your dependencies here
RUN ...

ENV PATH="/opt/ml/code:${PATH}"
# this environment variable is used by the SageMaker container to determine our user code directory.
ENV SAGEMAKER_SUBMIT_DIRECTORY /opt/ml/code
```

Additionally, when you define a PyTorch or TensorFlow estimator, you must specify that the entry_point for your training script. This should be the same path identified with ENV SAGEMAKER_SUBMIT_DIRECTORY in your Dockerfile.

```
smd_mp_estimator = Estimator(
    entry_point="your_training_script.py",
    role=sagemaker.get_execution_role(),
    instance_type='ml.p3.16xlarge',
    sagemaker_session=sagemaker_session,
    image_uri='your_aws_account_id.dkr.ecr.region.amazonaws.com/name:tag'
    instance_count=1,
    distribution={
        "smdistributed": smp_options,
        "mpi": mpi_options
    },
    base_job_name="SMD-MP-demo",
)

smd_mp_estimator.fit('s3://my_bucket/my_training_data/')
```

Create Your Own Docker Container with the SageMaker Distributed Model Parallel Library

To build your own Docker container for training and use the SageMaker model parallel library, you must include the correct dependencies and the binary files of the SageMaker distributed parallel libraries in your Dockerfile. This section provides the minimum set of code blocks you must include to properly prepare a SageMaker training environment and the model parallel library in your own Docker container.

**Note**
This custom Docker option with the SageMaker model parallel library as a binary is available only for PyTorch.
To create a Dockerfile with the SageMaker training toolkit and the model parallel library

1. Start with one of the NVIDIA CUDA base images.

```bash
FROM <cuda-cudnn-base-image>
```

**Tip**
The official AWS Deep Learning Container (DLC) images are built from the NVIDIA CUDA base images. We recommend you look into the official Dockerfiles of AWS Deep Learning Container for PyTorch to find which versions of the libraries you need to install and how to configure them. The official Dockerfiles are complete, benchmark tested, and managed by the SageMaker and Deep Learning Container service teams. In the provided link, choose the PyTorch version you use, choose the CUDA (cuxyz) folder, and choose the Dockerfile ending with .gpu or .sagemaker.gpu.

2. To set up a distributed training environment, you need to install software for communication and network devices, such as Elastic Fabric Adapter (EFA), NVIDIA Collective Communications Library (NCCL), and Open MPI. Depending on the PyTorch and CUDA versions you choose, you must install compatible versions of the libraries.

**Important**
Because the SageMaker model parallel library requires the SageMaker data parallel library in the subsequent steps, we highly recommend that you follow the instructions at Create Your Own Docker Container with the SageMaker Distributed Data Parallel Library (p. 2493) to properly set up a SageMaker training environment for distributed training.

For more information about setting up EFA with NCCL and Open MPI, see Get started with EFA and MPI and Get started with EFA and NCCL.

3. Add the following arguments to specify the URLs of the SageMaker distributed training packages for PyTorch. The SageMaker model parallel library requires the SageMaker data parallel library to use the cross-node Remote Direct Memory Access (RDMA).

```bash
ARG SMDATAPARALLEL_BINARY=https://smdataparallel.s3.amazonaws.com/binary/pytorch/1.10.2/cu113/2022-02-18/smdistributed_dataparallel-1.4.0-cp38-cp38-linux_x86_64.whl
```

4. Install dependencies that the SageMaker model parallel library requires.

   a. Install the METIS library.

   ```bash
   ARG METIS=metis-5.1.0
   RUN rm /etc/apt/sources.list.d/* \n   && wget -nv http://glaros.dtc.umn.edu/gkhome/fetch/sw/metis/${METIS}.tar.gz \n   && gunzip -f ${METIS}.tar.gz \n   && tar -xvf ${METIS}.tar \n   && cd ${METIS} \n   && apt-get update \n   && make config shared=1 \n   && make install \n   && cd .. \n   && rm -rff ${METIS}.tar \n   && rm -rff ${METIS} \n   && rm -rf /var/lib/apt/lists/* \n   && apt-get clean
   ```

   b. Install the RAPIDS Memory Manager library. This requires CMake 3.14 or later.
5. Install the SageMaker model parallel library.

```bash
ARG RMM_VERSION=0.15.0
RUN wget -nv https://github.com/rapidsai/rmm/archive/v${RMM_VERSION}.tar.gz \
    && tar -xvf v${RMM_VERSION}.tar.gz \
    && cd rmm-${RMM_VERSION} \
    && INSTALL_PREFIX=/usr/local ./build.sh librmm \
    && cd .. \
    && rm -rf v${RMM_VERSION}.tar* \
    && rm -rf rmm-${RMM_VERSION}
```

6. Install the SageMaker data parallel library.

```bash
RUN SMDATAPARALLEL_PT=1 pip install --no-cache-dir ${SMDATAPARALLEL_BINARY}
```

7. Install the `sagemaker-training` toolkit. The toolkit contains the common functionality that's necessary to create a container compatible with the SageMaker training platform and the SageMaker Python SDK.

```bash
RUN pip install sagemaker-training
```

8. After you finish creating the Dockerfile, see Adapting Your Own Training Container to learn how to build the Docker container and host it in Amazon ECR.

Tip
For more general information about creating a custom Dockerfile for training in SageMaker, see Use Your Own Training Algorithms.

Extended Features of the SageMaker Model Parallel Library for PyTorch

In addition to its core features, the SageMaker distributed model parallel library offers memory-saving features for training deep learning models with PyTorch: tensor parallelism, optimizer state sharding, activation checkpointing, and activation offloading.

**Note**
Extended memory-saving features are available through Deep Learning Containers for PyTorch, which implements the SageMaker distributed model parallel library v1.6.0 or later.

For each of the following features, you keep the same two-step workflow shown in the Run a SageMaker Distributed Training Job with Model Parallelism (p. 2522) section and add few additional parameters and code lines to the SageMaker PyTorch estimator and your training script.

To find an example of how to use the extended features, see Train GPT-2 with PyTorch 1.8.1 and Tensor Parallelism Using the SageMaker Model Parallelism Library.

**Topics**
- Tensor Parallelism (p. 2541)
- Optimizer State Sharding (p. 2551)
- Activation Checkpointing (p. 2552)
- Activation Offloading (p. 2553)
- Ranking Mechanism (p. 2554)
Tensor Parallelism

Tensor parallelism is a type of model parallelism in which specific model weights, gradients, and optimizer states are split across devices. In contrast to pipeline parallelism, which keeps individual weights intact but partitions the set of weights, tensor parallelism splits individual weights. This typically involves distributed computation of specific operations, modules, or layers of the model.

Tensor parallelism is required in cases in which a single parameter consumes most of the GPU memory (such as large embedding tables with a large vocabulary size or a large softmax layer with a large number of classes). In this case, treating this large tensor or operation as an atomic unit is inefficient and impedes balance of the memory load.

Tensor parallelism is also useful for extremely large models in which a pure pipelining is simply not enough. For example, with GPT-3-scale models that require partitioning over tens of instances, a pure microbatch pipelining is inefficient because the pipeline depth becomes too high and the overhead becomes prohibitively large.

Topics

- How Tensor Parallelism Works (p. 2541)
- Run a SageMaker Distributed Model Parallel Training Job with Tensor Parallelism (p. 2543)
- Instructions for Checkpointing with Tensor Parallelism (p. 2547)
- Support for Hugging Face Transformer Models (p. 2549)

How Tensor Parallelism Works

Tensor parallelism takes place at the level of `nn.Module`; it partitions specific modules in the model across tensor parallel ranks. This is in addition to the existing partition of the set of modules used in pipeline parallelism.

When a module is partitioned through tensor parallelism, its forward and backward propagation are distributed. The library handles the necessary communication across devices to implement the distributed execution of these modules. The modules are partitioned across multiple data parallel ranks. Contrary to the traditional distribution of workloads, each data parallel rank does not have the complete model replica when the library's tensor parallelism is used. Instead, each data parallel rank may have only a partition of the distributed modules, in addition to the entirety of the modules that are not distributed.

Example: Consider tensor parallelism across data parallel ranks, where the degree of data parallelism is 4 and the degree of tensor parallelism is 2. Assume that you have a data parallel group that holds the following module tree, after partitioning the set of modules.

```
A
|   
|   
|   
|### D
|   
### C
|   
### F
|   
### E
|   
### B
```

Assume that tensor parallelism is supported for the modules B, G, and H. One possible outcome of tensor parallel partition of this model could be:
dp_rank 0 (tensor parallel rank 0): A, B:0, C, D, G:0, H
dp_rank 1 (tensor parallel rank 1): A, B:1, C, D, G:1, H
dp_rank 2 (tensor parallel rank 0): A, B:0, C, D, G:0, H
dp_rank 3 (tensor parallel rank 1): A, B:1, C, D, G:1, H

Each line represents the set of modules stored in that dp_rank, and the notation X:y represents the yth fraction of the module X. Note the following:

1. Partitioning takes place across subsets of data parallel ranks, which we call TP_GROUP, not the entire DP_GROUP, so that the exact model partition is replicated across dp_rank 0 and dp_rank 2, and similarly across dp_rank 1 and dp_rank 3.
2. The modules E and F are no longer part of the model, since their parent module B is partitioned, and any execution that is normally a part of E and F takes place within the (partitioned) B module.
3. Even though H is supported for tensor parallelism, in this example it is not partitioned, which highlights that whether to partition a module depends on user input. The fact that a module is supported for tensor parallelism does not necessarily mean it is partitioned.

How the library adapts tensor parallelism to PyTorch’s nn.Linear module

When tensor parallelism is performed over data parallel ranks, a subset of the parameters, gradients, and optimizer states are partitioned across the tensor parallel devices for the modules that are partitioned. For the rest of the modules, the tensor parallel devices operate in a regular data parallel manner. To execute the partitioned module, a device first collects the necessary parts of all data samples across peer devices in the same tensor parallelism group. The device then runs the local fraction of the module on all these data samples, followed by another round of synchronization which both combines the parts of the output for each data sample and returns the combined data samples to the GPUs from which the data sample first originated. The following figure shows an example of this process over a partitioned nn.Linear module.
The first figure shows a small model with a large `nn.Linear` module with data parallelism over the two tensor parallelism ranks. The `nn.Linear` module is replicated into the two parallel ranks.

The second figure shows tensor parallelism applied on a larger model while splitting the `nn.Linear` module. Each `tp_rank` holds half the linear module, and the entirety of the rest of the operations. While the linear module runs, each `tp_rank` collects the relevant half of all data samples and passes it through their half of the `nn.Linear` module. The result needs to be reduce-scattered (with summation as the reduction operation) so that each rank has the final linear output for their own data samples. The rest of the model runs in the typical data parallel manner.

**Run a SageMaker Distributed Model Parallel Training Job with Tensor Parallelism**

In this section, you learn:

- How to configure a SageMaker PyTorch estimator and the SageMaker distributed model parallelism option to use tensor parallelism.
- How to adapt your training script using the extended `smdistributed.modelparallel` modules for tensor parallelism.

To learn more about the `smdistributed.modelparallel` modules, see the [SageMaker distributed model parallel APIs](https://sagemaker.readthedocs.io/en/stable/) in the *SageMaker Python SDK documentation*.

**Topics**

- Tensor parallelism alone (p. 2543)
- Tensor parallelism combined with pipeline parallelism (p. 2545)

**Tensor parallelism alone**

The following is an example of a distributed training option to activate tensor parallelism alone, without pipeline parallelism. Configure the `mpi_options` and `smp_options` dictionaries to specify distributed training options to the SageMaker PyTorch estimator.

**Note**

Extended memory-saving features are available through Deep Learning Containers for PyTorch, which implements the SageMaker distributed model parallel library v1.6.0 or later.

**Configure a SageMaker PyTorch estimator**

```python
mpi_options = {
    "enabled": True,
    "processes_per_host": 8,  # 8 processes
    "custom_mpi_options": "--mca btl_vader_single_copy_mechanism none"
}

smp_options = {
    "enabled": True,
    "parameters": {
        "pipeline_parallel_degree": 1,  # alias for "partitions"
        "placement_strategy": "cluster",
        "tensor_parallel_degree": 4,  # tp over 4 devices
        "ddp": True
    }
}

smp_estimator = PyTorch(
    entry_point='your_training_script.py',  # Specify
    role=role,
    instance_type='ml.p3.16xlarge',
    sagemaker_session=sagemaker_session,
    2543
)"
framework_version='1.12.0',
py_version='py36',
instance_count=1,
distribution={
    "smdistributed": {"modelparallel": smp_options},
    "mpi": mpi_options
},
base_job_name="SMD-MP-demo",
)
smp_estimator.fit('s3://my_bucket/my_training_data/')

Tip
To find a complete list of parameters for distribution, see Configuration Parameters for Model Parallelism in the SageMaker Python SDK documentation.

Adapt your PyTorch training script

The following example training script shows how to adapt the SageMaker distributed model parallelism library to a training script. In this example, it is assumed that the script is named your_training_script.py.

```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchnet.dataset import SplitDataset
from torchvision import datasets
import smdistributed.modelparallel.torch as smp

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, 3, 1)
        self.conv2 = nn.Conv2d(32, 64, 3, 1)
        self.fc1 = nn.Linear(9216, 128)
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = self.conv1(x)
        x = F.relu(x)
        x = self.conv2(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2)
        x = torch.flatten(x, 1)
        x = self.fc1(x)
        x = F.relu(x)
        x = self.fc2(x)
        return F.log_softmax(x, 1)

    def train(model, device, train_loader, optimizer):
        model.train()
        for batch_idx, (data, target) in enumerate(train_loader):
            data, target = data.to(device), target.to(device)
            optimizer.zero_grad()
            output = model(data)
            loss = F.nll_loss(output, target, reduction="mean")
            loss.backward()
            optimizer.step()

            # smdistributed: Initialize the backend
```
# smp.init(): Set the device to the GPU ID used by the current process.
# Input tensors should be transferred to this device.
torch.cuda.set_device(smp.local_rank())
device = torch.device("cuda")

# smpdistributed: Download only on a single process per instance.
# When this is not present, the file is corrupted by multiple processes trying
# to download and extract at the same time
if smp.local_rank() == 0:
    dataset = datasets.MNIST("../data", train=True, download=False)
smp.barrier()

# smpdistributed: Shard the dataset based on data parallel ranks
if smp.dp_size() > 1:
    partitions_dict = {f"{i}": 1 / smp.dp_size() for i in range(smp.dp_size())}
dataset = SplitDataset(dataset, partitions=partitions_dict)
dataset.select(f"{smp.dp_rank()}")

train_loader = torch.utils.data.DataLoader(dataset, batch_size=64)

# smpdistributed: Enable tensor parallelism for all supported modules in the model
# i.e., nn.Linear in this case. Alternatively, we can use
# smp.set_tensor_parallelism(model.fc1, True)
# to enable it only for model.fc1
with smp.tensor_parallelism():
    model = Net()

# smpdistributed: Use the DistributedModel wrapper to distribute the
# modules for which tensor parallelism is enabled
model = smp.DistributedModel(model)

optimizer = optim.AdaDelta(model.parameters(), lr=4.0)
optimizer = smp.DistributedOptimizer(optimizer)

train(model, device, train_loader, optimizer)

**Tensor parallelism combined with pipeline parallelism**

The following is an example of a distributed training option that enables tensor parallelism combined
with pipeline parallelism. Set up the mpi_options and smp_options parameters to specify distributed
model parallel options with tensor parallelism when you configure a SageMaker PyTorch estimator.

**Note**

Extended memory-saving features are available through Deep Learning Containers for PyTorch,
which implements the SageMaker distributed model parallel library v1.6.0 or later.

**Configure a SageMaker PyTorch estimator**

```python
mpi_options = {
    "enabled": True,
    "processes_per_host": 8,  # 8 processes
    "custom_mpi_options": "--mca btl_vader_single_copy_mechanism none "
}

smp_options = {
    "enabled": True,
    "parameters": {
        "microbatches": 4,
        "pipeline_parallel_degree": 2,  # alias for "partitions"
        "placement_strategy": "cluster",
        "tensor_parallel_degree": 2,  # tp over 2 devices
        "ddp": True
    }
```

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Adapt your PyTorch training script

The following example training script shows how to adapt the SageMaker distributed model parallelism library to a training script. Note that the training script now includes the `smp.step` decorator:

```python
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets
import smdistributed.modelparallel.torch as smp

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, 3, 1)
        self.conv2 = nn.Conv2d(32, 64, 3, 1)
        self.fc1 = nn.Linear(9216, 128)
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = self.conv1(x)
        x = F.relu(x)
        x = self.conv2(x)
        x = F.relu(x)
        x = F.max_pool2d(x, 2)
        x = torch.flatten(x, 1)
        x = self.fc1(x)
        x = F.relu(x)
        x = self.fc2(x)
        return F.log_softmax(x, 1)

    @smp.step
    def train_step(model, data, target):
        output = model(data)
        loss = F.nll_loss(output, target, reduction="mean")
        model.backward(loss)
        return output, loss

def train(model, device, train_loader, optimizer):
    # Training loop
    for batch in train_loader:
        data, target = batch
        data, target = data.to(device), target.to(device)
        optimizer.zero_grad()
        output, loss = model.train_step(data, target)
        loss.backward()
        optimizer.step()
```

```
model.train()
  for batch_idx, (data, target) in enumerate(train_loader):
    data, target = data.to(device), target.to(device)
    optimizer.zero_grad()
    _, loss_mb = train_step(model, data, target)
    loss = loss_mb.reduce_mean()
    optimizer.step()

# smdistributed: Initialize the backend
smp.init()

# smdistributed: Set the device to the GPU ID used by the current process.
# Input tensors should be transferred to this device.
torch.cuda.set_device(smp.local_rank())
device = torch.device("cuda")

# smdistributed: Download only on a single process per instance.
# When this is not present, the file is corrupted by multiple processes trying
# to download and extract at the same time
if smp.local_rank() == 0:
  dataset = datasets.MNIST("../data", train=True, download=False)
smp.barrier()

# smdistributed: Shard the dataset based on data parallel ranks
if smp.dp_size() > 1:
  partitions_dict = {f"{i}": 1 / smp.dp_size() for i in range(smp.dp_size())}
  dataset = SplitDataset(dataset, partitions=partitions_dict)
  dataset.select(f"{smp.dp_rank()}"

# smdistributed: Set drop_last=True to ensure that batch size is always divisible
# by the number of microbatches
train_loader = torch.utils.data.DataLoader(dataset, batch_size=64, drop_last=True)

model = Net()

# smdistributed: enable tensor parallelism only for model.fc1
smp.set_tensor_parallelism(model.fc1, True)

# smdistributed: Use the DistributedModel container to provide the model
# to be partitioned across different ranks. For the rest of the script,
# the returned DistributedModel object should be used in place of
# the model provided for DistributedModel class instantiation.
model = smp.DistributedModel(model)

optimizer = optim.AdaDelta(model.parameters(), lr=4.0)
optimizer = smp.DistributedOptimizer(optimizer)
train(model, device, train_loader, optimizer)

Instructions for Checkpointing with Tensor Parallelism

The SageMaker model parallel library supports saving partial or full checkpoints with tensor parallelism. The following guide shows how to modify your script to save and load a checkpoint when you use tensor parallelism.

1. Prepare a model object and wrap it with the library's wrapper function smp.DistributedModel().

```python
model = MyModel(...)```

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model = smp.DistributedModel(model)

2. Prepare an optimizer for the model. A set of model parameters is an iterable argument required by optimizer functions. To prepare a set of model parameters, you must process `model.parameters()` to assign unique IDs to individual model parameters.

If there are parameters with duplicated IDs in the model parameter iterable, loading the checkpointed optimizer state fails. To create an iterable of model parameters with unique IDs for your optimizer, see the following:

```python
unique_params = []
unique_params_set = set()
for p in model.parameters():
    if p not in unique_params_set:
        unique_params.append(p)
        unique_params_set.add(p)
del unique_params_set
optimizer = MyOpt(unique_params, ...)
```

3. Wrap the optimizer using the library's wrapper function `smp.DistributedOptimizer()`.

```python
optimizer = smp.DistributedOptimizer(optimizer)
```

4. Save the model and the optimizer state using `smp.save()`. Depending on how you want to save checkpoints, choose one of the following two options:

- **Option 1**: Save a partial model on each `mp_rank` for a single `MP_GROUP`.

```python
model_dict = model.local_state_dict()  # save a partial model
opt_dict = optimizer.local_state_dict()  # save a partial optimizer state
# Save the dictionaries at rdp_rank 0 as a checkpoint
if smp.rdp_rank() == 0:
    smp.save(
        {"model_state_dict": model_dict, "optimizer_state_dict": opt_dict},
        f"checkpoint.pt",
        partial=True,
    )
```

With tensor parallelism, the library saves checkpointed files named in the following format: `checkpoint.pt_{pp_rank}_{tp_rank}`.

**Note**

With tensor parallelism, make sure you set the `if` statement as `if smp.rdp_rank() == 0` instead of `if smp.dp_rank() == 0`. When the optimizer state is sharded with tensor parallelism, all reduced-data parallel ranks must save their own partition of the optimizer state. Using a wrong `if` statement for checkpointing might result in a stalling training job. For more information about using `if smp.dp_rank() == 0` without tensor parallelism, see General Instruction for Saving and Loading in the SageMaker Python SDK documentation.

- **Option 2**: Save the full model.

```python
if smp.rdp_rank() == 0:
    model_dict = model.state_dict(gather_to_rank0=True)  # save the full model
if smp.rank() == 0:
    smp.save(
        {"model_state_dict": model_dict},
        "checkpoint.pt",
        partial=False,
    )
```
Note
Consider the following for full checkpointing:

- If you set `gather_to_rank0=True`, all ranks other than 0 return empty dictionaries.
- For full checkpointing, you can only checkpoint the model. Full checkpointing of optimizer states is currently not supported.
- The full model only needs to be saved at `smp.rank() == 0`.

5. Load the checkpoints using `smp.load()`. Depending on how you checkpointed in the previous step, choose one of the following two options:

- **Option 1**: Load the partial checkpoints.

```python
checkpoint = smp.load("/checkpoint.pt", partial=True)
model.load_state_dict(checkpoint["model_state_dict"], same_partition_load=False)
optimizer.load_state_dict(checkpoint["optimizer_state_dict"])
```

You can set `same_partition_load=True` in `model.load_state_dict()` for a faster load, if you know that the partition will not change.

- **Option 2**: Load the full checkpoints.

```python
if smp.rdp_rank() == 0:
    checkpoint = smp.load("/checkpoint.pt", partial=False)
    model.load_state_dict(checkpoint["model_state_dict"])
```

The `if smp.rdp_rank() == 0` condition is not required, but it can help avoid redundant loading among different MP_GROUPS. Full checkpointing optimizer state dict is currently not supported with tensor parallelism.

Support for Hugging Face Transformer Models

The SageMaker model parallel library's tensor parallelism offers out-of-the-box support for the following Hugging Face Transformer models:

- GPT-2, BERT, and RoBERTa (Available in the SageMaker model parallel library v1.7.0 and later)
- GPT-J (Available in the SageMaker model parallel library v1.8.0 and later)
- GPT-Neo (Available in the SageMaker model parallel library v1.10.0 and later)

Note
For any other Transformers models, you need to use the `smdistributed.modelparallel.torch.tp_register_with_module()` API to apply tensor parallelism.

Note
To use tensor parallelism for training Hugging Face Transformer models, make sure you use Hugging Face Deep Learning Containers for PyTorch that has the SageMaker model parallel library v1.7.0 and later. For more information, see the [SageMaker model parallel library release notes](#).

Supported Models Out of the Box

For the Hugging Face transformer models supported by the library out of the box, you don't need to manually implement hooks to translate Transformer APIs to `smdistributed` transformer layers. You can activate tensor parallelism by using the context manager `smdistributed.modelparallel.torch.tensor_parallelism()` and wrapping the model by `smdistributed.modelparallel.torch.DistributedModel()`. You don't need to manually register hooks for tensor parallelism using the `smp.tp_register` API.
The `state_dict` translation functions between Hugging Face Transformers and smdistributed.modelparallel can be accessed as follows.

- `smdistributed.modelparallel.torch.nn.huggingface.gpt2.translate_state_dict_to_hf_gpt2(state_dict, max_seq_len=None)`
- `smdistributed.modelparallel.torch.nn.huggingface.gpt2.translate_hf_state_dict_to_smdistributed_gpt2(state_dict)` (Available in the SageMaker model parallel library v1.8.0 and later)
- `smdistributed.modelparallel.torch.nn.huggingface.bert.translate_state_dict_to_hf_bert(state_dict, max_seq_len=None)`
- `smdistributed.modelparallel.torch.nn.huggingface.bert.translate_hf_state_dict_to_smdistributed_bert(state_dict)` (Available in the SageMaker model parallel library v1.10.0 and later)
- `smdistributed.modelparallel.torch.nn.huggingface.roberta.translate_state_dict_to_hf_roberta(state_dict, max_seq_len=None)`
- `smdistributed.modelparallel.torch.nn.huggingface.roberta.translate_hf_state_dict_to_smdistributed_roberta(state_dict)` (Available in the SageMaker model parallel library v1.10.0 and later)
- `smdistributed.modelparallel.torch.nn.huggingface.gptj.translate_state_dict_to_hf_gptj(state_dict, max_seq_len=None)` (Available in the SageMaker model parallel library v1.8.0 and later)
- `smdistributed.modelparallel.torch.nn.huggingface.gptj.translate_hf_gptj_state_dict_to_smdistributed_gptj(state_dict)` (Available in the SageMaker model parallel library v1.10.0 and later)
- `smdistributed.modelparallel.torch.nn.huggingface.gptneo.translate_state_dict_to_hf_gptneo(state_dict, max_seq_len=None)` (Available in the SageMaker model parallel library v1.10.0 and later)
- `smdistributed.modelparallel.torch.nn.huggingface.gptneo.translate_hf_atlas_state_dict_to_smdistributed_gptneo(state_dict)` (Available in the SageMaker model parallel library v1.10.0 and later)

**Example usage of the GPT-2 translation function**

Start with wrapping the model as shown in the following code.

```python
from transformers import AutoModelForCausalLM
with smp.tensor_parallelism():
    model = AutoModelForCausalLM.from_config(hf_gpt2_config)
model = smp.DistributedModel(model)
```

Given a `state_dict` from the `DistributedModel` object, you can load the weights into the original Hugging Face GPT-2 model using the `translate_state_dict_to_hf_gpt2` function as shown in the following code.

```python
from smdistributed.modelparallel.torch.nn.huggingface.gpt2 import translate_state_dict_to_hf_gpt2
max_seq_len = 1024
# [...] code block for training [...]$
if smp.rdp_rank() == 0:
    state_dict = dist_model.state_dict()
    hf_state_dict = translate_state_dict_to_hf_gpt2(state_dict, max_seq_len)
    # can now call model.load_state_dict(hf_state_dict) to the original HF model
```

**Example usage of the RoBERTa translation function**

Similarly, given a supported HuggingFace model `state_dict`, you can use the `translate_hf_state_dict_to_smdistributed` function to convert it to a format readable by `smp.DistributedModel`. This can be useful in transfer learning use cases, where a pre-trained model is loaded into a `smp.DistributedModel` for model-parallel fine-tuning:
from smdistributed.modelparallel.torch.nn.huggingface.roberta import translate_state_dict_to_smdistributed
model = AutoModelForMaskedLM.from_config(roberta_config)
model = smp.DistributedModel(model)
pretrained_model = AutoModelForMaskedLM.from_pretrained("roberta-large")
translated_state_dict = translate_state_dict_to_smdistributed(pretrained_model.state_dict())
# load the translated pretrained weights into the smp.DistributedModel
model.load_state_dict(translated_state_dict)
# start fine-tuning...

### Optimizer State Sharding

Optimizer state sharding is a useful memory-saving technique that shards the optimizer state (the set of weights that describes the state of optimizer) across data parallel device groups. You can use optimizer state sharding whenever you use a stateful optimizer (such as Adam) or an FP16 optimizer (which stores both FP16 and FP32 copies of the parameters).

#### How to Use Optimizer State Sharding

You can turn on optimizer state sharding by setting "shard_optimizer_state": True in the modelparallel configuration.

When this feature is turned on, the library partitions the set of model parameters based on the data parallelism degree. The gradients corresponding to the ith partition get reduced only at the ith data parallel rank. At the end of the first call to an smp.step decorator function, the optimizer wrapped by smp.DistributedOptimizer redefines its parameters to be only limited to those parameters corresponding to the partition of the current data parallel rank. The redefined parameters are called virtual parameters and share underlying storage with the original parameters. During the first call to optimizer.step, the optimizer states are created based on these redefined parameters, which are sharded because of the original partition. After the optimizer update, the AllGather operation (as part of the optimizer.step call) runs across the data parallel ranks to achieve consistent parameter states.

**Tip**

Optimizer state sharding can be useful when the degree of data parallelism is greater than 1 and the model has more than a billion parameters.

The degree of data parallelism is calculated by (processes_per_host * instance_count / pipeline_parallel_degree), and the smp.dp_size() function handles the sizing in the background.

#### Configure a SageMaker PyTorch estimator

```python
tpl_options = {
    "enabled": True,
    "processes_per_host": 8,  # 8 processes
    "custom_mpi_options": "--mca btl_vader_single_copy_mechanism none "
}
smp_options = {
    "enabled": True,
    "parameters": {
        "microbatches": 4,
        "pipeline_parallel_degree": 2,  # alias for "partitions"
        "placement_strategy": "cluster",
        "tensor_parallel_degree": 2,  # tp over 2 devices
        "ddp": True,
    }
}
Adapt your PyTorch training script

See Adapt your PyTorch training script (p. 2546) in the Tensor parallelism combined with pipeline parallelism section. There's no additional modification required for the script.

Activation Checkpointing

Activation checkpointing (or gradient checkpointing) is a technique to reduce memory usage by clearing activations of certain layers and recomputing them during a backward pass. Effectively, this trades extra computation time for reduced memory usage. If a module is checkpointed, at the end of a forward pass, the inputs to and outputs from the module stay in memory. Any intermediate tensors that would have been part of the computation inside that module are freed up during the forward pass. During the backward pass of checkpointed modules, these tensors are recomputed. At this point, the layers beyond this checkpointed module have finished their backward pass, so the peak memory usage with checkpointing can be lower.

How to Use Activation Checkpointing

With `smdistributed.modelparallel`, you can use activation checkpointing at the granularity of a module. For all `torch.nn` modules except `torch.nn.Sequential`, you can only checkpoint a module tree if it lies within one partition from the perspective of pipeline parallelism. In case of the `torch.nn.Sequential` module, each module tree inside the sequential module must lie completely within one partition for activation checkpointing to work. When you use manual partitioning, be aware of these restrictions.

When you use automated model partitioning, you can find the partitioning assignment logs starting with `Partition assignments:` in the training job logs. If a module is partitioned across multiple ranks (for example, with one descendant on one rank and another descendant on a different rank), the library ignores the attempt to checkpoint the module and raises a warning message that the module won't be checkpointed.

Note

The SageMaker model parallel library supports both overlapping and non-overlapping allreduce operation in combination with checkpointing.

Note

PyTorch's native checkpointing API is not compatible with `smdistributed.modelparallel`.

Example 1: The following sample code shows how to use activation checkpointing when you have a model definition in your script.

```python
import torch.nn as nn
import torch.nn.functional as F
from smdistributed.modelparallel.torch.patches.checkpoint import checkpoint

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, 3, 1)
        self.conv2 = nn.Conv2d(32, 64, 3, 1)
        self.fc1 = nn.Linear(9216, 128)
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = F.relu(self.conv2(x))
        x = x.view(-1, 9216)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x
```
Example 2: The following sample code shows how to use activation checkpointing when you have a sequential model in your script.

```python
import torch.nn as nn
from smdistributed.modelparallel.torch.patches.checkpoint import checkpoint_sequential

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.seq = nn.Sequential(
            nn.Conv2d(1,20,5),
            nn.ReLU(),
            nn.Conv2d(20,64,5),
            nn.ReLU()
        )

    def forward(self, x):
        # This call of self.seq will be checkpointed
        x = checkpoint_sequential(self.seq, x)
        return F.log_softmax(x, 1)
```

Example 3: The following sample code shows how to use activation checkpointing when you import a prebuilt model from a library, such as PyTorch and Hugging Face Transformers. Whether you checkpoint sequential modules or not, do the following:

1. Wrap the model by `smp.DistributedModel()`.
2. Define an object for sequential layers.
3. Wrap the sequential layer object by `smp.set_activation_checkpointing()`.

```python
import smdistributed.modelparallel.torch as smp
from transformers import AutoModelForCausalLM
smp.init()
model = AutoModelForCausalLM(*args, **kwargs)
model = smp.DistributedModel(model)
# Call set_activation_checkpointing API
transformer_layers = model.module.module.module.transformer.seq_layers
smp.set_activation_checkpointing(
    transformer_layers, pack_args_as_tuple=True, strategy='each')
```

**Activation Offloading**

When activation checkpointing and pipeline parallelism are turned on and the number of microbatches is greater than one, activation offloading is an additional feature that can further reduce memory usage. Activation offloading asynchronously moves the checkpointed activations corresponding to their microbatches that are not currently running in the CPU. Right before the GPU needs the activations for the microbatch's backward pass, this functionality prefetches the offloaded activations back from the CPU.
How to Use Activation Offloading

Use activation offloading to reduce memory usage when the number of microbatches is greater than 1, and activation checkpointing is turned on (see Activation Checkpointing (p. 2552)). When the activation checkpointing is not used, activation offloading has no effect. When it is used with only one microbatch, it does not save memory.

To use activation offloading, set "offload_activations": True in the modelparallel configuration.

Activation offloading moves the checkpointed activations in nn.Sequential modules to CPU asynchronously. The data transfer over the PCIe link overlaps with GPU computation. The offloading happens immediately, as soon as the forward pass for a particular checkpointed layer is computed. The activations are loaded back to the GPU shortly before they are needed for the backward pass of a particular microbatch. The CPU-GPU transfer similarly overlaps with computation.

To adjust how early the activations are loaded back into the GPU, you can use the configuration parameter "activation_loading_horizon" (default is set to 4, must be int larger than 0). A larger activation loading horizon would cause the activations to be loaded back to the GPU earlier. If the horizon is too large, the memory-saving impact of activation offloading might be diminished. If the horizon is too small, the activations may not be loaded back in time, reducing the amount of overlap and degrading performance.

Tip
Activation offloading can be useful for large models with over a hundred billion parameters.

Configure a SageMaker PyTorch estimator

```python
mpi_options = {
    "enabled": True,
    "processes_per_host": 8, # 8 processes
    "custom_mpi_options": "--mca btl_vader_single_copy_mechanism none "
}

smp_options = {
    "enabled": True,
    "parameters": {
        "microbatches": 4,
        "pipeline_parallel_degree": 2, # alias for "partitions"
        "placement_strategy": "cluster",
        "tensor_parallel_degree": 2, # tp over 2 devices
        "ddp": True,
        "offload_activations": True,
        "activation_loading_horizon": 4 # optional. default is 4.
    }
}
```

Ranking Mechanism

This section explains how the ranking mechanism of model parallelism works with tensor parallelism. This is extended from the Ranking Basics for Core Features of the SageMaker Model Parallel Library (p. 2518). With tensor parallelism, the library introduces three types of ranking and process group APIs: smp.tp_rank() for tensor parallel rank, smp.pp_rank() for pipeline parallel rank, and smp.rdp_rank() for reduced-data parallel rank. The corresponding communication process groups are tensor parallel group (TP_GROUP), pipeline parallel group (PP_GROUP), and reduced-data parallel group (RDP_GROUP). These groups are defined as follows:

- A tensor parallel group (TP_GROUP) is an evenly divisible subset of the data parallel group, over which tensor parallel distribution of modules takes place. When the degree of pipeline parallelism is 1, TP_GROUP is the same as model parallel group (MP_GROUP).
• A pipeline parallel group (PP_GROUP) is the group of processes over which pipeline parallelism takes place. When the tensor parallelism degree is 1, PP_GROUP is the same as MP_GROUP.

• A reduced-data parallel group (RDP_GROUP) is a set of processes that hold both the same pipeline parallelism partitions and the same tensor parallel partitions, and perform data parallelism among themselves. This is called the reduced data parallel group because it is a subset of the entire data parallelism group, DP_GROUP. For the model parameters that are distributed within the TP_GROUP, the gradient allreduce operation is performed only for reduced-data parallel group, while for the parameters that are not distributed, the gradient allreduce takes place over the entire DP_GROUP.

• A model parallel group (MP_GROUP) refers to a group of processes that collectively store the entire model. It consists of the union of the PP_GROUPs of all the ranks that are in the TP_GROUP of the current process. When the degree of tensor parallelism is 1, MP_GROUP is equivalent to PP_GROUP. It is also consistent with the existing definition of MP_GROUP from previous smdistributed releases. Note that the current TP_GROUP is a subset of both the current DP_GROUP and the current MP_GROUP.

To learn more about the communication process APIs in the SageMaker distributed model parallelism library, see the Common API and the PyTorch-specific APIs in the SageMaker Python SDK documentation.

This figure shows ranking mechanism, parameter distribution, and associated AllReduce operations of tensor parallelism.

For example, consider process groups for a single node with 8 GPUs, where the degree of tensor parallelism is 2, the degree of pipeline parallelism is 2, and the degree of data parallelism is 4. The upper center part of the preceding figure shows an example of a model with 4 layers. The lower left and lower right parts of figure illustrate the 4-layer model distributed across 4 GPUs using both pipeline parallelism and tensor parallelism, where tensor parallelism is used for the middle two layers. These two lower figures are simple copies to illustrate different group boundary lines. The partitioned model is replicated for data parallelism across GPUs 0-3 and 4-7. The lower left figure shows the definitions of MP_GROUP,
PP\_GROUP, and TP\_GROUP. The lower right figure shows RDP\_GROUP, DP\_GROUP, and WORLD over the same set of GPUs. The gradients for the layers and layer slices that have the same color are allreduced together for data parallelism. For example, the first layer (light blue) gets the allreduce operations across DP\_GROUP, whereas the dark orange slice in the second layer only gets the allreduce operations within the RDP\_GROUP of its process. The bold dark red arrows represent tensors with the batch of its entire TP\_GROUP.

| GPU0: pp_rank 0, tp_rank 0, rdp_rank 0, dp_rank 0, mp_rank 0 |
| GPU1: pp_rank 1, tp_rank 0, rdp_rank 0, dp_rank 0, mp_rank 1 |
| GPU2: pp_rank 0, tp_rank 1, rdp_rank 0, dp_rank 1, mp_rank 2 |
| GPU3: pp_rank 1, tp_rank 1, rdp_rank 0, dp_rank 1, mp_rank 3 |
| GPU4: pp_rank 0, tp_rank 0, rdp_rank 1, dp_rank 2, mp_rank 0 |
| GPU5: pp_rank 1, tp_rank 0, rdp_rank 1, dp_rank 2, mp_rank 1 |
| GPU6: pp_rank 0, tp_rank 1, rdp_rank 1, dp_rank 3, mp_rank 2 |
| GPU7: pp_rank 1, tp_rank 1, rdp_rank 1, dp_rank 3, mp_rank 3 |

In this example, pipeline parallelism occurs across the GPU pairs (0,1); (2,3); (4,5) and (6,7). In addition, data parallelism (allreduce) takes place across GPUs 0, 2, 4, 6, and independently over GPUs 1, 3, 5, 7. Tensor parallelism happens over subsets of DP\_GROUPs, across the GPU pairs (0,2); (1,3); (4,6) and (5,7).

**FP16 Training with Model Parallelism**

For FP16 training, apply the following modifications to your training script and estimator.

**Note**

This feature is available in the SageMaker model parallel library v1.10.0 and later.

**Adapt your PyTorch training script**

1. Wrap your model using the `smdistributed.modelparallel.torch.model_creation()` context manager.

```python
# fp16_training_script.py
import torch
import smdistributed.modelparallel.torch as smp

with smp.model_creation(
    dtype=torch.float16 if args.fp16 else torch.get_default_dtype()
):
    model = ... 
```

**Tip**

If you are using tensor parallelism, add `tensor_parallelism=smp.tp_size() > 1` to the `smp.model_creation` context manager. Adding this line also helps automatically detect whether tensor parallelism is activated or not.

```python
with smp.model_creation(
    ...,
    tensor_parallelism=smp.tp_size() > 1
):
    model = ... 
```

2. When you wrap the optimizer with `smdistributed.modelparallel.torch.DistributedOptimizer`, set either the static_loss_scaling or dynamic_loss_scaling argument. By default, static_loss_scaling is set to 1.0, and dynamic_loss_scaling is set to False. If you set `dynamic_loss_scale=True`, you can feed dynamic loss scaling options as a dictionary through the dynamic_loss_args argument. In most cases, we recommend you use dynamic loss scaling with the
default options. For more information, options, and examples of the optimizer wrapper function, see the smdistributed.modelparallel.torch.DistributedOptimizer API.

The following code is an example of wrapping an Adadelta optimizer object with dynamic loss scaling for FP16 training.

```python
optimizer = torch.optim.Adadelta(...)
optimizer = smp.DistributedOptimizer(
    optimizer,
    static_loss_scale=None,
    dynamic_loss_scale=True,
    dynamic_loss_args={
        "scale_window": 1000,
        "min_scale": 1,
        "delayed_shift": 2
    }
)
```

**Configure a SageMaker PyTorch estimator**

Add the FP16 parameter ("fp16") to the distribution configuration for model parallelism when creating a SageMaker PyTorch estimator object. For a complete list of the configuration parameters for model parallelism, see Parameters for smdistributed.

```python
from sagemaker.pytorch import PyTorch
smp_options = {
    "enabled": True,
    "parameters": {
        "microbatches": 4,
        "pipeline_parallel_degree": 2,
        "tensor_parallel_degree": 2,
        ...

        "fp16": True
    }
}
fp16_estimator = PyTorch(
    entry_point="fp16_training_script.py", # Specify your train script
    ...

distribution={
    "smdistributed": smp_options,
    "mpi": {...}
}
)
fp16_estimator.fit(...)"
Tip
When using `torch.optim.lr_scheduler` and FP16 training, you need to pass `optimizer.optimizer` to the LR scheduler rather than the optimizer. See the following example code.

```python
from torch.optim.lr_scheduler import StepLR

scheduler = StepLR(
    optimizer.optimizer if smp.state.cfg.fp16 else optimizer,
    step_size=1,
    gamma=args.gamma
)
```

**Checkpointing Distributed Models and Optimizer States**

The SageMaker model parallel library provides checkpoint APIs to save and load distributed models and optimizer states.

**Note**
This feature is available in the SageMaker model parallel library v1.10.0 and later.

To save a checkpoint of a model trained with model parallelism, use the `smdistributed.modelparallel.torch.save_checkpoint` API with the partial checkpointing (partial=True) that saves each model partition individually. In addition to the model and the optimizer state, you can also save any additional custom data through the `user_content` argument.

The checkpointed model, optimizer, and user content are saved as separate files. The `save_checkpoint` API call creates checkpoint folders in the following structure.

```
- path
  - ${tag}_partial (folder for partial checkpoints)
    - model_rankinfo.pt
    - optimizer_rankinfo.pt
    - fp16_states_rankinfo.pt
    - user_content.pt
  - $tag (checkpoint file for full checkpoints)
  - user_content_$tag (user_content file for full checkpoints)
  - newest (a file that indicates the newest checkpoint)
```

To resume training from a checkpoint, use the `smdistributed.modelparallel.torch.resume_from_checkpoint` API with partial=True, using the checkpoint directory and the tag used while saving the checkpoint. Note that the actual loading of model weights happens after model partitioning, during the first run of the `smdistributed.modelparallel.torch.step`-decorated training step function.

When saving a partial checkpoint, the library also saves the model partition decision as files with .pt file extension. Conversely, when resuming from the partial checkpoint, the library loads the partition decision files together. Once the partition decision is loaded, you can't change the partition.

To save the final model artifact for inference purposes, use the `smdistributed.modelparallel.torch.save_checkpoint` API with partial=False, which combines the model partitions to create a single model artifact. Note that this does not combine the optimizer states.

To initialize training with particular weights, given a full model checkpoint, you can use the `smdistributed.modelparallel.torch.resume_from_checkpoint` API with partial=False. Note that this does not load optimizer states.

**Note**
With tensor parallelism, in general, the `state_dict` must be translated between the original model implementation and the `DistributedModel` implementation.
Optionally, you can provide the state_dict translation function as an argument to the smdistributed.modelparallel.torch.resume_from_checkpoint. However, for the section called “Supported Models Out of the Box” (p. 2549), the library takes care of this translation automatically.

The following code shows an example of how to use the checkpoint APIs for saving and loading a model trained with model parallelism.

```python
import smdistributed.modelparallel.torch as smp

model = ...
model = smp.DistributedModel(model)
optimizer = ...
optimizer = smp.DistributedOptimizer(optimizer)
user_content = ...  # additional custom data
checkpoint_path = "/opt/ml/checkpoint/model_parallel"

# Save a checkpoint.
smp.save_checkpoint(
    path=checkpoint_path,
    tag=f"total_steps{total_steps}",
    partial=True,
    model=model,
    optimizer=optimizer,
    user_content=user_content
    num_kept_partial_checkpoints=5
)

# Load a checkpoint.
# This automatically loads the most recently saved checkpoint.
smp_checkpoint = smp.resume_from_checkpoint(path=checkpoint_path, partial=True)
```

**Sharded Data Parallelism**

*Sharded data parallelism* is a memory-saving distributed training technique that splits the training state of a model (model parameters, gradients, and optimizer states) across GPUs in a data parallel group.

**Note**

This feature is available in the SageMaker model parallel library v1.11.0 and later.

When scaling up your training job to a large GPU cluster, you can reduce the per-GPU memory footprint of the model by sharding the training state over multiple GPUs. This returns two benefits: you can fit larger models, which would otherwise run out of memory with standard data parallelism, or you can increase the batch size using the freed-up GPU memory.

The standard data parallelism technique replicates the training states across the GPUs in the data parallel group, and performs gradient aggregation based on the AllReduce operation. Sharded data parallelism modifies the standard data-parallel distributed training procedure to account for the sharded nature of the optimizer states. A group of ranks over which the model and optimizer states are sharded is called a *sharding group*. The sharded data parallelism technique shards the trainable parameters of a model and corresponding gradients and optimizer states across the GPUs in the *sharding group*.

SageMaker implements sharded data parallelism through the MiCS implementation, which is discussed in the AWS blog post Near-linear scaling of gigantic-model training on AWS. In this implementation, you can set the sharding degree as a configurable parameter, which must be less than the data parallelism degree. During each forward and backward pass, MiCS temporarily recombines the model parameters in all GPUs through the AllGather operation. After the forward or backward pass of each layer, MiCS shards the parameters again to save GPU memory. During the backward pass, MiCS reduces gradients and simultaneously shards them across GPUs through the ReduceScatter operation. Finally, MiCS applies the local reduced and sharded gradients to their corresponding local parameter shards, using
the local shards of optimizer states. To bring down communication overhead, the SageMaker model
parallel library prefetches the upcoming layers in forward or backward pass, and overlaps the network
communication with the computation.

The training state of the model is replicated across the sharding groups. This means that before
gradients are applied to the parameters, the AllReduce operation must take place across the sharding
groups, in addition to the ReduceScatter operation that takes place within the sharding group.

In effect, sharded data parallelism introduces a tradeoff between the communication overhead and GPU
memory efficiency. Using sharded data parallelism increases the communication cost, but the memory
footprint per GPU (excluding the memory usage due to activations) is divided by the sharded data
parallelism degree, thus larger models can be fit in the GPU cluster.

The selected sharded data parallelism degree must evenly divide the data parallelism degree. For
example, for an 8-way data parallelism job, choose 2, 4, or 8 for the sharded data parallelism degree.
While choosing the sharded data parallelism degree, we recommend that you start with a small number,
and gradually increase it until the model fits in the memory together with the desired batch size.

Topics

- How to Apply Sharded Data Parallelism to Your Training Job (p. 2560)
- Mixed Precision Training with Sharded Data Parallelism (p. 2561)
- Tips and Considerations for Using Sharded Data Parallelism (p. 2562)

How to Apply Sharded Data Parallelism to Your Training Job

To use sharded data parallelism, apply the following modifications to your training script and estimator.

Adapt your PyTorch training script

Follow the instructions at Step 1: Modify a PyTorch Training Script (p. 2528) to wrap the model
and optimizer objects with the smdistributed.modelparallel.torch wrappers of the
torch.nn.parallel and torch.distributed modules.

Configure a SageMaker PyTorch estimator

As part of configuring a SageMaker PyTorch estimator in the section called “Step 2: Launch a Training
Job" (p. 2534), add the parameters for sharded data parallelism.

To turn on sharded data parallelism, add the sharded_data_parallel_degree parameter to the
SageMaker PyTorch Estimator. This parameter specifies the number of GPUs over which the training
state is sharded. The value for sharded_data_parallel_degree must be an integer between one and
the data parallelism degree and must evenly divide the data parallelism degree. Note that the library
automatically detects the number of GPUs so thus the data parallel degree. The following additional
parameters are available for configuring sharded data parallelism.

- "sdp_reduce_bucket_size" (int, default: 5e8) – Specifies the size of PyTorch DDP gradient buckets
  in number of elements of the default dtype.
- "sdp_param_persistence_threshold" (int, default: 1e6) – Specifies the size of a parameter tensor
  in number of elements that can persist at each GPU. Sharded data parallelism splits each parameter
tensor across GPUs of a data parallel group. If the number of elements in the parameter tensor
is smaller than this threshold, the parameter tensor is not split; this helps reduce communication
overhead because the parameter tensor is replicated across data-parallel GPUs.
- "sdp_max_live_parameters" (int, default: 1e9) – Specifies the maximum number of parameters
  that can simultaneously be in a recombined training state during the forward and backward pass.
  Parameter fetching with the AllGather operation pauses when the number of active parameters
  reaches the given threshold. Note that increasing this parameter increases the memory footprint.
• "sdp_hierarchical_allgather" (bool, default: True) – If set to True, the AllGather operation runs hierarchically: it runs within each node first, and then runs across nodes. For multi-node distributed training jobs, the hierarchical AllGather operation is automatically activated.
• "sdp_gradient_clipping" (float, default: 1.0) – Specifies a threshold for gradient clipping the L2 norm of the gradients before propagating them backward through the model parameters. When sharded data parallelism is activated, gradient clipping is also activated. The default threshold is 1.0. Adjust this parameter if you have the exploding gradients problem.

The following code shows an example of how to configure sharded data parallelism.

```python
import sagemaker
from sagemaker.pytorch import PyTorch

smp_options = {
    "enabled": True,
    "parameters": {
        # "pipeline_parallel_degree": 1,    # Optional, default is 1
        # "tensor_parallel_degree": 1,       # Optional, default is 1
        "ddp": True,
        # parameters for sharded data parallelism
        "sharded_data_parallel_degree": 2,    # Add this to activate sharded data parallelism
        "sdp_reduce_bucket_size": int(5e8),   # Optional
        "sdp_param_persistence_threshold": int(1e6), # Optional
        "sdp_max_live_parameters": int(1e9),  # Optional
        "sdp_hierarchical_allgather": True,   # Optional
        "sdp_gradient_clipping": 1.0          # Optional
    }
}

mpi_options = {
    "enabled": True,                     # Required
    "processes_per_host": 8              # Required
}

smp_estimator = PyTorch(
    entry_point="your_training_script.py", # Specify your train script
    role=sagemaker.get_execution_role(),
    instance_count=1,
    instance_type='ml.p3.16xlarge',
    framework_version='1.12.0',
    py_version='py36',
    distribution={
        "smdistributed": {"modelparallel": smp_options},
        "mpi": mpi_options
    },
    base_job_name="sharded-data-parallel-job"
)

smp_estimator.fit('s3://my_bucket/my_training_data/')
```
To run FP16 training with sharded data parallelism, add "fp16": True to the smp_options configuration dictionary. In your training script, you can choose between the static and dynamic loss scaling options through the smp.DistributedOptimizer module. For more information, see the section called “FP16 Training with Model Parallelism” (p. 2556).

```python
smp_options = {
    "enabled": True,
    "parameters": {
        "ddp": True,
        "sharded_data_parallel_degree": 2,
        "fp16": True
    }
}
```

For BF16 Training with Sharded Data Parallelism

The sharded data parallelism feature of SageMaker supports training in BF16 data type. The BF16 data type uses 8 bits to represent the exponent of a floating point number, while the FP16 data type uses 5 bits. Preserving the 8 bits for the exponent allows to keep the same representation of the exponent of a 32-bit single precision floating point (FP32) number. This makes the conversion between FP32 and BF16 simpler and significantly less prone to cause overflow and underflow issues that arise often in FP16 training, especially when training larger models. While both data types use 16 bits in total, this increased representation range for the exponent in the BF16 format comes at the expense of reduced precision. For training large models, this reduced precision is often considered an acceptable trade-off for the range and training stability.

**Note**
Currently, BF16 training works only when sharded data parallelism is activated.

To run BF16 training with sharded data parallelism, add "bf16": True to the smp_options configuration dictionary.

```python
smp_options = {
    "enabled": True,
    "parameters": {
        "ddp": True,
        "sharded_data_parallel_degree": 2,
        "bf16": True
    }
}
```

Tips and Considerations for Using Sharded Data Parallelism

Consider the following when using the SageMaker model parallel library's sharded data parallelism.

- Sharded data parallelism is compatible with FP16 training. To run FP16 training, see the section called “FP16 Training with Model Parallelism” (p. 2556).
- Sharded data parallelism currently is not compatible with tensor parallelism (p. 2541), pipeline parallelism (p. 2509), and optimizer state sharding (p. 2551). To activate sharded data parallelism, set tensor and pipeline parallelism degrees to 1, and turn off optimizer state sharding.

  The activation checkpointing (p. 2552) and activation offloading (p. 2553) features are compatible with sharded data parallelism.
- To use sharded data parallelism with gradient accumulation, set the backward_passes_per_step argument to the number of accumulation steps while wrapping your model with the smdistributed.modelparallel.torch.DistributedModel module. This ensures that the gradient AllReduce operation across the model replication groups (sharding groups) takes place at the boundary of gradient accumulation.
• You can checkpoint your models trained with sharded data parallelism using the library's checkpointing APIs, `smp.save_checkpoint` and `smp.resume_from_checkpoint`. For more information, see the section called “Checkpointing Distributed Models and Optimizer States” (p. 2558).

• The behavior of the `delayed_parameter_initialization` configuration parameter changes under sharded data parallelism. When these two features are simultaneously turned on, parameters are immediately initialized upon model creation in a sharded manner instead of delaying the parameter initialization, so that each rank initializes and stores its own shard of parameters.

• When sharded data parallelism is activated, the library performs gradient clipping internally when the `optimizer.step()` call runs. You don't need to use utility APIs for gradient clipping, such as `torch.nn.utils.clip_grad_norm_()`. To adjust the threshold value for gradient clipping, you can set it through the `sdp_gradient_clipping` parameter for the distribution parameter configuration when you construct the SageMaker PyTorch estimator, as shown in the the section called “How to Apply Sharded Data Parallelism to Your Training Job” (p. 2560) section.

SageMaker Distributed Model Parallel Best Practices

Use the following guidelines when you run a distributed training job with the SageMaker model parallel library.

Setting Up the Right Configuration for a Given Model

When scaling up a model, we recommend you to go over the following list in order. Each list item discusses the advantage of using the library's techniques along with the tradeoffs that might arise.

Tip

If a model can fit well using a subset of the library's features, adding more model parallelism or memory saving features does not usually improve performance.

Using large GPU instance types

• In the realm of model parallelism, it is best to use powerful instances with large GPU memories to handle overhead from model parallelism operations such as partitioning models across multiple GPUs. We recommend using `ml.p4d` or `ml.p3dn` instances for training large DL models. These instances are also equipped with Elastic Fabric Adapter (EFA), which provides higher network bandwidth and enables large-scale training with model parallelism.

Sharding optimizer state

• The impact of sharding optimizer state depends on the number of data parallel ranks. Typically, a higher degree of data parallelism (proportional to the size of compute node) can improve the efficiency of memory usage.

When you want to downsize a cluster, make sure you check the optimizer state sharding configuration. For example, a large DL model with optimizer state sharding that fits on a node with 16 GPUs won't fit on a node with 8 GPUs because there are simply not enough GPUs across which to shard the optimizer state.

For more information, see Optimizer State Sharding (p. 2551).

Activation checkpointing

• Memory efficiency can be improved by using activation checkpointing for a group of modules. The more you group the modules, the more efficient the memory usage. When checkpointing sequential modules for layers, the `strategy` argument of the `smp.set_activation_checkpointing` function groups the layers together for checkpointing. For example, grouping two or more layers
together for checkpointing is more memory efficient than checkpointing one layer at a time, and this trades extra computation time for reduced memory usage.

For more information, see Activation Checkpointing (p. 2552).

**Tensor parallelism**

- The degree of tensor parallelism should be a power of two \( (2, 4, 8, \ldots, 2^n) \), where the maximum degree must be equal to the number of GPUs per node. For example, if you use a node with 8 GPUs, possible numbers for the degree of tensor parallelism are 2, 4, and 8. We don't recommend arbitrary numbers (such as 3, 5, 6, and 7) for the degree of tensor parallelism. When you use multiple nodes, misconfiguring the degree of tensor parallelism might result in running tensor parallelism across the nodes; this adds significant overhead from communication of activations across the nodes and can become computationally expensive.

For more information, see Tensor Parallelism (p. 2541).

**Pipeline parallelism across nodes**

- You can run pipeline parallelism both within a single node and across multiple nodes. When you use pipeline parallelism in combination with tensor parallelism, we recommend running pipeline parallelism across multiple nodes and keeping tensor parallelism within individual nodes.

- Pipeline parallelism comes with the following three knobs: microbatches, active_microbatches, and prescaled_batch.
  - When you use tensor parallelism with pipeline parallelism, we recommend activating prescaled_batch so that the batch size per model parallel group can be increased for efficient pipelining. With prescaled_batch activated, the batch size set in the training script becomes \( \text{tp\_size} \times \text{batch\_size} \) for each rank without prescaled_batch.
  - Increasing the number of microbatches helps achieve efficient pipelining and better performance. Note that the effective microbatch size is the batch size divided by the number of microbatches. If you increase the number of microbatches while keeping batch size constant, each microbatch processes fewer samples.
  - The number of active_microbatches is the maximum number of microbatches that are simultaneously in process during pipelining. For each active microbatch in process, its activations and gradients take up GPU memory. Therefore, increasing active_microbatches takes up more GPU memory.
  - If both GPU and GPU memory are underutilized, increase active_microbatches for better parallelization during pipelining.
  - For more information about how to use tensor parallelism with pipeline parallelism, see Tensor parallelism combined with pipeline parallelism (p. 2545).
  - To find descriptions of the aforementioned parameters, see Parameters for smdistributed in the SageMaker Python SDK documentation.

**Offloading activations to CPU**

- Make sure that this is used in combination with activation checkpointing and pipeline parallelism. To ensure that the offloading and preloading happen in the background, specify a value greater than 1 to the microbatches parameter.

- When offloading activations, you might be able to increase active_microbatches and sometimes match with the total number of microbatches. This depends on which modules are checkpointed and how the model is partitioned.

For more information, see Activation Offloading (p. 2553).
Reference configurations

The SageMaker distributed model parallel training team provides the following reference points based on experiments with the GPT-2 model, the sequence length of 512, and the vocabulary size of 50,000.

<table>
<thead>
<tr>
<th>The number of model parameters</th>
<th>Instance type</th>
<th>Pipeline parallelism</th>
<th>Tensor parallelism</th>
<th>Optimizer state sharding</th>
<th>Activation checkpoint</th>
<th>Prescaled batch</th>
<th>Batch size</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 billion</td>
<td>ml.p4d.24xlarge</td>
<td>1</td>
<td>4</td>
<td>True</td>
<td>Each transformer layer</td>
<td>True</td>
<td>batch_size=40</td>
</tr>
<tr>
<td>30 billion</td>
<td>ml.p4d.24xlarge</td>
<td>1</td>
<td>8</td>
<td>True</td>
<td>Each transformer layer</td>
<td>True</td>
<td>batch_size=32</td>
</tr>
<tr>
<td>60 billion</td>
<td>ml.p4d.24xlarge</td>
<td>2</td>
<td>8</td>
<td>True</td>
<td>Each transformer layer</td>
<td>True</td>
<td>batch_size=56, microbatches=4, active_microbatches=2</td>
</tr>
</tbody>
</table>

You can extrapolate from the preceding configurations to estimate GPU memory usage for your model configuration. For example, if you increase the sequence length for a 10-billion-parameter model or increase the size of the model to 20 billion, you might want to lower batch size first. If the model still doesn’t fit, try increasing the degree of tensor parallelism.

Modifying Your Training Script

- Before you use the SageMaker model parallel library’s features in your training script, review SageMaker Distributed Model Parallel Configuration Tips and Pitfalls (p. 2566).
- To launch a training job faster, use the SageMaker local mode. This helps you quickly run a training job locally on a SageMaker notebook instance. Depending on the scale of the ML instance on which your SageMaker notebook instance is running, you might need to adjust the size of your model by changing the model configurations, such as the hidden width, number of transformer layers, and attention heads. Validate if the reduced model runs well on the notebook instance before using a large cluster for training the full model.

Monitoring and Logging a Training Job Using the SageMaker Console and Amazon CloudWatch

To monitor system-level metrics such as CPU memory utilization, GPU memory utilization, and GPU utilization, use visualization provided through the SageMaker console.

1. In the left navigation pane, choose Training.
2. Choose Training jobs.
3. In the main pane, choose the training job name for which you want to see more details.
4. Browse the main pane and find the Monitor section to see the automated visualization.
5. To see training job logs, choose View logs in the Monitor section. You can access the distributed training job logs of the training job in CloudWatch. If you launched multi-node distributed training, you should see multiple log streams with tags in the format of algo-n-1234567890. The algo-1 log stream tracks training logs from the main (0th) node.
For more information, see Monitor and Analyze Training Jobs Using Amazon CloudWatch Metrics (p. 2704).

Permissions

To run a SageMaker training job with model parallelism or the SageMaker distributed training example notebooks, make sure you have the right permissions in your IAM role, such as the following:

- To use FSx for Lustre, add AmazonFSxFullAccess.
- To use Amazon S3 as a data channel, add AmazonS3FullAccess.
- To use Docker, build your own container, and push it to Amazon ECR, add AmazonEC2ContainerRegistryFullAccess.
- To have a full access to use the entire suite of SageMaker features, add AmazonSageMakerFullAccess.

SageMaker Distributed Model Parallel Configuration Tips and Pitfalls

Review the following tips and pitfalls before using Amazon SageMaker’s distributed model parallel library. This list includes tips that are applicable across frameworks. For TensorFlow and PyTorch specific tips, see Modify a TensorFlow Training Script (p. 2523) and Modify a PyTorch Training Script (p. 2528), respectively.

Batch Size and Number of Microbatches

- The library is most efficient when the batch size is increased. For use cases where the model fits within a single device, but can only be trained with a small batch size, batch size can and should be increased after the library is integrated. Model parallelism saves memory for large models, enabling you to train using batch sizes that previously did not fit in memory.

- Choosing a number of microbatches that is too small or too large can lower performance. The library executes each microbatch sequentially in each device, so microbatch size (batch size divided by number of microbatches) must be large enough to fully utilize each GPU. At the same time, pipeline efficiency increases with the number of microbatches, so striking the right balance is important. Typically, a good starting point is to try 2 or 4 microbatches, increasing the batch size to the memory limit, and then experiment with larger batch sizes and numbers of microbatches. As the number of microbatches is increased, larger batch sizes might become feasible if an interleaved pipeline is used.

- Your batch size must be always divisible by the number of microbatches. Note that depending on the size of the dataset, sometimes the last batch of every epoch can be of a smaller size than the rest, and this smaller batch needs to be divisible by the number of microbatches as well. If it is not, you can set drop_remainder=True in the tf.Dataset.batch() call (in TensorFlow), or set drop_last=True in DataLoader (in PyTorch), so that this last, small batch is not used. If you are using a different API for the data pipeline, you might need to manually skip the last batch whenever it is not divisible by the number of microbatches.

Manual Partitioning

- If you use manual partitioning, be mindful of the parameters that are consumed by multiple operations and modules in your model, such as the embedding table in transformer architectures. Modules that share the same parameter must be placed in the same device for correctness. When auto-partitioning is used, the library automatically enforces this constraint.
Data Preparation

- If the model takes multiple inputs, make sure you seed the random operations in your data pipeline (e.g., shuffling) with `smp.dp_rank()`. If the dataset is being deterministically sharded across data parallel devices, make sure that the shard is indexed by `smp.dp_rank()`. This is to make sure that the order of the data seen on all ranks that form a model partition is consistent.

Returning Tensors from `smp.DistributedModel`

- Any tensor that is returned from the `smp.DistributedModel.call` (for TensorFlow) or `smp.DistributedModel.forward` (for PyTorch) function is broadcast to all other ranks, from the rank that computed that particular tensor. As a result, any tensor that is not needed outside the call and forward methods (intermediate activations, for example) should not be returned, as this causes needless communication and memory overhead and hurts performance.

The `@smp.step` Decorator

- If an `smp.step`-decorated function has a tensor argument that does not have a batch dimension, the argument name must be provided in the `non_split_inputs` list when calling `smp.step`. This prevents the library from attempting to split the tensor into microbatches. For more information see `smp.step` in the API documentation.

Delaying Parameter Initialization

For very large models over 100 billion parameters, weight initialization through the CPU memory might result in an out-of-memory error. To get around this, the library offers `smp.delay_param_initialization` context manager. This delays the physical allocation of parameters until they move to GPU during the first execution of a `smp.step`-decorated function. This avoids unnecessary memory usage of the CPU during the initialization of training. Use the context manager when you create a model object as shown in the following code.

```python
with smp.delay_param_initialization(enabled=True):
    model = MyModel()
```

Tensor Parallelism for PyTorch

- If you are using a seed for deterministic results, set the seed based on `smp.dp_rank()` (for example, `torch.manual_seed(42 + smp.dp_rank())`). If you do not do this, different partitions of an `nn.Parameter` are initialized in the same way, impacting convergence.

- SageMaker's model parallelism library uses NCCL to implement collectives needed for the distribution of the modules. Especially for smaller models, if too many NCCL calls are scheduled on the GPU at the same time, memory usage might increase because of additional space used by NCCL. To counteract this, `smp` throttles the NCCL calls so that the number of ongoing NCCL operations at any given time is less than or equal to a given limit. The default limit is 8, but this can be adjusted using the environment variable `SMP_NCCL_THROTTLE_LIMIT`. If you observe more memory usage than you expect while using tensor parallelism, you can try reducing this limit. However, choosing a limit that is too small might cause throughput loss. To disable throttling altogether, you can set `SMP_NCCL_THROTTLE_LIMIT=-1`.

- The following identity, which holds when the degree of tensor parallelism is 1, does not hold when the degree of tensor parallelism is greater than 1: `smp.mp_size() * smp.dp_size() == smp.size()`. This is because the tensor parallel group is part of both the model parallelism group and the data parallelism group. If your code has existing references to `mp_rank`, `mp_size`, `MP_GROUP`, and...
so on, and if you want to work with only the pipeline parallel group, you might need to replace the
references with smp.pp_size(). The following identities are always true:
- smp.mp_size() * smp.rdp_size() == smp.size()
- smp.pp_size() * smp.dp_size() == smp.size()
- smp.pp_size() * smp.tp_size() * smp.rdp_size() == smp.size()

Since the smp.DistributedModel wrapper modifies the model parameters when tensor parallelism
is enabled, the optimizer should be created after calling smp.DistributedModel, with the
distributed parameters. For example, the following does not work:

```python
## WRONG
model = MyModel()
optimizer = SomeOptimizer(model.parameters())
model = smp.DistributedModel(model)  # optimizer now has outdated parameters!
```

Instead, the optimizer should be created with the parameters of the smp.DistributedModel as
follows:

```python
## CORRECT
model = smp.DistributedModel(MyModel())
optimizer = SomeOptimizer(model.optimizers())
```

- When a module is replaced with its distributed counterpart through tensor parallelism, the distributed
  module does not inherit its weights from the original module, and initializes new weights. This means
  that, for instance, if the weights need to be initialized in a particular call (for example, through a
  load_state_dict call), this needs to happen after the smp.DistributedModel call, once the
  module distribution takes place.
- When accessing the parameters of distributed modules directly, note that the weight does not have
  the same shape as the original module. For instance,

```python
with smp.tensor_parallelism():
    linear = nn.Linear(60, 60)
    # will pass
    assert tuple(linear.weight.shape) == (60, 60)

distributed_linear = smp.DistributedModel(linear)
    # will fail. the number of input channels will have been divided by smp.tp_size()
    assert tuple(distributed_linear.module.weight.shape) == (60, 60)
```

- Using torch.utils.data.distributed.DistributedSampler is strongly recommended for
tensor parallelism. This ensures that every data parallel rank receives the same number of data
samples, which prevents hangs that might result from different dp_ranks taking a different number of steps.
- If you use the join API of PyTorch's DistributedDataParallel class to handle cases in which
different data parallel ranks have different numbers of batches, you still need to make sure that ranks
that are in the same TP_GROUP have the same number of batches; otherwise the communication
collectives used in distributed execution of modules may hang. Ranks that are in different TP_GROUPS
can have different numbers of batches, as long as join API is used.
- If you want to checkpoint your model and use tensor parallelism, consider the following:
  - To avoid stalling and race conditions while saving and loading models when you use tensor
    parallelism, make sure you call appropriate functions from the following model and optimizer states
    inside a reduced-data parallelism rank.
  - If you are transitioning an existing pipeline parallel script and enabling tensor parallel for the script,
    ensure that you modify any if smp.dp_rank() == 0 block used for saving and loading with if
    smp.rdp_rank() == 0 blocks. Otherwise, it might cause your training job to stall.
• Full checkpointing of optimizer states is currently not supported with tensor parallelism. If you want to resume training from a checkpoint, use partial checkpointing instead.

For more information about checkpointing a model with tensor parallelism, see Instructions for Checkpointing with Tensor Parallelism (p. 2547).

Model Parallel Troubleshooting

If you run into an error, you can use the following list to try to troubleshoot your training job. If the problem persists, contact AWS Support.

Topics
• Considerations for Using SageMaker Debugger with SageMaker Distributed Model Parallel (p. 2569)
• Saving Checkpoints (p. 2569)
• Convergence Using Model Parallel and TensorFlow (p. 2571)
• Stalling or Crashing Distributed Training Jobs (p. 2571)
• Receiving NCCL Error for a PyTorch Training Job (p. 2572)
• Receiving RecursionError for a PyTorch Training Job (p. 2572)

Considerations for Using SageMaker Debugger with SageMaker Distributed Model Parallel

SageMaker Debugger is not available for SageMaker distributed model parallel. Debugger is enabled by default for all SageMaker TensorFlow and PyTorch training jobs, and you might see an error that looks like the following:

```
FileNotFoundError: [Errno 2] No such file or directory: '/opt/ml/checkpoints/metadata.json.sagemaker-uploading'
```

To fix this issue, disable Debugger by passing `debugger_hook_config=False` when creating a framework estimator as shown in the following example.

```
bucket=sagemaker.Session().default_bucket()
base_job_name="sagemaker-checkpoint-test"
checkpoint_in_bucket="checkpoints"
# The S3 URI to store the checkpoints
checkpoint_s3_bucket="s3://{}//{}//{}".format(bucket, base_job_name, checkpoint_in_bucket)
estimator = TensorFlow(
    ...
    distribution="smdistributed": {"modedparallel": { "enabled": True }},
    checkpoint_s3_uri=checkpoint_s3_bucket,
    checkpoint_local_path="/opt/ml/checkpoints",
    debugger_hook_config=False
)
```

Saving Checkpoints

You might run into the following error when saving checkpoints of a large model on SageMaker:

```
InternalServerError: We encountered an internal error. Please try again
```
This could be caused by a SageMaker limitation while uploading the local checkpoint to Amazon S3 during training. To disable checkpointing in SageMaker, use the following example to explicitly upload the checkpoints.

If you run into the preceding error, do not use checkpoint_s3_uri with the SageMaker estimator call. While saving checkpoints for larger models, we recommend saving checkpoints to a custom directory and passing the same to the helper function (as a local_path argument).

```python
import os

def aws_s3_sync(source, destination):
    """aws s3 sync in quiet mode and time profile""
    import time, subprocess
    cmd = ["aws", "s3", "sync", "--quiet", source, destination]
    print("Syncing files from {} to {}".format(source, destination))
    start_time = time.time()
    p = subprocess.Popen(cmd, stdout=subprocess.PIPE, stderr=subprocess.PIPE)
    p.wait()
    end_time = time.time()
    print("Time Taken to Sync: ", (end_time-start_time))
    return

def sync_local_checkpoints_to_s3(local_path="/opt/ml/checkpoints",
s3_uri=os.path.dirname(os.path.dirname(os.getenv('SM_MODULE_DIR', '')))+'/checkpoints'):
    """ sample function to sync checkpoints from local path to s3 ""
    import boto3
    #check if local path exists
    if not os.path.exists(local_path):
        raise RuntimeError("Provided local path {} does not exist. Please check".format(local_path))
    #check if s3 bucket exists
    s3 = boto3.resource('s3')
    if not s3_uri.startswith("s3://"):
        raise ValueError(f"Provided s3 uri {s3_uri} is not valid.")
    s3_bucket = s3_uri.replace('s3://','').split('/')[0]
    print(f"S3 Bucket: {s3_bucket}")
    try:
        s3.meta.client.head_bucket(Bucket=s3_bucket)
    except Exception as e:
        raise e
    aws_s3_sync(local_path, s3_uri)
    return

def sync_s3_checkpoints_to_local(local_path="/opt/ml/checkpoints",
s3_uri=os.path.dirname(os.path.dirname(os.getenv('SM_MODULE_DIR', '')))+'/checkpoints'):
    """ sample function to sync checkpoints from s3 to local path ""
    import boto3
    #try to create local path if it does not exist
    if not os.path.exists(local_path):
        print("Provided local path {} does not exist. Creating...".format(local_path))
        try:
            os.makedirs(local_path)
        except Exception as e:
            raise RuntimeError("Failed to create {}".format(local_path))
    #check if s3 bucket exists
    s3 = boto3.resource('s3')
    if not s3_uri.startswith("s3://"):
        raise ValueError(f"Provided s3 uri {s3_uri} is not valid.")
    s3_bucket = s3_uri.replace('s3://','').split('/')[0]
```

print(f"S3 Bucket: {s3_bucket}")
try:
    s3.meta.client.head_bucket(Bucket=s3_bucket)
except Exception as e:
    raise e
aws_s3_sync(s3_uri, local_path)
return

Usage of helper functions:

#base_s3_uri - user input s3 uri or save to model directory (default)
#curr_host - to save checkpoints of current host
#iteration - current step/epoch during which checkpoint is saved

# save checkpoints on every node using local_rank
if smp.local_rank() == 0:
    base_s3_uri = os.path.dirname(os.path.dirname(os.getenv('SM_MODULE_DIR', '')))
    curr_host = os.environ['SM_CURRENT_HOST']
    full_s3_uri = f'{base_s3_uri}/checkpoints/{curr_host}/{iteration}'
    sync_local_checkpoints_to_s3(local_path=checkpoint_dir, s3_uri=full_s3_uri)

Convergence Using Model Parallel and TensorFlow

When you use SageMaker multi-node training with TensorFlow and distributed model parallel, the loss may not converge as expected because the order of training input files may be different on each node. This may cause different ranks in the same model parallel group to work on different input files, causing inconsistencies. To prevent this, ensure the input files are ordered the same way in all the ranks before they get converted to TensorFlow datasets. One way to achieve this is to sort the input file names in the training script.

Stalling or Crashing Distributed Training Jobs

If your training job has stalling, crashing, or not responding issues, read the following troubleshooting items to identify what's the cause of the issue. If you need any further support, reach out to the SageMaker distributed training team through AWS Support.

- If you see a distributed training job stalling at the NCCL initialization step, consider the following:
  - If you are using one of the EFA-enabled instances (ml.p4d or ml.p3dn instances) with a custom VPC and its subnet, ensure that the security group used has inbound and outbound connections for all ports to and from the same SG. You also generally need outbound connections to any IP as a separate rule (for internet access). To find instructions on how to add inbound and outbound rules for EFA communication, refer to SageMaker Distributed Training Job Stalling During Initialization (p. 2506).
  - If you see a distributed training job stalling when checkpointing the full model, this might be because the state_dict() call on the model or optimizer was not made on all ranks with rdp_rank()==0 (when using tensor parallelism) or dp_rank()==0 (when using only pipeline parallelism). These ranks need to communicate to construct the checkpoint to be saved. Similar stalling issues can also happen when checkpointing partial optimizer if shard_optimizer_state is enabled.

For more information about checkpointing a model with model parallelism, see General Instruction for Saving and Loading and Instructions for Checkpointing with Tensor Parallelism (p. 2547).

- If the training job crashes with a CUDA Out of Memory error, this means that the distributed training configuration needs to be adjusted to fit the model on the GPU cluster. For more information and best practices, see Setting Up the Right Configuration for a Given Model (p. 2563).

- If the training job crashes with an uncorrectable ECC error, this means that one of the GPUs in the cluster has gone bad. If you need technical support, share the job ARN with the AWS team and restart your training job from a checkpoint if possible.
• In rare cases, a job configuration that worked previously but is close to the limits of GPU memory might fail later with a different cluster due to a **CUDA Out of Memory error**. This could be because some GPU has lower available memory than usual due to ECC errors.

• **Network timeout crash** might happen when running a multinode job which doesn't use all GPUs in the node. To get around this, use all GPUs on the node by ensuring that the processes_per_host parameter is set to the number of GPUs in each instance. For example, this is processes_per_host=8 for ml.p3.16xlarge, ml.p3dn.24xlarge, and ml.p4d.24xlarge instances.

• If you find that your training job takes a long time during the data downloading stage, make sure the Amazon S3 path you provided to checkpoint_s3_uri for the SageMaker Estimator class is unique for the current training job. If this path is reused across multiple training jobs running simultaneously, all those checkpoints are uploaded and downloaded to the same Amazon S3 path and might significantly increase checkpoint loading time.

• Use FSx for Lustre when you deal with large data and models.
  - If your dataset is large and fetching it takes a long time, we recommend keeping your dataset in FSx for Lustre.
  - When training models are beyond 10 billion parameters, we recommend using FSx for Lustre for checkpointing.
  - After you create a file system, make sure to wait for the status to become available before starting a training job using it.

**Receiving NCCL Error for a PyTorch Training Job**

If you encountered the following error, it might be due to a process running out of GPU memory.

```
NCCL error in: ../torch/lib/c10d/ProcessGroupNCCL.cpp:825, unhandled system error, NCCL version 2.7.8
ncclSystemError: System call (socket, malloc, munmap, etc) failed.
```

You can resolve this by reducing the batch size or active_microbatches. If auto partitioning is not resulting in a well-balanced partitioning, you might have to consider manual partitioning. For more information, see [Pipeline parallelism across nodes](p. 2564).

**Receiving RecursionError for a PyTorch Training Job**

The library does not support calling `super.forward()` inside a module's forward call. If you use `super.forward()`, you might receive the following error message.

```
RecursionError: maximum recursion depth exceeded
```

To fix the error, instead of calling `super.forward()`, you should call `super._orig_forward()`.

Amazon SageMaker Distributed Training Notebook Examples

The following case studies and notebooks provide examples of implementing the SageMaker distributed training libraries for the supported deep learning frameworks (PyTorch, TensorFlow, and HuggingFace) and models, such as CNN and MaskRCNN for vision, and BERT for natural language processing.

These notebooks are provided in the SageMaker examples GitHub repository. You can also browse them on the SageMaker examples website.

The examples are set up to use p3.16xlarge instances for the worker nodes, but you may choose ml.p3dn.24xlarge or ml.p4d.24xlarge instance types for which the SageMaker distributed training...
libraries are optimized. You can test the notebooks using a cluster of a single node; however, to see a performance improvement as shown in the Training Benchmarks section, use a cluster of multiple nodes (two or more). The examples call out the section in which you modify this configuration.

Blogs and Case Studies

The following blogs discuss case studies about using the SageMaker distributed training libraries.

SageMaker Distributed Data Parallel

- Hyundai reduces ML model training time for autonomous driving models using Amazon SageMaker
- Distributed Training: Train BART/T5 for Summarization using Transformers and Amazon SageMaker in the HuggingFace documentation
- Training YOLOv5 on AWS with PyTorch and the SageMaker distributed data parallel library in Medium
- Speed up EfficientNet model training on SageMaker with PyTorch and the SageMaker distributed data parallel library in Medium
- Speed up EfficientNet training on AWS with the SageMaker distributed data parallel library in Towards Data Science

PyTorch Examples

SageMaker Distributed Data Parallel

- CNN with PyTorch 1.6 and SageMaker Data Parallel
- MaskRCNN with PyTorch 1.6 and SageMaker Data Parallel
- BERT with PyTorch 1.6 and SageMaker Data Parallel

SageMaker Distributed Model Parallel

- Train GPT-2 with PyTorch 1.8.1 and Tensor Parallelism Using the SageMaker Model Parallelism Library
- BERT with PyTorch 1.6 and SageMaker Model Parallel

TensorFlow Examples

SageMaker Distributed Data Parallel

- CNN with TensorFlow 2.3.1 and SageMaker Data Parallel
- MaskRCNN with TensorFlow 2.3.1 and SageMaker Data Parallel
- BERT with TensorFlow 2.3.1 and SageMaker Data Parallel

SageMaker Distributed Model Parallel

- CNN with TensorFlow 2.3.1 and SageMaker Model Parallel

HuggingFace Examples

The following HuggingFace on SageMaker examples are available in the HuggingFace notebooks repository.

SageMaker Distributed Data Parallel
How to Access or Download the SageMaker Distributed Training Notebook Examples

Follow instructions to access or download the SageMaker distributed training example notebooks.

Option 1: Use a SageMaker notebook instance

To use the aforementioned examples, we recommend that you use an Amazon SageMaker notebook instance. A notebook instance runs Jupyter Notebook and JupyterServer apps on Amazon EC2 instances, which are optimized for machine learning. If you do not have an active notebook instance, follow the instructions in Create a Notebook Instance (p. 296) in the SageMaker developer guide to create one.

After you have created an instance, in the Notebook instances page of the SageMaker console, do the following:

1. Open JupyterLab.
2. Select the examples icon ( ) in the left tray.
3. Browse the examples for Training and look for notebooks titled Distributed Data Parallel or Distributed Model Parallel.

Option 2: Clone the SageMaker example repository to SageMaker Studio or notebook instance

To download and use the aforementioned example notebooks, do the following to clone the example GitHub repositories:

1. Open a terminal.
2. In the command line, navigate to the SageMaker folder.
   
   ```
   cd SageMaker
   ```

3. Clone the SageMaker examples GitHub repository.
   
   ```
   git clone https://github.com/aws/amazon-sagemaker-examples.git
   ```

   **Note**

   To download the HuggingFace example notebooks (p. 2573), clone the HuggingFace notebooks GitHub repository:

   ```
   git clone https://github.com/huggingface/notebooks huggingface-notebooks
   ```

---

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4. In the JupyterLab interface, navigate into the `amazon-sagemaker-examples` folder.
5. In the `training/distributed_training` folder, there are folders for frameworks, and in each of these, there are folders for `data_parallel` and `model_parallel`. Choose the example of your choice and follow the instructions to launch distributed training with an SageMaker distributed training library.

**Amazon SageMaker Training Compiler**

Use Amazon SageMaker Training Compiler to train deep learning (DL) models faster on scalable GPU instances managed by SageMaker.

**What Is SageMaker Training Compiler?**

State-of-the-art deep learning (DL) models consist of complex multi-layered neural networks with billions of parameters that can take thousands of GPU hours to train. Optimizing such models on training infrastructure requires extensive knowledge of DL and systems engineering; this is challenging even for narrow use cases. Although there are open-source implementations of compilers that optimize the DL training process, they can lack the flexibility to integrate DL frameworks with some hardware such as GPU instances.

SageMaker Training Compiler is a capability of SageMaker that makes these hard-to-implement optimizations to reduce training time on GPU instances. The compiler optimizes DL models to accelerate training by more efficiently using SageMaker machine learning (ML) GPU instances. SageMaker Training Compiler is available at no additional charge within SageMaker and can help reduce total billable time as it accelerates training.

SageMaker Training Compiler is integrated into the AWS Deep Learning Containers (DLCs). Using the SageMaker Training Compiler–enabled AWS DLCs, you can compile and optimize training jobs on GPU instances with minimal changes to your code. Bring your deep learning models to SageMaker and enable SageMaker Training Compiler to accelerate the speed of your training job on SageMaker ML instances for accelerated computing.

**How It Works**

SageMaker Training Compiler converts DL models from their high-level language representation to hardware-optimized instructions. Specifically, SageMaker Training Compiler applies graph-level optimization, dataflow-level optimizations, and backend optimizations to produce an optimized model that efficiently uses hardware resources. As a result, you can train your models faster than when you train them without compilation.
It is a two-step process to activate SageMaker Training Compiler for your training job:

1. Bring your own DL script and, if needed, adapt to compile and train with SageMaker Training Compiler. To learn more, see Bring Your Own Deep Learning Model (p. 2589).
2. Create a SageMaker estimator object with the compiler configuration parameter using the SageMaker Python SDK.
   a. Enable SageMaker Training Compiler by adding
      ```python
      compiler_config=TrainingCompilerConfig()
      ```
      to the SageMaker estimator class.
   b. Adjust hyperparameters (`batch_size` and `learning_rate`) to maximize the benefit that SageMaker Training Compiler provides. SageMaker Training Compiler reduces the memory footprint of your model during training, which typically allows you to fit a larger `batch_size` in the GPU memory. Using a larger `batch_size` results in a better GPU utilization and reduces the total training time. For reference of `batch_size` tested for popular models, see Tested Models (p. 2578).
   c. By running the `estimator.fit()` class method, SageMaker compiles your model and starts the training job.

For instructions on how to launch a training job, see Enable SageMaker Training Compiler (p. 2596).

SageMaker Training Compiler does not alter the final trained model, while allowing you to accelerate the training job by more efficiently using the GPU memory and fitting a larger `batch_size` per iteration. The final trained model from the compiler-accelerated training job is identical to the one from the ordinary training job.

**Tip**
SageMaker Training Compiler only compiles DL models for training on supported GPU instances managed by SageMaker. To compile your model for inference and deploy it to run anywhere in the cloud and at the edge, use SageMaker Neo compiler.

**Topics**
- Supported Frameworks, AWS Regions, Instance Types, and Tested Models (p. 2576)
- Bring Your Own Deep Learning Model (p. 2589)
- Enable SageMaker Training Compiler (p. 2596)
- SageMaker Training Compiler Example Notebooks and Blogs (p. 2608)
- SageMaker Training Compiler Best Practices and Considerations (p. 2608)
- SageMaker Training Compiler FAQ (p. 2610)
- SageMaker Training Compiler Troubleshooting (p. 2612)
- Amazon SageMaker Training Compiler Release Notes (p. 2613)

**Supported Frameworks, AWS Regions, Instance Types, and Tested Models**

Before using SageMaker Training Compiler, check if your framework of choice is supported, the instance types are available in your AWS account, and your AWS account is in one of the supported AWS Regions.

**Note**
SageMaker Training Compiler is available in the SageMaker Python SDK v2.70.0 or later.
Supported Frameworks

SageMaker Training Compiler supports the following deep learning frameworks and is available through AWS Deep Learning Containers.

**Topics**
- PyTorch (p. 2577)
- TensorFlow (p. 2577)

### PyTorch

<table>
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<th>Framework version</th>
<th>Deep Learning Container URI</th>
<th>Extendable for Docker customization</th>
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### TensorFlow

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## Supported Frameworks, AWS Regions, Instance Types, and Tested Models

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</table>

For more information, see Available Images in the AWS Deep Learning Containers GitHub repository.

## AWS Regions

The SageMaker Training Compiler Containers are available in the AWS Regions where AWS Deep Learning Containers are in service except the China regions.

## Supported Instance Types

SageMaker Training Compiler is tested on and supports the following ML instance types.

- P4 instances
- P3 instances
- G4dn instances
- G5 instances

For specs of the instance types, see the Accelerated Computing section in the Amazon EC2 Instance Types page. For information about instance pricing, see Amazon SageMaker Pricing.

If you encountered an error message similar to the following, follow the instructions at Request a service quota increase for SageMaker resources.

ResourceLimitExceeded: An error occurred (ResourceLimitExceeded) when calling the CreateTrainingJob operation: The account-level service limit 'ml.p3dn.24xlarge for training job usage' is 0 Instances, with current utilization of 0 Instances and a request delta of 1 Instances. Please contact AWS support to request an increase for this limit.

## Tested Models

The following table includes a list of the models that have been tested with SageMaker Training Compiler. For reference, the largest batch size that is able to fit into memory is also included alongside other training parameters. SageMaker Training Compiler can change the memory footprint of the model training process; as a result, a larger batch size can often be used during the training process, further...
decreasing total training time. You must retune your model with the compiler enabled to find this increased batch size. To save time, use the reference table to pick up the largest batch sizes that can be used with the tested models.

**Note**
The batch sizes are local batch size that fit into each individual GPU of an instance type. You should also adjust the learning rate when changing the batch size.

**TensorFlow 2.10.0**

**Computer Vision (CV) models**

Tested using [TensorFlow Model Garden](https://github.com/tensorflow/models) with Automatic Mixed Precision (AMP) as indicated.

<table>
<thead>
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<th>Single-node single-GPU/multi-GPU</th>
<th>Framework</th>
<th>Instance Type</th>
<th>Batch Size</th>
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<tr>
<td>DetectionTransformer-ResNet50 COCO-2017</td>
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<td>MaskRCNN-ResNet50-FPN COCO-2017</td>
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<td>MaskRCNN-ResNet50-FPN COCO-2017</td>
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<td>ResNet50 ImageNet</td>
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<td>ResNet50 ImageNet</td>
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<td>ResNet152 ImageNet</td>
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<td>VisionTransformer ImageNet</td>
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</table>
### Supported Frameworks, AWS Regions, Instance Types, and Tested Models

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<thead>
<tr>
<th>Single-node single-GPU/multi-GPU</th>
<th>VisionTransformer</th>
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**Natural Language Processing (NLP) models**

Tested using Transformer models with Sequence_Len=128 and Automatic Mixed Precision (AMP) as indicated.

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**TensorFlow 2.9.1**

Tested using [TensorFlow Model Garden](https://github.com/tensorflow/models) with Automatic Mixed Precision (AMP).

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* The batch sizes marked with the asterisk symbol (*) indicate the largest batch size tested by the SageMaker Training Compiler developer team. For the marked cells, the instance may be able to fit a larger batch size than what is indicated.

**Transformers 4.21.1 with PyTorch 1.11.0**

Tested with `Sequence_Len=512` and Automatic Mixed Precision (AMP).

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### Amazon SageMaker Developer Guide

#### Supported Frameworks, AWS Regions, Instance Types, and Tested Models

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**Transformers 4.17.0 with PyTorch 1.10.2**

Tested with Sequence_Len=512 and Automatic Mixed Precision (AMP).

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**Transformers 4.11.0 with PyTorch 1.9.0**

Tested with Sequence Len=512 and Automatic Mixed Precision (AMP).

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### Single-node single-GPU

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### Single-node multi-GPU

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### Transformers 4.17.0 with TensorFlow 2.6.3

Tested with Sequence Len=128 and Automatic Mixed Precision (AMP).

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**Transformers 4.11.0 with TensorFlow 2.5.1**

Tested with Sequence_Len=128 and Automatic Mixed Precision (AMP).

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Bring Your Own Deep Learning Model

This guide walks you through how to adapt your training script for a compiler-accelerated training job. The preparation of your training script depends on the following:

- Training settings such as single-core or distributed training.
- Frameworks and libraries that you use to create the training script.

Choose one of the following topics depending on the framework you use.

**Topics**

- **PyTorch** (p. 2589)
- **TensorFlow** (p. 2593)

**Note**

After you finish preparing your training script, you can run a SageMaker training job using the SageMaker framework estimator classes. For more information, see the previous topic at [Enable SageMaker Training Compiler](p. 2596).

**PyTorch**

Bring your own PyTorch model to SageMaker, and run the training job with SageMaker Training Compiler.

**PyTorch Models with Hugging Face Transformers**

PyTorch models with [Hugging Face Transformers](https://huggingface.co) are based on PyTorch's `torch.nn.Module` API. Hugging Face Transformers also provides `Trainer` and pretrained model classes for PyTorch to help reduce the effort for configuring natural language processing (NLP) models. After creating your own training script using the Transformers library, you'll run the training script using the SageMaker HuggingFace estimator with the SageMaker Training Compiler configuration class as shown in the previous topic at [Enable SageMaker Training Compiler](p. 2596).

**Tip**

When you create a tokenizer for an NLP model using Transformers in your training script, make sure that you use a static input tensor shape by specifying `padding='max_length'`. Do not use `padding='longest'` because padding to the longest sequence in the batch can change the tensor shape for each training batch. The dynamic input shape can trigger recompilation of the model and might increase total training time. For more information about padding options of the Transformers tokenizers, see [Padding and truncation](https://huggingface.co/main/docs/transformers/main/en/model_doc/transformers#padding-truncation) in the Hugging Face Transformers documentation.

**Topics**

- **Using the Hugging Face Transformers Trainer API** (p. 2589)
- **Using PyTorch (without the Hugging Face Transformers Trainer API)** (p. 2590)
- **Best Practices to Enable SageMaker Training Compiler for PyTorch without the Hugging Face Trainer API** (p. 2593)

**Using the Hugging Face Transformers Trainer API**

If you use the transformers library's `Trainer` class, you don't need to make any additional changes to your training script. SageMaker Training Compiler automatically compiles your Trainer model if you enable it through the estimator class. The following code shows the basic form of a PyTorch training script with Hugging Face Trainer API.
from transformers import Trainer, TrainingArguments
training_args=TrainingArguments(**kwargs)
trainer=Trainer(args=training_args, **kwargs)

For single GPU training
You don't need to change your code when you use the Transformers Trainer API.

For distributed training

For Transformers v4.21.1 with PyTorch v1.11.0
To run distributed training with SageMaker Training Compiler, you must add the following _mp_fn() function in your training script and wrap the main() function. It redirects the _mp_fn(index) function calls from the SageMaker distributed runtime for PyTorch (pytorchxla) to the main() function of your training script.

def _mp_fn(index):
    main()

This function accepts the index argument to indicate the rank of the current GPU in the cluster for distributed training. To find more example scripts, see the Hugging Face Transformers language modeling example scripts.

For Transformers v4.17 and before with PyTorch v1.10.2 and before
SageMaker Training Compiler uses an alternate mechanism for launching a distributed training job, and you don't need to make any modification in your training script. Instead, SageMaker Training Compiler requires you to pass a SageMaker distributed training launcher script to the entry_point argument and pass your training script to the hyperparameters argument in the SageMaker Hugging Face estimator.

After you have completed adapting your training script, proceed to the section called “Run PyTorch Training Jobs with Training Compiler” (p. 2596).

Using PyTorch (without the Hugging Face Transformers Trainer API)
If you have a training script that uses PyTorch directly, you need to make additional changes to your PyTorch training script. Follow the instructions to modify your script using PyTorch/XLA.

Topics
- For single GPU training (p. 2590)
- For distributed training (p. 2591)

For single GPU training
1. Import the optimization libraries.

import torch_xla
import torch_xla.core.xla_model as xm

2. Change the target device to be XLA instead of torch.device("cuda")

device=xm.xla_device()

3. If you're using PyTorch's Automatic Mixed Precision (AMP), do the following:
   a. Replace torch.cuda.amp with the following:
import torch_xla.amp

b. Replace torch.optim.SGD and torch.optim.Adam with the following:

import torch_xla.amp.syncfree.Adam as adam
import torch_xla.amp.syncfree.SGD as SGD

c. Replace torch.cuda.amp.GradScaler with the following:

import torch_xla.amp.GradScaler as grad_scaler

4. If you're not using AMP, replace optimizer.step() with the following:

xm.optimizer_step(optimizer)

5. If you're using a distributed dataloader, wrap your dataloader in the PyTorch/XLA's ParallelLoader class:

import torch_xla.distributed.parallel_loader as pl
parallel_loader=pl.ParallelLoader(dataloader, [device]).per_device_loader(device)

6. Add mark_step at the end of the training loop when you're not using parallel_loader:

xm.mark_step()

7. To checkpoint your training, use the PyTorch/XLA's model checkpoint method:

xm.save(model.state_dict(), path_to_save)

After you have completed adapting your training script, proceed to the section called “Run PyTorch Training Jobs with Training Compiler” (p. 2596).

For distributed training

In addition to the changes listed in the previous For single GPU training (p. 2590) section, add the following changes to properly distribute workload across GPUs.

1. If you're using AMP, add all_reduce after scaler.scale(loss).backward():

    gradients=xm._fetch_gradients(optimizer)
xm.all_reduce('sum', gradients, scale=1.0/xm.xrt_world_size())

2. If you need to set variables for local_ranks and world_size, use similar code to the following:

    local_rank=xm.get_local_ordinal()
world_size=xm.xrt_world_size()

3. For any world_size (num_gpus_per_node*num_nodes) greater than 1, you must define a train sampler which should look similar to the following:

    import torch_xla.core.xla_model as xm

    if xm.xrt_world_size() > 1:
        train_sampler=torch.utils.data.distributed.DistributedSampler(
            train_dataset,
            num_replicas=xm.xrt_world_size(),
        )
```
        rank=xm.get_ordinal(),
        shuffle=True
    )

train_loader=torch.utils.data.DataLoader(
    train_dataset,
    batch_size=args.batch_size,
    sampler=train_sampler,
    drop_last=args.drop_last,
    shuffle=False if train_sampler else True,
    num_workers=args.num_workers
)

4. Make the following changes to make sure you use the parallel_loader provided by the torch_xla distributed module.

```python
import torch_xla.distributed.parallel_loader as pl
train_device_loader=pl.MpDeviceLoader(train_loader, device)
```

The `train_device_loader` functions like a regular PyTorch loader as follows:

```python
for step, (data, target) in enumerate(train_device_loader):
    optimizer.zero_grad()
    output=model(data)
    loss=torch.nn.NLLLoss(output, target)
    loss.backward()
```

With all of these changes, you should be able to launch distributed training with any PyTorch model without the Transformer Trainer API. Note that these instructions can be used for both single-node multi-GPU and multi-node multi-GPU.

5. **For Transformers v4.21.1 with PyTorch v1.11.0**

To run distributed training with SageMaker Training Compiler, you must add the following `_mp_fn()` function in your training script and wrap the `main()` function. It redirects the `_mp_fn(index)` function calls from the SageMaker distributed runtime for PyTorch (pytorchxla) to the `main()` function of your training script.

```python
def _mp_fn(index):
    main()
```

This function accepts the `index` argument to indicate the rank of the current GPU in the cluster for distributed training. To find more example scripts, see the Hugging Face Transformers language modeling example scripts.

**For Transformers v4.17 and before with PyTorch v1.10.2 and before**

SageMaker Training Compiler uses an alternate mechanism for launching a distributed training job and requires you to pass a SageMaker distributed training launcher script to the `entry_point` argument and pass your training script to the `hyperparameters` argument in the SageMaker Hugging Face estimator.

After you have completed adapting your training script, proceed to the section called “Run PyTorch Training Jobs with Training Compiler” (p. 2596).
Best Practices to Enable SageMaker Training Compiler for PyTorch without the Hugging Face Trainer API

If you want to leverage the SageMaker Training Compiler on your native PyTorch training script, you may want to first get familiar with PyTorch on XLA devices. The following sections list some best practices to enable XLA for PyTorch.

Note
This guide assumes that you use the following Python modules:

```python
import torch_xla.core.xla_model as xm
import torch_xla.distributed.parallel_loader as pl
```

Understand the lazy mode in PyTorch/XLA

One significant difference between PyTorch/XLA and native PyTorch is that the PyTorch/XLA system runs in lazy mode while the native PyTorch runs in eager mode. Tensors in lazy mode are placeholders for building the computational graph until they are materialized after the compilation and evaluation are complete. The PyTorch/XLA system builds the computational graph on the fly when you call PyTorch APIs to build the computation using tensors and operators. The computational graph gets compiled and executed when `xm.mark_step()` is called explicitly or implicitly by `pl.MpDeviceLoader/pl.ParallelLoader`, or when you explicitly request the value of a tensor such as by calling `loss.item()` or `print(loss)`.

Minimize the number of compilation-and-executions using `pl.MpDeviceLoader/pl.ParallelLoader and xm.step_closure`

For best performance, you should keep in mind the possible ways to initiate compilation-and-executions as described in Understand the lazy mode in PyTorch/XLA (p. 2593) and should try to minimize the number of compilation-and-executions. Ideally, only one compilation-and-execution is necessary per training iteration and is initiated automatically by `pl.MpDeviceLoader/pl.ParallelLoader`. The `MpDeviceLoader` is optimized for XLA and should always be used if possible for best performance. During training, you might want to examine some intermediate results such as loss values. In such case, the printing of lazy tensors should be wrapped using `xm.add_step_closure()` to avoid unnecessary compilation-and-executions.

Use AMP and syncfree optimizers

Training in Automatic Mixed Precision (AMP) mode significantly accelerates your training speed by leveraging the Tensor cores of NVIDIA GPUs. SageMaker Training Compiler provides syncfree optimizers that are optimized for XLA to improve AMP performance. Currently, the following three syncfree optimizers are available and should be used if possible for best performance.

```python
torch_xla.amp.syncfree.SGD
torch_xla.amp.syncfree.Adam
torch_xla.amp.syncfree.AdamW
```

These syncfree optimizers should be paired with `torch_xla.amp.GradScaler` for gradient scaling/unscaling.

**TensorFlow**

Bring your own TensorFlow model to SageMaker, and run the training job with SageMaker Training Compiler.

**TensorFlow Models**

SageMaker Training Compiler automatically optimizes model training workloads that are built on top of the native TensorFlow API or the high-level Keras API.
Tip
For preprocessing your input dataset, ensure that you use a static input shape. Dynamic input shape can initiate recompilation of the model and might increase total training time.

Using Keras (Recommended)
For the best compiler acceleration, we recommend using models that are subclasses of TensorFlow Keras (tf.keras.Model).

For single GPU training
There's no additional change you need to make in the training script.

Without Keras
SageMaker Training Compiler does not support eager execution in TensorFlow. Accordingly, you should wrap your model and training loops with the TensorFlow function decorator (@tf.function) to leverage compiler acceleration.

SageMaker Training Compiler performs a graph-level optimization, and uses the decorator to make sure your TensorFlow functions are set to run in graph mode.

For single GPU training
TensorFlow 2.0 or later has the eager execution on by default, so you should add the @tf.function decorator in front of every function that you use for constructing a TensorFlow model.

TensorFlow Models with Hugging Face Transformers
TensorFlow models with Hugging Face Transformers are based on TensorFlow's tf.keras.Model API. Hugging Face Transformers also provides pretrained model classes for TensorFlow to help reduce the effort for configuring natural language processing (NLP) models. After creating your own training script using the Transformers library, you can run the training script using the SageMaker HuggingFace estimator with the SageMaker Training Compiler configuration class as shown in the previous topic at Run TensorFlow Training Jobs with SageMaker Training Compiler (p. 2602).

SageMaker Training Compiler automatically optimizes model training workloads that are built on top of the native TensorFlow API or the high-level Keras API, such as the TensorFlow transformer models.

Tip
When you create a tokenizer for an NLP model using Transformers in your training script, make sure that you use a static input tensor shape by specifying padding='max_length'. Do not use padding='longest' because padding to the longest sequence in the batch can change the tensor shape for each training batch. The dynamic input shape can initiate recompilation of the model and might increase total training time. For more information about padding options of the Transformers tokenizers, see Padding and truncation in the Hugging Face Transformers documentation.

Topics
- Using Keras (p. 2594)
- Without Keras (p. 2595)

Using Keras
For the best compiler acceleration, we recommend using models that are subclasses of TensorFlow Keras (tf.keras.Model). As noted in the Quick tour page in the Hugging Face Transformers documentation, you can use the models as regular TensorFlow Keras models.

For single GPU training
There's no additional change you need to make in the training script.
For distributed training

SageMaker Training Compiler acceleration works transparently for multi-GPU workloads when the model is constructed and trained using Keras APIs within the scope of `tf.distribute.Strategy.scope()` call.

1. Choose the right distributed training strategy.
   a. For single-node multi-GPU, use `tf.distribute.MirroredStrategy` to set the strategy.

   ```python
   strategy = tf.distribute.MirroredStrategy()
   ```

   b. For multi-node multi-GPU, add the following code to properly set the TensorFlow distributed training configuration before creating the strategy.

   ```python
def set_sm_dist_config():
    DEFAULT_PORT = '8890'
    DEFAULT_CONFIG_FILE = '/opt/ml/input/config/resourceconfig.json'
    with open(DEFAULT_CONFIG_FILE) as f:
        config = json.loads(f.read())
        current_host = config['current_host']
    tf_config = {
        'cluster': {
            'worker': [],
        },
        'task': {'type': 'worker', 'index': -1}
    }
    for i, host in enumerate(config['hosts']):
        if current_host == host:
            tf_config['task']['index'] = i
    os.environ['TF_CONFIG'] = json.dumps(tf_config)
    set_sm_dist_config()

   Use `tf.distribute.MultiWorkerMirroredStrategy` to set the strategy.

   ```python
   strategy = tf.distribute.MultiWorkerMirroredStrategy()
   ```

2. Using the strategy of your choice, wrap the model.

   ```python
   with strategy.scope():
       # create a model and do fit
   ```

Without Keras

If you want to bring custom models with custom training loops using TensorFlow without Keras, you should wrap the model and the training loop with the TensorFlow function decorator (`@tf.function`) to leverage compiler acceleration.

SageMaker Training Compiler performs a graph-level optimization, and uses the decorator to make sure your TensorFlow functions are set to run in graph mode.

For single GPU training

TensorFlow 2.0 or later has the eager execution on by default, so you should add the `@tf.function` decorator in front of every function that you use for constructing a TensorFlow model.
For distributed training

In addition to the changes needed for Using Keras for distributed training, you need to ensure that functions to be run on each GPU are annotated with @tf.function, while cross-GPU communication functions are not annotated. An example training code should look like the following:

```python
@tf.function()
def compiled_step(inputs, outputs):
    with tf.GradientTape() as tape:
        pred=model(inputs, training=True)
        total_loss=loss_object(outputs, pred)/args.batch_size
        gradients=tape.gradient(total_loss, model.trainable_variables)
    return total_loss, pred, gradients

def train_step(inputs, outputs):
    total_loss, pred, gradients=compiled_step(inputs, outputs)
    if args.weight_decay > 0.:
        gradients=[g+v*args.weight_decay for g,v in zip(gradients, model.trainable_variables)]
    optimizer.apply_gradients(zip(gradients, model.trainable_variables))
    train_loss.update_state(total_loss)
    train_accuracy.update_state(outputs, pred)

@tf.function()
def train_step_dist(inputs, outputs):
    strategy.run(train_step, args= (inputs, outputs))
```

Note that this instruction can be used for both single-node multi-GPU and multi-node multi-GPU.

Enable SageMaker Training Compiler

SageMaker Training Compiler is built into the SageMaker Python SDK and AWS Deep Learning Containers so that you don’t need to change your workflows to enable Training Compiler. Choose one of the following topics that matches with your use case.

**Topics**

- Run PyTorch Training Jobs with SageMaker Training Compiler (p. 2596)
- Run TensorFlow Training Jobs with SageMaker Training Compiler (p. 2602)

**Run PyTorch Training Jobs with SageMaker Training Compiler**

You can use any of the SageMaker interfaces to run a training job with SageMaker Training Compiler: Amazon SageMaker Studio, Amazon SageMaker notebook instances, AWS SDK for Python (Boto3), and AWS Command Line Interface.

**Topics**

- Using the SageMaker Python SDK (p. 2596)
- Using the SageMaker CreateTrainingJob API Operation (p. 2601)

**Using the SageMaker Python SDK**

To turn on SageMaker Training Compiler, add the `compiler_config` parameter to the SageMaker Hugging Face estimator. Import the `TrainingCompilerConfig` class and pass an instance of it to the `compiler_config` parameter. The following code examples show the structure of SageMaker estimator classes with SageMaker Training Compiler turned on.
Tip
To get started with prebuilt models provided by the Transformers library, try using the batch sizes provided in the reference table at Tested Models (p. 2578).

Note
SageMaker Training Compiler for PyTorch is currently available through the SageMaker Hugging Face framework estimator.

For information that fits your use case, see one of the following options.

For single GPU training

Hugging Face Transformers with PyTorch

To compile and train a transformer model with PyTorch, configure a SageMaker Hugging Face estimator with SageMaker Training Compiler as shown in the following code example.

```python
from sagemaker.huggingface import HuggingFace, TrainingCompilerConfig

# the original max batch size that can fit into GPU memory without compiler
batch_size_native=12
learning_rate_native=float('5e-5')

# an updated max batch size that can fit into GPU memory with compiler
batch_size=64

# update learning rate
learning_rate=learning_rate_native/batch_size_native*batch_size

hyperparameters={
    "n_gpus": 1,
    "batch_size": batch_size,
    "learning_rate": learning_rate
}

pytorch_huggingface_estimator=HuggingFace(
    entry_point='train.py',
    instance_count=1,
    instance_type='ml.p3.2xlarge',
    transformers_version='4.21.1',
    pytorch_version='1.11.0',
    hyperparameters=hyperparameters,
    compiler_config=TrainingCompilerConfig(),
    disable_profiler=True,
    debugger_hook_config=False
)

pytorch_huggingface_estimator.fit()
```

To prepare your training script, see the following pages.

- For single GPU training (p. 2590) of a PyTorch model using Hugging Face Transformers' Trainer API
- For single GPU training (p. 2590) of a PyTorch model without Hugging Face Transformers' Trainer API

To find end-to-end examples, see the following notebooks:

- Compile and Train a Hugging Face Transformers Trainer Model for Question and Answering with the SQuAD dataset
Enable Training Compiler

- Compile and Train a Hugging Face Transformer BERT Model with the SST Dataset using SageMaker Training Compiler
- Compile and Train a Binary Classification Trainer Model with the SST2 Dataset for Single-Node Single-GPU Training

For distributed training

For Transformers v4.21 with PyTorch v1.11 and later

For PyTorch v1.11 and later, SageMaker Training Compiler is available for distributed training with the `pytorch_xla` option specified to the `distribution` parameter.

```python
from sagemaker.huggingface import HuggingFace, TrainingCompilerConfig

# choose an instance type, specify the number of instances you want to use, # and set the num_gpus variable the number of GPUs per instance.
instance_count=1
instance_type='ml.p3.8xlarge'
num_gpus=4

# the original max batch size that can fit to GPU memory without compiler
batch_size_native=16
learning_rate_native=float('5e-5')

# an updated max batch size that can fit to GPU memory with compiler
batch_size=26

# update learning rate
learning_rate=learning_rate native/batch_size*batch_size*num_gpus*instance_count

training_script="your_training_script.py"

hyperparameters={
    "n_gpus": num_gpus,
    "batch_size": batch_size,
    "learning_rate": learning_rate
}

pytorch_huggingface_estimator=HuggingFace(
    entry_point='your_training_script.py',
    instance_count=instance_count,
    instance_type=instance_type,
    transformers_version='4.21.1',
    pytorch_version='1.11.0',
    hyperparameters=hyperparameters,
    compiler_config=TrainingCompilerConfig(),
    distribution ={'pytorchxla' : { 'enabled': True }},
    disable_profiler=True,
    debugger_hook_config=False
)

pytorch_huggingface_estimator.fit()
```

**Tip**

To prepare your training script, see the following pages.

- For distributed training (p. 2590) of a PyTorch model using Hugging Face Transformers' Trainer API
- For distributed training (p. 2591) of a PyTorch model without Hugging Face Transformers' Trainer API
For the supported version of PyTorch v1.10.2 and before, SageMaker Training Compiler requires an alternate mechanism for launching a distributed training job. To run distributed training, SageMaker Training Compiler requires you to pass a SageMaker distributed training launcher script to the `entry_point` argument, and pass your training script to the `hyperparameters` argument. The following code example shows how to configure a SageMaker Hugging Face estimator applying the required changes.

```python
from sagemaker.huggingface import HuggingFace, TrainingCompilerConfig

# choose an instance type, specify the number of instances you want to use, # and set the num_gpus variable the number of GPUs per instance.
instance_count=1
instance_type='ml.p3.8xlarge'
um_gpus=4

# the original max batch size that can fit to GPU memory without compiler
batch_size_native=16
learning_rate_native=float('5e-5')

# an updated max batch size that can fit to GPU memory with compiler
batch_size=26

# update learning rate
learning_rate=learning_rate_native/batch_size_native*batch_size*num_gpus*instance_count

hyperparameters={
    "n_gpus": num_gpus,
    "batch_size": batch_size,
    "learning_rate": learning_rate,
    "training_script": training_script  # Specify the file name of your training script.
}

pytorch_huggingface_estimator=HuggingFace(
    entry_point='distributed_training_launcher.py',  # Specify the distributed training launcher script.
    instance_count=instance_count,
    instance_type=instance_type,
    transformers_version='4.17.0',
    pytorch_version='1.10.2',
    hyperparameters=hyperparameters,
    compiler_config=TrainingCompilerConfig(),
    disable_profiler=True,
    debugger_hook_config=False
)

pytorch_huggingface_estimator.fit()
```

The launcher script should look like the following. It wraps your training script and configures the distributed training environment depending on the size of the training instance of your choice.

```python
#!/bin/python

import subprocess
import sys

if __name__ == '__main__':
    pass
```

arguments_command = " " + "\".join([arg for arg in sys.argv[1:]]))

The following line takes care of setting up an inter-node communication as well as managing intra-node workers for each GPU.
subprocess.check_call("python -m torch_xla.distributed.sm_dist " + arguments_command, shell=True)

Tip
To prepare your training script, see the following pages.

- For distributed training (p. 2590) of a PyTorch model using Hugging Face Transformers' Trainer API
- For distributed training (p. 2591) of a PyTorch model without Hugging Face Transformers' Trainer API

Tip
To find end-to-end examples, see the following notebooks:

- Compile and Train the GPT2 Model using the Transformers Trainer API with the SST2 Dataset for Single-Node Multi-GPU Training
- Compile and Train the GPT2 Model using the Transformers Trainer API with the SST2 Dataset for Multi-Node Multi-GPU Training

The following list is the minimal set of parameters required to run a SageMaker training job with the compiler.

**Note**
When using the SageMaker Hugging Face estimator, you must specify the transformers_version, pytorch_version, hyperparameters, and compiler_config parameters to enable SageMaker Training Compiler. You cannot use image_uri to manually specify the Training Compiler integrated Deep Learning Containers that are listed at Supported Frameworks (p. 2577).

- **entry_point (str)** – Required. Specify the file name of your training script.

  **Note**
  To run a distributed training with SageMaker Training Compiler and PyTorch v1.10.2 and before, specify the file name of a launcher script to this parameter. The launcher script should be prepared to wrap your training script and configure the distributed training environment. For more information, see the following example notebooks:

  - Compile and Train the GPT2 Model using the Transformers Trainer API with the SST2 Dataset for Single-Node Multi-GPU Training
  - Compile and Train the GPT2 Model using the Transformers Trainer API with the SST2 Dataset for Multi-Node Multi-GPU Training

- **instance_count (int)** – Required. Specify the number of instances.
- **instance_type (str)** – Required. Specify the instance type.
- **transformers_version (str)** – Required only when using the SageMaker Hugging Face estimator. Specify the Hugging Face Transformers library version supported by SageMaker Training Compiler. To find available versions, see Supported Frameworks (p. 2577).
- **framework_version or pytorch_version (str)** – Required. Specify the PyTorch version supported by SageMaker Training Compiler. To find available versions, see Supported Frameworks (p. 2577).

  **Note**
  When using the SageMaker Hugging Face estimator, you must specify both transformers_version and pytorch_version.
• hyperparameters (dict) – Optional. Specify hyperparameters for the training job, such as n_gpus, batch_size, and learning_rate. When you enable SageMaker Training Compiler, try larger batch sizes and adjust the learning rate accordingly. To find case studies of using the compiler and adjusted batch sizes to improve training speed, see the section called “Tested Models” (p. 2578) and SageMaker Training Compiler Example Notebooks and Blogs (p. 2608).

  Note

  To run a distributed training with SageMaker Training Compiler and PyTorch v1.10.2 and before, you need to add an additional parameter, "training_script", to specify your training script, as shown in the preceding code example.

• compiler_config (TrainingCompilerConfig object) – Required to activate SageMaker Training Compiler. Include this parameter to turn on SageMaker Training Compiler. The following are parameters for the TrainingCompilerConfig class.
  • enabled (bool) – Optional. Specify True or False to turn on or turn off SageMaker Training Compiler. The default value is True.
  • debug (bool) – Optional. To receive more detailed training logs from your compiler-accelerated training jobs, change it to True. However, the additional logging might add overhead and slow down the compiled training job. The default value is False.
  • distribution (dict) – Optional. To run a distributed training job with SageMaker Training Compiler, add distribution = {'pytorchxla': {'enabled': True}}.

  Warning

  If you turn on SageMaker Debugger, it might impact the performance of SageMaker Training Compiler. We recommend that you turn off Debugger when running SageMaker Training Compiler to make sure there's no impact on performance. For more information, see the section called “Performance Considerations” (p. 2609). To turn the Debugger functionalities off, add the following two arguments to the estimator:

  disable_profiler=True,
  debugger_hook_config=False

If the training job with the compiler is launched successfully, you receive the following logs during the job initialization phase:

• With TrainingCompilerConfig(debug=False)

  Found configuration for Training Compiler
  Configuring SM Training Compiler...

• With TrainingCompilerConfig(debug=True)

  Found configuration for Training Compiler
  Configuring SM Training Compiler...
  Training Compiler set to debug mode

Using the SageMaker CreateTrainingJob API Operation

SageMaker Training Compiler configuration options must be specified through the AlgorithmSpecification and HyperParameters field in the request syntax for the CreateTrainingJob API operation.

"AlgorithmSpecification": {
  "TrainingImage": "<sagemaker-training-compiler-enabled-dlc-image>
},

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"HyperParameters": {
  "sagemaker_training_compiler_enabled": "true",
  "sagemaker_training_compiler_debug_mode": "false",
  "sagemaker_pytorch_xla_multi_worker_enabled": "false"  // set to "true" for distributed training
}

To find a complete list of deep learning container image URIs that have SageMaker Training Compiler implemented, see Supported Frameworks (p. 2577).

Run TensorFlow Training Jobs with SageMaker Training Compiler

You can use any of the SageMaker interfaces to run a training job with SageMaker Training Compiler: Amazon SageMaker Studio, Amazon SageMaker notebook instances, AWS SDK for Python (Boto3), and AWS Command Line Interface.

Topics
- Using the SageMaker Python SDK (p. 2602)
- Using the SageMaker Python SDK and Extending SageMaker Framework Deep Learning Containers (p. 2605)
- Enable SageMaker Training Compiler Using the SageMaker CreateTrainingJob API Operation (p. 2607)

Using the SageMaker Python SDK

To turn on SageMaker Training Compiler, add the compiler_config parameter to the SageMaker TensorFlow or Hugging Face estimator. Import the TrainingCompilerConfig class and pass an instance of it to the compiler_config parameter. The following code examples show the structure of the SageMaker estimator classes with SageMaker Training Compiler turned on.

Tip
To get started with prebuilt models provided by the TensorFlow and Transformers libraries, try using the batch sizes provided in the reference table at Tested Models (p. 2578).

Note
SageMaker Training Compiler for TensorFlow is available through the SageMaker TensorFlow and Hugging Face framework estimators.

For information that fits your use case, see one of the following options.

For single GPU training

TensorFlow

```python
from sagemaker.tensorflow import TensorFlow, TrainingCompilerConfig

# the original max batch size that can fit into GPU memory without compiler
batch_size_native=12
learning_rate_native=float('5e-5')

# an updated max batch size that can fit into GPU memory with compiler
batch_size=64

# update the global learning rate
learning_rate=learning_rate_native/batch_size_native*batch_size

hyperparameters={
  "n_gpus": 1,
```
"batch_size": batch_size,
"learning_rate": learning_rate
}
tensorflow_estimator=TensorFlow(
    entry_point='train.py',
    instance_count=1,
    instance_type='ml.p3.2xlarge',
    framework_version='2.9.1',
    hyperparameters=hyperparameters,
    compiler_config=TrainingCompilerConfig(),
    disable_profiler=True,
    debugger_hook_config=False
)
tensorflow_estimator.fit()

To prepare your training script, see the following pages.

- For single GPU training (p. 2594) of a model constructed using TensorFlow Keras (tf.keras.*).
- For single GPU training (p. 2594) of a model constructed using TensorFlow modules (tf.* excluding the TensorFlow Keras modules).

Hugging Face Estimator with TensorFlow

```
from sagemaker.huggingface import HuggingFace, TrainingCompilerConfig

# the original max batch size that can fit into GPU memory without compiler
batch_size_native=12
learning_rate_native=float('5e-5')

# an updated max batch size that can fit into GPU memory with compiler
batch_size=64

# update the global learning rate
learning_rate=learning_rate_native/batch_size_native*batch_size

hyperparameters={
    "n_gpus": 1,
    "batch_size": batch_size,
    "learning_rate": learning_rate
}

tensorflow_huggingface_estimator=HuggingFace(
    entry_point='train.py',
    instance_count=1,
    instance_type='ml.p3.2xlarge',
    transformers_version='4.21.1',
    tensorflow_version='2.6.3',
    hyperparameters=hyperparameters,
    compiler_config=TrainingCompilerConfig(),
    disable_profiler=True,
    debugger_hook_config=False
)
tensorflow_huggingface_estimator.fit()
```

To prepare your training script, see the following pages.

- For single GPU training (p. 2594) of a TensorFlow Keras model with Hugging Face Transformers
- For single GPU training (p. 2595) of a TensorFlow model with Hugging Face Transformers
For distributed training

Hugging Face Estimator with TensorFlow

```python
from sagemaker.huggingface import HuggingFace, TrainingCompilerConfig

# choose an instance type, specify the number of instances you want to use, # and set the num_gpus variable the number of GPUs per instance.
instance_count=1
instance_type='ml.p3.8xlarge'
num_gpus=4

# the original max batch size that can fit to GPU memory without compiler
batch_size_native=16
learning_rate_native=float('5e-5')

# an updated max batch size that can fit to GPU memory with compiler
batch_size=26

# update learning rate
learning_rate=learning_rate_native/batch_size_native*batch_size*num_gpus*instance_count

hyperparameters={
    "n_gpus": num_gpus,
    "batch_size": batch_size,
    "learning_rate": learning_rate
}

tensorflow_huggingface_estimator=HuggingFace(
    entry_point='train.py',
    instance_count=instance_count,
    instance_type=instance_type,
    transformers_version='4.21.1',
    tensorflow_version='2.6.3',
    hyperparameters=hyperparameters,
    compiler_config=TrainingCompilerConfig(),
    disable_profiler=True,
    debugger_hook_config=False
)

tensorflow_huggingface_estimator.fit()
```

**Tip**

To prepare your training script, see the following pages.

- For distributed training (p. 2595) of a TensorFlow Keras model with Hugging Face Transformers
- For distributed training (p. 2596) of a TensorFlow model with Hugging Face Transformers

The following list is the minimal set of parameters required to run a SageMaker training job with the compiler.

**Note**

When using the SageMaker Hugging Face estimator, you must specify the transformers_version, tensorflow_version, hyperparameters, and compiler_config parameters to enable SageMaker Training Compiler. You cannot use image_uri to manually specify the Training Compiler integrated Deep Learning Containers that are listed at Supported Frameworks (p. 2577).

- entry_point (str) – Required. Specify the file name of your training script.
- instance_count (int) – Required. Specify the number of instances.
Enable Training Compiler

- **instance_type** (str) – Required. Specify the instance type.
- **transformers_version** (str) – Required only when using the SageMaker Hugging Face estimator. Specify the Hugging Face Transformers library version supported by SageMaker Training Compiler. To find available versions, see [Supported Frameworks](p. 2577).
- **framework_version** or **tensorflow_version** (str) – Required. Specify the TensorFlow version supported by SageMaker Training Compiler. To find available versions, see [Supported Frameworks](p. 2577).

**Note**
When using the SageMaker TensorFlow estimator, you must specify `framework_version`. When using the SageMaker Hugging Face estimator, you must specify both `transformers_version` and `tensorflow_version`.

- **hyperparameters** (dict) – Optional. Specify hyperparameters for the training job, such as `n_gpus`, `batch_size`, and `learning_rate`. When you enable SageMaker Training Compiler, try larger batch sizes and adjust the learning rate accordingly. To find case studies of using the compiler and adjusted batch sizes to improve training speed, see the section called “Tested Models” (p. 2578) and [SageMaker Training Compiler Example Notebooks and Blogs](p. 2608).

- **compiler_config** (TrainingCompilerConfig object) – Required. Include this parameter to turn on SageMaker Training Compiler. The following are parameters for the TrainingCompilerConfig class.
  - **enabled** (bool) – Optional. Specify True or False to turn on or turn off SageMaker Training Compiler. The default value is True.
  - **debug** (bool) – Optional. To receive more detailed training logs from your compiler-accelerated training jobs, change it to True. However, the additional logging might add overhead and slow down the compiled training job. The default value is False.

**Warning**
If you turn on SageMaker Debugger, it might impact the performance of SageMaker Training Compiler. We recommend that you turn off Debugger when running SageMaker Training Compiler to make sure there's no impact on performance. For more information, see the section called “Performance Considerations” (p. 2609). To turn the Debugger functionalities off, add the following two arguments to the estimator:

```
    disable_profiler=True,
    debugger_hook_config=False
```

If the training job with the compiler is launched successfully, you receive the following logs during the job initialization phase:

- With `TrainingCompilerConfig(debug=False)`

```
    Found configuration for Training Compiler
    Configuring SM Training Compiler...
```

- With `TrainingCompilerConfig(debug=True)`

```
    Found configuration for Training Compiler
    Configuring SM Training Compiler...
    Training Compiler set to debug mode
```

**Using the SageMaker Python SDK and Extending SageMaker Framework Deep Learning Containers**

AWS Deep Learning Containers (DLC) for TensorFlow use adapted versions of TensorFlow that include changes on top of the open-source TensorFlow framework. The [SageMaker Framework Deep Learning](...)
Containers are optimized for the underlying AWS infrastructure and Amazon SageMaker. With the advantage of using the DLCs, SageMaker Training Compiler integration adds more performance improvements over the native TensorFlow. Furthermore, you can create a custom training container by extending the DLC image.

**Note**
This Docker customization feature is currently available only for TensorFlow.

To extend and customize the SageMaker TensorFlow DLCs for your use-case, use the following instructions.

**Create a Dockerfile**

Use the following Dockerfile template to extend the SageMaker TensorFlow DLC. You must use the SageMaker TensorFlow DLC image as the base image of your Docker container. To find the SageMaker TensorFlow DLC image URIs, see supported frameworks.

```
# SageMaker TensorFlow Deep Learning Container image
FROM 763104351884.dkr.ecr.<aws-region>.amazonaws.com/tensorflow-training:<image-tag>

ENV PATH="/opt/ml/code:${PATH}"
# This environment variable is used by the SageMaker container
# to determine user code directory.
ENV SAGEMAKER_SUBMIT_DIRECTORY /opt/ml/code
# Add more code lines to customize for your use-case
...
```

For more information, see Step 2: Create and upload the Dockerfile and Python training scripts.

Consider the following pitfalls when extending SageMaker Framework DLCs:

- Do not explicitly uninstall or change the version of TensorFlow packages in SageMaker containers. Doing so causes the AWS optimized TensorFlow packages to be overwritten by open-source TensorFlow packages, which might result in performance degradation.
- Watch out for packages that have a particular TensorFlow version or flavor as a dependency. These packages might implicitly uninstall the AWS optimized TensorFlow and install open-source TensorFlow packages.

For example, there's a known issue that the tensorflow/models and tensorflow/text libraries always attempt to reinstall open source TensorFlow. If you need to install these libraries to choose a specific version for your use case, we recommend that you look into the SageMaker TensorFlow DLC Dockerfiles for v2.9 or later. The paths to the Dockerfiles are typically in the following format: tensorflow/training/docker/<tensorflow-version>/py3/<cuda-version>/Dockerfile.gpu. In the Dockerfiles, you should find the code lines to reinstall AWS managed TensorFlow binary (specified to the TF_URL environment variable) and other dependencies in order. The reinstallation section should look like the following example:

```
# tf-models does not respect existing installations of TensorFlow
# and always installs open source TensorFlow
RUN pip3 install --no-cache-dir -U 
    tf-models-official==x.y.z

RUN pip3 uninstall -y tensorflow tensorflow-gpu 
    ; pip3 install --no-cache-dir -U 
    $(TF_URL) 
    tensorflow-io==x.y.z 
```

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Build and push to ECR

To build and push your Docker container to Amazon ECR, follow the instructions in the following links:

- Step 3: Build the container
- Step 4: Test the container
- Step 5: Push the container to Amazon ECR

Run using the SageMaker Python SDK Estimator

Use the SageMaker TensorFlow framework estimator as usual. You must specify `image_uri` to use the new container you hosted in Amazon ECR.

```python
import sagemaker, boto3
from sagemaker import get_execution_role
from sagemaker.tensorflow import TensorFlow, TrainingCompilerConfig
account_id = boto3.client('sts').get_caller_identity().get('Account')
ecr_repository = 'tf-custom-container-test'
tag = ':latest'
region = boto3.session.Session().region_name
uri_suffix = 'amazonaws.com'
byoc_image_uri = '{}/.dkr.ecr.{}.amazonaws.com/{}'.format(account_id, region, ecr_repository + tag)

# This should return something like
# 111122223333.dkr.ecr.us-east-2.amazonaws.com/tf-custom-container-test:latest

estimator = TensorFlow(
    image_uri=byoc_image_uri,
    role=get_execution_role(),
    base_job_name='tf-custom-container-test-job',
    instance_count=1,
    instance_type='ml.p3.8xlarge',
    compiler_config=TrainingCompilerConfig(),
    disable_profiler=True,
    debugger_hook_config=False
)

# Start training
estimator.fit()
```

Enable SageMaker Training Compiler Using the SageMaker CreateTrainingJob API Operation

SageMaker Training Compiler configuration options must be specified through the `AlgorithmSpecification` and `HyperParameters` field in the request syntax for the `CreateTrainingJob API operation`.

```json
"AlgorithmSpecification": {
    "TrainingImage": "<sagemaker-training-compiler-enabled-dlc-image>
},
```
"HyperParameters": {
    "sagemaker_training_compiler_enabled": "true",
    "sagemaker_training_compiler_debug_mode": "false"
}

To find a complete list of deep learning container image URIs that have SageMaker Training Compiler implemented, see Supported Frameworks (p. 2577).

SageMaker Training Compiler Example Notebooks and Blogs

The following blogs, case studies, and notebooks provide examples of how to implement SageMaker Training Compiler.

Example notebooks are provided in the SageMaker examples GitHub repository, and you can also browse them on the SageMaker examples website.

Blogs and Case Studies

The following blogs discuss case studies about using SageMaker Training Compiler.

- New – Introducing SageMaker Training Compiler
- Hugging Face Transformers BERT fine-tuning using Amazon SageMaker Training Compiler
- Speed up Hugging Face Training Jobs on AWS by Up to 50% with SageMaker Training Compiler

Examples Notebooks

To find examples of using SageMaker Training Compiler, see the Training Compiler page in the Amazon SageMaker Example Read the Docs website.

SageMaker Training Compiler Best Practices and Considerations

Review the following best practices and considerations when using SageMaker Training Compiler.

Best Practices

Use the following guidelines to achieve the best results when you run training jobs with SageMaker Training Compiler.

General Best Practices

- Make sure that you use one of the Supported Instance Types (p. 2578) and Tested Models (p. 2578).
- When you create a tokenizer for an NLP model using the Hugging Face Transformers library in your training script, make sure that you use a static input tensor shape by specifying padding='max_length'. Do not use padding='longest' because padding to the longest sequence in the batch can change the tensor shape for each training batch. The dynamic input shape can initiate recompilation of the model and might increase total training time. For more information about padding options of the Transformers tokenizers, see Padding and truncation in the Hugging Face Transformers documentation.
• Measure GPU memory utilization to make sure that you use the maximum batch size that can fit into the GPU memory. Amazon SageMaker Training Compiler reduces the memory footprint of your model during training, which typically allows you to fit a larger batch_size in the GPU memory. Using a larger batch_size results in a better GPU utilization and reduces the total training time.

When you adjust the batch size, you also have to adjust the learning_rate appropriately. For example, if you increased the batch size by a factor of k, you need to adjust learning_rate linearly (simple multiplication by k) or multiply by the square root of k. This is to achieve the same or similar convergence behavior in the reduced training time. For reference of batch_size tested for popular models, see Tested Models (p. 2578).

• To debug the compiler-accelerated training job, enable the debug flag in the compiler_config parameter. This enables SageMaker to put the debugging logs into SageMaker training job logs.

```python
huggingface_estimator=HuggingFace(
    ...
    compiler_config=TrainingCompilerConfig(debug=True)
)
```

Note that if you enable full debugging of the training job with the compiler, this might add some overhead.

**Best Practices for PyTorch**

• If you bring a PyTorch model and want to checkpoint it, make sure you use PyTorch/XLA's model save function to properly checkpoint your model. For more information about the function, see `torch_xla.core.xla_model.save` in the PyTorch on XLA Devices documentation.

To learn how to add the modifications to your PyTorch script, see Using PyTorch (without the Hugging Face Transformers Trainer API) (p. 2590).

For more information about the actual application of using the model save function, see Checkpoint Writing and Loading in the Hugging Face on PyTorch/XLA TPUs: Faster and cheaper training blog.

• To achieve the most optimal training time for distributed training, consider the following.

  • Use instances with multiple GPUs instead of using single-gpu instances. For example, a single ml.p3dn.24xlarge instance has faster training time compared to 8 x ml.p3.2xlarge instances.
  
  • Use instances with EFA support such as ml.p3dn.24xlarge and ml.p4d.24xlarge. These instance types have accelerated networking speed and reduce training time.
  
  • Tune the preprocessing_num_workers parameter for datasets, so that model training is not delayed by slow preprocessing.

**Performance Considerations**

Consider the following when using SageMaker Training Compiler.

• Avoid logging, checkpointing, and profiling model tensors that lead to explicit evaluations. To understand what an explicit evaluation is, consider the following code compiling example.

```python
a = b+c
e = a+d
```

A compiler interprets the code as follows and reduces the memory footprint for the variable a:

```python
e = b+c+d
```
Now consider the following case in which the code is changed to add a print function for the variable \( a \).

\[
\begin{align*}
a &= b + c \\
e &= a + d \\
print(a)
\end{align*}
\]

The compiler makes an explicit evaluation of the variable \( a \) as follows.

\[
\begin{align*}
e &= b + c + d \\
a &= b + c \quad \# \text{Explicit evaluation} \\
print(a)
\end{align*}
\]

In PyTorch, for example, avoid using `torch.tensor.items()`, which might introduce explicit evaluations. In deep learning, such explicit evaluations can cause overhead because they break fused operations in a compilation graph of a model and lead to recomputation of the tensors.

If you still want to periodically evaluate the model during training while using SageMaker Training Compiler, we recommend logging and checkpointing at a lower frequency to reduce overhead due to explicit evaluations. For example, log every 10 epochs instead of every epoch.

- Graph compilation runs during the first few steps of training. As a result, the first few steps are expected to be exceptionally slow. However, this is a one-time compilation cost and can be amortized by training for a longer duration because compilation makes future steps much faster. The initial compilation overhead depends on the size of the model, the size of the input tensors, and the distribution of input tensor shapes.

## SageMaker Training Compiler FAQ

Use the following FAQ items to find answers to commonly asked questions about SageMaker Training Compiler.

**Q. How do I know SageMaker Training Compiler is working?**

If you successfully launched your training job with SageMaker Training Compiler, you receive the following log messages:

- With `TrainingCompilerConfig(debug=False)`

```
Found configuration for Training Compiler
Configuring SM Training Compiler...
```

- With `TrainingCompilerConfig(debug=True)`

```
Found configuration for Training Compiler
Configuring SM Training Compiler...
Training Compiler set to debug mode
```

**Q. Which models does SageMaker Training Compiler accelerate?**

SageMaker Training Compiler supports the most popular deep learning models from the Hugging Face transformers library. With most of the operators that the compiler supports, these models can be trained faster with SageMaker Training Compiler. Compilable models include but are not limited to the following: `bert-base-cased`, `bert-base-chinese`, `bert-base-uncased`, `distilbert-base-uncased`, `distilbert-base-uncased-finetuned-sst-2-english`, `gpt2`, `roberta-base`,...
roberta-large, t5-base, and xlm-roberta-base. The compiler works with most DL operators and data structures and can accelerate many other DL models beyond those that have been tested.

**Q. What happens if I enable SageMaker Training Compiler with a model that isn't tested?**

For an untested model, you might need to first modify the training script to be compatible with SageMaker Training Compiler. For more information, see Bring Your Own Deep Learning Model (p. 2589) and follow the instructions on how to prepare your training script.

Once you have updated your training script, you can start the training job. The compiler proceeds to compile the model. However, training speed may not increase and might even decrease relative to the baseline with an untested model. You might need to retune training parameters such as batch_size and learning_rate to achieve any speedup benefits.

If compilation of the untested model fails, the compiler returns an error. See SageMaker Training Compiler Troubleshooting (p. 2612) for detailed information about the failure types and error messages.

**Q. Will I always get a faster training job with SageMaker Training Compiler?**

No, not necessarily. First, SageMaker Training Compiler adds some compilation overhead before the ongoing training process can be accelerated. The optimized training job must run sufficiently long to amortize and make up for this incremental compilation overhead at the beginning of the training job.

Additionally, as with any model training process, training with suboptimal parameters can increase training time. SageMaker Training Compiler can change the characteristics of the training job by, for example, changing the memory footprint of the job. Because of these differences, you might need to retune your training job parameters to speed up training. A reference table specifying the best performing parameters for training jobs with different instance types and models can be found at Tested Models (p. 2578).

Finally, some code in a training script might add additional overhead or disrupt the compiled computation graph and slow training. If working with a customized or untested model, see the instructions at Best Practices to Enable SageMaker Training Compiler for PyTorch without the Hugging Face Trainer API (p. 2593).

**Q. Can I always use a larger batch size with SageMaker Training Compiler?**

Batch size increases in most, but not all, cases. The optimizations made by SageMaker Training Compiler can change the characteristics of your training job, such as the memory footprint. Typically, a Training Compiler job occupies less memory than an uncompiled training job with the native framework, which allows for a larger batch size during training. A larger batch size, and a corresponding adjustment to the learning rate, increases training throughput and can decrease total training time.

However, there could be cases where SageMaker Training Compiler might actually increase memory footprint based on its optimization scheme. The compiler uses an analytical cost model to predict the execution schedule with the lowest cost of execution for any compute-intensive operator. This model could find an optimal schedule that increases memory use. In this case, you won't be able to increase batch sizes, but your sample throughput is still higher.

**Q. Does SageMaker Training Compiler work with other SageMaker training features, such as the SageMaker distributed training libraries and SageMaker Debugger?**

SageMaker Training Compiler is currently not compatible with SageMaker’s distributed training libraries. SageMaker Training Compiler is compatible with SageMaker Debugger, but Debugger might degrade computational performance by adding overhead.

**Q. Does SageMaker Training Compiler support custom containers (bring your own container)?**

SageMaker Training Compiler is provided through AWS Deep Learning Containers, and you can extend a subset of the containers to customize for your use-case. Containers that are extended from AWS DLCs are supported by SageMaker Training Compiler. For more information, see Supported
If you run into an error, you can use the following list to try to troubleshoot your training job. If you need further support, reach out to the SageMaker team through AWS Support or AWS Developer Forums for Amazon SageMaker.

Training Job Fails Due to Missing XLA Configuration

If a training job fails with the Missing XLA configuration error message, it might be due to a misconfiguration in the number of GPUs per instance that you use.

XLA requires additional environment variables to compile the training job. The most common missing environment variable is GPU_NUM_DEVICES. For the compiler to work properly, you must set this environment variable equal to the number of GPUs per instance.

There are three approaches to set the GPU_NUM_DEVICES environment variable:

• **Approach 1** – Use the environment argument of the SageMaker estimator class. For example, if you use an ml.p3.8xlarge instance that has four GPUs, do the following:

```python
# Using the SageMaker Python SDK's HuggingFace estimator
hf_estimator=HuggingFace(
    ...
    instance_type="ml.p3.8xlarge",
    hyperparameters={...},
    environment={
        ...
        "GPU_NUM_DEVICES": "4"  # corresponds to number of GPUs on the specified instance
    },
)
```

• **Approach 2** – Use the hyperparameters argument of the SageMaker estimator class and parse it in your training script.

1. To specify the number of GPUs, add a key-value pair to the hyperparameters argument.

For example, if you use an ml.p3.8xlarge instance that has four GPUs, do the following:

```python
# Using the SageMaker Python SDK's HuggingFace estimator
hf_estimator=HuggingFace(
    ...
    entry_point = "train.py",
    instance_type= "ml.p3.8xlarge",
    hyperparameters = {
        ...
        "n_gpus": 4  # corresponds to number of GPUs on specified instance
    }
)
hf_estimator.fit()
```

2. In your training script, parse the n_gpus hyperparameter and specify it as an input for the GPU_NUM_DEVICES environment variable.

```python
# train.py
```
import os, argparse

if __name__ == "__main__":
    parser = argparse.ArgumentParser()
    ...
    # Data, model, and output directories
    parser.add_argument("--output_data_dir", type=str,
                        default=os.environ["SM_OUTPUT_DATA_DIR"])
    parser.add_argument("--model_dir", type=str, default=os.environ["SM_MODEL_DIR"])
    parser.add_argument("--training_dir", type=str,
                        default=os.environ["SM_CHANNEL_TRAIN"])
    parser.add_argument("--test_dir", type=str, default=os.environ["SM_CHANNEL_TEST"])
    parser.add_argument("--n_gpus", type=str, default=os.environ["SM_NUM_GPUS"])

    args, _ = parser.parse_known_args()
    os.environ["GPU_NUM_DEVICES"] = args.n_gpus

• Approach 3 – Hard-code the GPU_NUM_DEVICES environment variable in your training script. For example, add the following to your script if you use an instance that has four GPUs.

```python
import os
os.environ["GPU_NUM_DEVICES"] = 4
```

Tip

To find the number of GPU devices on machine learning instances that you want to use, see Accelerated Computing in the Amazon EC2 Instance Types page.

Incorrect API Uses for PyTorch without Hugging Face Trainer API

PyTorch/XLA defines a set of APIs to replace some of the existing PyTorch training APIs. Failing to use them properly leads PyTorch training to fail.

• One of the most typical errors when compiling a PyTorch model is due to a wrong device type for operators and tensors. To properly compile a PyTorch model, make sure you use XLA devices (`xm.xla_device()`) instead of using CUDA or mixing CUDA devices and XLA devices.
• `mark_step()` is a barrier just for XLA. Failing to set it correctly causes a training job to stall.
• PyTorch/XLA provides additional distributed training APIs. Failing to program the APIs properly causes gradients to be collected incorrectly, which causes a training convergence failure.

To properly set up your PyTorch script and avoid the aforementioned incorrect API uses, see Using PyTorch (without the Hugging Face Transformers Trainer API) (p. 2590) and Best Practices to Enable SageMaker Training Compiler for PyTorch without the Hugging Face Trainer API (p. 2593).

SageMaker Training Compiler Does Not Reduce the Total Training Time

If the total training time does not decrease with SageMaker Training Compiler, we highly recommend you to go over the SageMaker Training Compiler Best Practices and Considerations (p. 2608) page to check your training configuration, padding strategy for the input tensor shape, and hyperparameters.

Amazon SageMaker Training Compiler Release Notes

See the following release notes to track the latest updates for Amazon SageMaker Training Compiler.
SageMaker Training Compiler Release Notes: October 4, 2022

Currency Updates

• Added support for TensorFlow v2.10.0.

Other Changes

• Added Hugging Face NLP models using the Transformers library to TensorFlow framework tests. To find the tested Transformer models, see the section called “Tested Models” (p. 2578).

Migration to AWS Deep Learning Containers

This release passed benchmark testing and is migrated to the following AWS Deep Learning Container:

• TensorFlow v2.10.0

763104351884.dkr.ecr.<region>.amazonaws.com/tensorflow-training:2.10.0-gpu-py39-cu112-ubuntu20.04-sagemaker

To find a complete list of the prebuilt containers with Amazon SageMaker Training Compiler, see Supported Frameworks, AWS Regions, Instance Types, and Tested Models (p. 2576).

SageMaker Training Compiler Release Notes: September 1, 2022

Currency Updates

• Added support for Hugging Face Transformers v4.21.1 with PyTorch v1.11.0.

Improvements

• Implemented a new distributed training launcher mechanism to activate SageMaker Training Compiler for Hugging Face Transformer models with PyTorch. To learn more, see Run PyTorch Training Jobs with SageMaker Training Compiler for Distributed Training (p. 2598).

• Integrated with EFA to improve the collective communication in distributed training.

• Added support for G5 instances for PyTorch training jobs. For more information, see the section called “Supported Frameworks, AWS Regions, Instance Types, and Tested Models” (p. 2576).

Migration to AWS Deep Learning Containers

This release passed benchmark testing and is migrated to the following AWS Deep Learning Container:

• HuggingFace v4.21.1 with PyTorch v1.11.0


To find a complete list of the prebuilt containers with Amazon SageMaker Training Compiler, see Supported Frameworks, AWS Regions, Instance Types, and Tested Models (p. 2576).
SageMaker Training Compiler Release Notes: June 14, 2022

New Features

• Added support for TensorFlow v2.9.1. SageMaker Training Compiler fully supports compiling TensorFlow modules (tf.*) and TensorFlow Keras modules (tf.keras.*).

• Added support for custom containers created by extending AWS Deep Learning Containers for TensorFlow. For more information, see Enable SageMaker Training Compiler Using the SageMaker Python SDK and Extending SageMaker Framework Deep Learning Containers (p. 2605).

• Added support for G5 instances for TensorFlow training jobs.

Migration to AWS Deep Learning Containers

This release passed benchmark testing and is migrated to the following AWS Deep Learning Container:

• TensorFlow 2.9.1

763104351884.dkr.ecr.<region>.amazonaws.com/tensorflow-training:2.9.1-gpu-py39-cu112-ubuntu20.04-sagemaker

To find a complete list of the pre-built containers with Amazon SageMaker Training Compiler, see Supported Frameworks, AWS Regions, Instance Types, and Tested Models (p. 2576).

SageMaker Training Compiler Release Notes: April 26, 2022

Improvements

• Added support for all of the AWS Regions where AWS Deep Learning Containers are in service except the China regions.

SageMaker Training Compiler Release Notes: April 12, 2022

Currency Updates

• Added support for Hugging Face Transformers v4.17.0 with TensorFlow v2.6.3 and PyTorch v1.10.2.

SageMaker Training Compiler Release Notes: February 21, 2022

Improvements

• Completed benchmark test and confirmed training speed-ups on the ml.g4dn instance types. To find a complete list of tested ml instances, see Supported Instance Types (p. 2578).

SageMaker Training Compiler Release Notes: December 01, 2021

New Features

• Launched Amazon SageMaker Training Compiler at AWS re:Invent 2021.
Amazon SageMaker Developer Guide  
Clarify Bias Detection and Model Explainability

Migration to AWS Deep Learning Containers

- Amazon SageMaker Training Compiler passed benchmark testing and is migrated to AWS Deep Learning Containers. To find a complete list of the prebuilt containers with Amazon SageMaker Training Compiler, see Supported Frameworks, AWS Regions, Instance Types, and Tested Models (p. 2576).

Amazon SageMaker Clarify Bias Detection and Model Explainability

This topic describes how to configure an Amazon SageMaker Clarify processing job capable of computing bias metrics and feature attributions for explainability. It is implemented using a specialized SageMaker Clarify container image. Instructions are provided for how to locate and download one of these container images. A brief overview of how SageMaker Clarify works is sketched. The parameters needed to configure the processing job and type of analysis are described. Prerequisites are outlined and some advice about compute resources consumed by SageMaker Clarify processing job is provided. For additional information about bias metrics and explainability and how to interpret them, see Learn How Amazon SageMaker Clarify Helps Detect Bias, Fairness Measures for Machine Learning in Finance, and the Amazon AI Fairness and Explainability Whitepaper.

Sample Notebooks

Amazon SageMaker Clarify provides the following sample notebook for posttraining bias detection and model explainability:

- Amazon SageMaker Clarify Processing – Use SageMaker Clarify to create a processing job for the detecting bias and explaining model predictions with feature attributions. Examples include using CSV and JSON Lines data formats, bringing your own container, and running processing jobs with Spark.

This notebook has been verified to run in Amazon SageMaker Studio only. If you need instructions on how to open a notebook in Amazon SageMaker Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133). If you're prompted to choose a kernel, choose Python 3 (Data Science).

Topics

- Prerequisites (p. 2616)
- How SageMaker Clarify Processing Jobs Work (p. 2617)
- Get Started with a SageMaker Clarify Container (p. 2618)
- Configure a SageMaker Clarify Processing Job Container’s Input and Output Parameters (p. 2619)
- Configure the Analysis (p. 2620)
- Run SageMaker Clarify Processing Jobs for Bias Analysis and Explainability (p. 2627)
- Detect Posttraining Data and Model Bias with Amazon SageMaker Clarify (p. 2630)
- Amazon SageMaker Clarify Model Explainability (p. 2652)
- Troubleshoot SageMaker Clarify Processing Jobs (p. 2660)

Prerequisites

Before you begin, you need to meet the following prerequisites:
You need to provide an input dataset as tabular files in CSV or JSON Lines format. The input dataset must include a label column for bias analysis. The dataset should be prepared for machine learning with any pre-processing needed, such as data cleaning or feature engineering, already completed.

You need to provide a model artifact that supports either the CSV or JSON Lines file format as one of its content type inputs. For posttraining bias metrics and explainability, we use the dataset to make inferences with the model artifact. Each row minus the label column must be ready to be used as payload for inferences.

When creating processing jobs with the SageMaker container image, you need the following:

- Network isolation must be disabled for the processing job.
- If the model is in a VPC, the processing job must be in the same VPC as the model.
- The IAM user/role of the caller must have permissions for SageMaker APIs. We recommend that you use the "arn:aws:iam::aws:policy/AmazonSageMakerFullAccess" managed policy.

### How SageMaker Clarify Processing Jobs Work

A SageMaker processing job uses the SageMaker Clarify container at several stages in the lifecycle of the machine learning workflow. You can use the SageMaker Clarify container with your datasets and models to compute the following types of analysis:

- pretraining bias metrics
- posttraining bias metrics
- SHAP values for explainability
- Partial dependence plots (PDP)

You can control which of these analyses are computed when you configure the processing job. For pretraining bias metrics, you need to provide the dataset. You can compute posttraining bias metrics and explainability after your model has been trained by providing the dataset and model name. You must configure the necessary parameters in the form of a JSON configuration file and provide this as an input to the processing job.

After the processing job completes, the result of the analyses is saved in the output location specified in the ProcessingOutput parameters of the processing job. You can then download it from there and view the outputs or you can view the results in Studio if you have run a notebook there.

In order to compute posttraining bias metrics and SHAP values, the computation needs to get inferences for the model name provided. To accomplish this, the processing job creates an ephemeral endpoint with the model name, known as a shadow endpoint. The processing job deletes the shadow endpoint after the computations are completed.

At a high level, the processing job completes the following steps:

1. Validate inputs and parameters.
2. Create the shadow endpoint.
3. Compute pretraining bias metrics.
5. Compute local and global feature attributions.
6. Delete shadow endpoint.
7. Generate output files.
Get Started with a SageMaker Clarify Container

Amazon SageMaker provides prebuilt SageMaker Clarify container images that include the libraries and other dependencies needed to compute bias metrics and feature attributions for explainability. This image has been enabled to run SageMaker Process Data (p. 1022) in your account.

The image URIs for the containers are in the following form:

<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/sagemaker-clarify-processing:1.0

For example:

205585389593.dkr.ecr.us-east-1.amazonaws.com/sagemaker-clarify-processing:1.0

The following table lists the addresses by AWS Region.

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<th>Image address</th>
</tr>
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</tr>
</tbody>
</table>
Configure a SageMaker Clarify Processing Job
Container's Input and Output Parameters

The Processing Job requires that you specify the following input parameters: a dataset files with input name "dataset" as Amazon S3 object or prefix, and an analysis configuration file with input name "analysis_config" as an Amazon S3 object. The job also requires an output parameter: the output location as an Amazon S3 prefix.

You can create and run a processing job with SageMaker CreateProcessingJob API using the AWS SDK or CLI or SageMaker Python SDK.

Using SageMaker Python SDK, create a Processor using the SageMaker Clarify container image URI:

```python
from sagemaker import clarify
clarify_processor = clarify.SageMakerClarifyProcessor(role=role,
instance_count=1,
instance_type='ml.c5.xlarge',
max_runtime_in_seconds=1200,
volume_size_in_gb=100)
```

After you finish creating the Clarify processor, you need to set up the input and output object for the processor.
Note
If you provide the "dataset_uri" through the "analysis_config.json" (see the following topic at Configure the Analysis (p. 2620)), you don't need to create the dataset_input object.

```python
dataset_path = "s3://my_bucket/my_folder/train.csv"
analysis_config_path = "s3://my_bucket/my_folder/analysis_config.json"
analysis_result_path = "s3://my_bucket/my_folder/output"

analysis_config_input = ProcessingInput(
    input_name="analysis_config",
    source=analysis_config_path,
    destination="/opt/ml/processing/input/config",
    s3_data_type="S3Prefix",
    s3_input_mode="File",
    s3_compression_type="None")
dataset_input = ProcessingInput(  
    input_name="dataset",
    source=dataset_path,
    destination="/opt/ml/processing/input/data",
    s3_data_type="S3Prefix",
    s3_input_mode="File",
    s3_compression_type="None")
analysis_result_output = ProcessingOutput(
    source="/opt/ml/processing/output",
    destination=analysis_result_path,
    output_name="analysis_result",
    s3_upload_mode="EndOfJob")
```

Configure the Analysis

The inputs for the analysis are configured by the parameters of the ProcessingInput API. The "analysis_config" value of the input_name specifies the JSON file named analysis_config.json that contains the configuration values. The path to the JSON file is provided in the source parameter of ProcessingInput. Examples of analysis configuration JSON files are provided for JSON files for CSV, JSON Lines, image, and text datasets following the parameter descriptions.

Topics
- Parameters for JSON configuration files (p. 2620)
- Example JSON configuration files (p. 2624)

Parameters for JSON configuration files

In the JSON configuration file, you can specify the following parameters.

- "version" – (Optional) Schema version of the configuration file. If not provided, the latest supported version is used.
- "dataset_type" – (Required) Format of the dataset. Valid values are "text/csv" for CSV, "application/jsonlines" for JSON Lines, application/x-parquet for Apache Parquet, and application/x-image to enable computer vision explainability. For more information see Common Data Formats for Inference.
- "dataset_uri" – (Optional) Dataset S3 prefix/object URI (if not given as ProcessingInput). If it is a prefix, the processing job recursively collects all S3 files under the prefix. For computer vision, the URI is required and it can either be a path to the image manifest file, or to the bucket of images to be explained.
- "headers" – (Optional) A list of column names in the dataset. If the dataset_type is "application/jsonlines" and "label" is specified, then the last header shall be the header of label column.
Configure the Analysis

- "label" – (Optional) Target attribute for the model to be used for bias metrics. Specified as a column name, or as index if the dataset format is CSV, or as JSONPath if the dataset format is JSON Lines.

- "probability_threshold" – (Optional) A float value to indicate the threshold to select the binary label in the case of binary classification. This parameter is used in object detection to filter out objects detected with confidence scores lower than the probability_threshold value. The default value is 0.5.

- "features" – (Optional) JSONPath for locating the feature columns for bias metrics, if the dataset format is JSON Lines.

- "label_values_or_threshold" – (Optional) List of label values or threshold. Indicates positive outcome used for bias metrics.

- "facet" – (Optional) A list of features that are sensitive attributes, referred to as facets. Facets are used for bias metrics in the form of pairs, and include the following:
  - "name_or_index" – Facet column name or index.
  - "value_or_threshold" – (Optional) List of values or threshold that the facet column can take. Indicates the sensitive group, such as the group that is used to measure bias against. If not provided, bias metrics are computed as one group for every unique value (rather than all values). If the facet column is numeric, this threshold value is applied as the lower bound to select the sensitive group.

- "group_variable" – (Optional) A column name or index to indicate the group variable to be used for the bias metric Conditional Demographic Disparity.

- "joinsource_name_or_index" – (Optional) The name or index of the column in the dataset that acts as an identifier column, for example, while performing a join. This column is only used as an identifier, and not used for any other computations. This is an optional field in all cases except when the dataset contains more than one file, and "save_local_shap_values" is set to true.

- "methods" – A list of methods and their parameters for the analyses and reports. If any section is omitted, then it is not computed.
  - "pre_training_bias" – (Optional) Section on pretraining bias metrics.
  - "methods" – A list of pretraining metrics to be computed.
  - "post_training_bias" – (Optional) Section on posttraining bias metrics.
  - "methods" – A list of posttraining metrics to be computed.

- "shap" – (Optional) Section on SHAP value computation.
  - "agg_method" – Aggregation method for global SHAP values. Valid values are as follows:
    - "mean_abs" – Mean of absolute SHAP values for all instances.
    - "median" – Median of SHAP values for all instances.
    - "mean_sq" – Mean of squared SHAP values for all instances.
  - "baseline" – (Optional) A list of rows (at least one), or an S3 object URI. To be used as the baseline dataset (also known as a background dataset) in the Kernel SHAP algorithm. The format should be the same as the dataset format. Each row should contain only the feature columns (or values) and omit any column that must be excluded before being sent to the model. This includes label column, joinsource column, and columns included in the "exclude_column" field.
    - For Computer Vision, a path to the baseline image that is used to mask out features from the input image. Default: RGB Noise mask.
    - For natural language processing (NLP) of text columns, the baseline value should be the value used to replace the unit of text specified by the granularity in the "text_config". Valid values for the unit of text are token, sentence, and paragraph.
  - "num_clusters" – (Optional) If "baseline" is not provided, Clarify attempts to compute a baseline by clustering the dataset. The "num_clusters" determines the number of clusters that the dataset is clustered into. Each cluster contributes to a baseline, so the number of clusters directly affects the runtime of SHAP explanations.
  - "num_samples" – Number of samples to be used in the Kernel SHAP algorithm. This number determines the size of the generated synthetic dataset to compute the SHAP values.
• "seed" – (Optional) Seed value for the random number generator to obtain a deterministic SHAP result.

• "text_config" – (Required) The configuration that specifies the natural language processing (NLP) features. If this config is provided, text features are treated as text and explanations are provided for individual units of text. The unit of text is specified by the "granularity".

• "granularity" – (Required) For NLP, determines the unit of granularity for the analysis of text features. Valid values are "token", "sentence", or "paragraph". Each of these units is considered a feature, and SHAP values are computed for the feature specified.


• "use_logit" – (Optional) Boolean value to indicate if the logit function is to be applied to the model predictions. If "use_logit" is true, then the SHAP values have log-odds units. The default value is false.

• "image_config" – (Optional) Section for configuring SHAP configuration parameters for computer vision explainability.
  • "model_type" – Either an object detection model or an image classification model.
  • "num_segments" – (Optional) Determines the approximate number of segments to be labeled in the input image. The default is 20.
  • "segment_compactness" – (Optional) Determines the shape and size of the image segments generated by SKLearn's slic method. For more details, see scikit-image slic documentation. The default is 5.
  • "max_objects" – (Optional) Used to filter objects detected by the computer vision model by top confidence score. The default is 3.
  • "iou_threshold" – (Optional) Minimum intersection over union (IOU) metric for evaluating predictions against the original detections. Used because detection boxes will shift during masking. The default value is 0.5.
  • "context" – (Optional) Masks the area around the bounding box of the detected object when running SHAP. Valid values are 0 to mask everything, or 1 to mask nothing. The default value is 1.
  • "save_local_shap_values" – (Optional) Boolean value to indicate if local SHAP values are to be saved in the output location. Use true to save them; false to not save them. The default is false.

• "pdp" – (Optional) Section for configuring partial dependence plots (PDP). Shows the dependence of the target response on a set of input features of interest. Marginalizes over the values of all other input features.
  • "features": ["pdp_feature_1", "pdp_feature_2"...] – (Optional) The list of feature names or indices for which partial dependence plots are to be computed and plotted. If SHAP is not requested, the features must be provided.
  • "grid_resolution" – (Required) Used for numerical features. Represents that number of buckets into which the range of numerical values is divided. This specifies the granularity of the grid for the PDP plot.
• "top_k_features" – (Optional) If the features parameter is not provided, and shap is provided, Clarify chooses the top k features based on SHAP attributions. You can set this value to specify how many of the top features must be used for PDP plots. The default is 10.

• "predictor" – (Optional) Section on model parameters, required if "shap" and "post_training_bias" sections are present.
  • "model_name" – Model name created by CreateModel API, with container mode as SingleModel.
  • "instance_type" – Instance type for the shadow endpoint.
  • "initial_instance_count" – Instance count for the shadow endpoint.
  • "content_type" – (Optional) The model input format to be used for getting inferences with the shadow endpoint. Valid values are "text/csv" for CSV, "application/jsonlines" for JSON Lines, application/x-parquet for Apache Parquet, and application/x-image to enable Computer Vision explainability. The default value is the same as the dataset_type format.
  • "accept_type" – (Optional) The model output format to be used for getting inferences with the shadow endpoint. Valid values are "text/csv" for CSV, "application/jsonlines" for JSON Lines, application/x-parquet for Apache Parquet, and application/x-image to enable Computer Vision explainability. The default value is the same as content_type.
  • "accelerator_type" – (Optional) The type of Elastic Inference (EI) accelerator to attach to the instance. Example: ml.eia1.medium. For more information, see Use Amazon SageMaker Elastic Inference (EI) (p. 3129).
  • "custom_attributes" – (Optional) Provides additional information about a request for an inference that is submitted to a model hosted on an Amazon SageMaker endpoint. The information is an opaque value that is forwarded verbatim. You can use this value, for example, to provide an ID that tracks a request. You can also use this value to provide metadata that a service endpoint was programmed to process. The value must consist of no more than 1024 visible US-ASCII characters, as specified in Section 3.3.6. Field Value Components of the Hypertext Transfer Protocol (HTTP/1.1).
  • "label" – (Optional) Index or JSONPath location in the model output for the target attribute that is used by the bias metrics. If the label is not provided in the CSV accept_type case, then Clarify assumes that the model output is a single numeric value corresponding to the score or probability.
  • "probability" – (Optional) Index or JSONPath location in the model output for probabilities or scores to be used for explainability. If the model output is JSON Lines with a list of labels and probabilities, for example, then the label that corresponds to the maximum probability is selected for bias computations. For explainability method, currently all probabilities are explained.
  • "endpoint_name-prefix" – (Optional) Provides a custom prefix to the name of the temporary endpoint.
  • "endpoint_name" – (Optional) Specifies an existing endpoint to use for getting predictions. Using an existing endpoint reduces the bootstrap time, but can cause a significant load increase for existing endpoints. Be cautious when specifying an existing production endpoint.
  • "target_model" – (Optional) Sets the target model name when using a multi-model endpoint. For more information about multi-model endpoints, see Request Syntax.
  • "label_headers" – (Optional) A list of values that the "label" takes in the dataset. Associates the scores returned by the model endpoint with their corresponding label values. Used to extract the label value with the highest score as the predicted label.
  • "content_template" – (Optional) A template string used to construct the model input from dataset instances. It is only used when "content_type" is "application/jsonlines". The template should have only one placeholder, $features, which is replaced by the features list at runtime. For example, given "content_template": "{\"myfeatures\":$features\}" , if an instance (no label) is 1, 2, 3, then model input becomes JSON Line '{"myFeatures":[1,2,3]}'.
  • "report" – (Optional) Section on report parameters. A report is generated if this section is present.
  • "name" – (Optional) Filename prefix for the report notebook and PDF file. The default name is "report".
• "title" – (Optional) Title string for the report notebook and PDF file. The default title is "SageMaker Analysis Report".

Example JSON configuration files

Here are examples of analysis configuration JSON files for CSV, JSON Lines, image, and text datasets.

Topics

• Analysis configuration JSON file for a CSV dataset (p. 2624)
• Analysis configuration JSON file for a JSON Lines dataset (p. 2625)
• Analysis configuration JSON file for an image dataset (p. 2626)
• NLP analysis configuration JSON file for a text dataset (p. 2627)

Analysis configuration JSON file for a CSV dataset

The following code sample shows how to configure an analysis for a CSV dataset.

```json
{
    "dataset_type": "text/csv",
    "headers": [
        "feature_0",
        "feature_1",
        "feature_2",
        "feature_3",
        "target"
    ],
    "label": "target",
    "label_values_or_threshold": [1],
    "probability_threshold": 0.7,
    "facet": [
        {
            "name_or_index": "feature_1",
            "value_or_threshold": [1]
        },
        {
            "name_or_index": "feature_2",
            "value_or_threshold": [0.7]
        }
    ],
    "group_variable": "feature_3",
    "joinsource_name_or_index": 'column_name',
    "methods": {
        "shap": {
            "baseline": [
                ["yes",
                 3,
                 0.9,
                 1
                ],
                "num_samples": 1000,
                "agg_method": "mean",
                "use_logit": true,
                "save_local_shap_values": true,
                "num_clusters": 5,
                "seed": 1234
            },
            "pre_training_bias": {
                "methods": "all"
            }
        }
    }
}
```
Model output as CSV is as follows:

Current, [0.02896845165491104, 0.8253824710845947, 0.028993206098675728, 0.02898673340678215, 0.029557107016444206, 0.0290389321744442, 0.02905467338860035]

Corresponding predictor configuration is as follows:

```
"predictor": {
   "accept_type": "text/csv",
   "label": 0,
   "probability": 1,
   ...
}
```

**Analysis configuration JSON file for a JSON Lines dataset**

The following code sample shows how to configure an analysis for a JSON Lines dataset.

```
{
   "dataset_type": "application/jsonlines",
   "dataset_uri": "s3://my_bucket/my_folder/dataset.jsonl",
   "headers": ["Label", "Feature1", "Feature2"],
   "label": "data.label",
   "features": "data.features.values",
   "facet": [  
      {  
         "name_or_index": "Feature1",
         "value_or_threshold": [1,5]
      },  
      {  
         "name_or_index": "Feature2",
         "value_or_threshold": [2,6]
      }  
   ],
   "methods": {  
      "shap": {  
         "baseline": [  
         
```
Dataset as S3 prefix is as follows:

```
"dataset_uri": "s3://my_bucket/my_folder"
```

Dataset as S3 object is as follows:

```
"dataset_uri": "s3://my_bucket/my_folder/train.csv"
```

Baseline as S3 object is as follows:

```
"baseline": "s3://my_bucket/my_folder/baseline.csv"
```

Model output as JSON Lines is as follows:

```
[{"predicted_label": "Current", "score": [0.028986845165491104, 0.8253824710845947, 0.028993206098675728, 0.02898673340678215, 0.028993206098675728, 0.02898673340678215, 0.0290389321744442, 0.02905467338860035]}
```

Corresponding predictor configuration is as follows:

```
"predictor": {
   ...,
   "accept_type": "application/jsonlines",
   "label": "predicted_label",
   "probability": "score",
   ...
}
```

**Analysis configuration JSON file for an image dataset**

The following code sample shows how to configure an analysis for object detection with Computer Vision.

```
"dataset_type": "application/x-image",
"dataset_uri": "s3://<BUCKET/KEY>
"probability_threshold": 0.7,
"methods": {
   "shap": {  
      "num_samples": 500,
      "baseline": "s3://path/to/baseline/image/noise_rgb.png",
      "image_config": {  
         "model_type": "(OBJECT_DETECTION|IMAGE_CLASSIFICATION)",
         "num_segments": 20,
         "segment_compactness": (5|10|100),
         "max_objects": 3,
         "overlap": 0.5,
         "context": 1.0
      }
   }
```

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NLP analysis configuration JSON file for a text dataset

The following code sample shows how to configure an analysis for natural processing.

```json
{
    "dataset_type": ...
    "methods": {
        "shap": {
            "baseline": "...",
            "num_samples": 100
            "text_config": {
                "granularity": "(token|sentence|paragraph)"
            }
        }
    }
}
```

Run SageMaker Clarify Processing Jobs for Bias Analysis and Explainability

You use SageMaker Clarify processing jobs to analyze potential sources of bias in your training data and to check your trained model for bias. For the procedure to analyze the data in SageMaker Studio, see Generate Reports for Bias in Pretraining Data in SageMaker Studio (p. 810). The focus here is on posttraining bias metric and SHAP values for explainability. Model predictions can be a source of bias (for example, if they make predictions that more frequently produce a negative result for one group than another). SageMaker Clarify is integrated with SageMaker Experiments so that after a model has been trained, you can identify attributes you would like to check for bias (for example, income). SageMaker runs a set of algorithms to check the trained model and provides you with a visual report on the different types of bias for each attribute, such as whether high-income earners receive more positive predictions compared to low-income earners.

Topics

- Compute Resources Required for SageMaker Clarify Processing Jobs (p. 2627)
- Run the Clarify Processing Job (p. 2628)
- Run the Clarify Processing Job with Spark (p. 2629)
- Get the Analysis Results (p. 2629)

Compute Resources Required for SageMaker Clarify Processing Jobs

Take the following into consideration when determining the compute resources you need to run SageMaker Clarify processing jobs:
Run the Clarify Processing Job

For an example notebook with instructions on how to run a SageMaker Clarify processing job in Studio to detect posttraining model bias, see **Explainability and bias detection with Amazon SageMaker Clarify**.

If you need instructions on how to open a notebook in Amazon SageMaker Studio, see **Create or Open an Amazon SageMaker Studio Notebook (p. 133)**. The following code samples are taken from the example notebook listed previously.

After you have trained your model, instantiate the SageMaker Clarify processor using the following command:

```python
from sagemaker import clarify
clarify_processor = clarify.SageMakerClarifyProcessor(
    role=role,
    instance_count=1,
    instance_type='ml.c4.xlarge',
    sagemaker_session=session)
```

Next, configure the input dataset, where to store the output, the label column targeted with a `DataConfig` object, specify information about your trained model with `ModelConfig`, and provide information about the formats of your predictions with `ModelPredictedLabelConfig`.

```python
bias_report_output_path = 's3://{}/clarify-bias'.format(bucket, prefix)
bias_data_config = clarify.DataConfig(
    s3_data_input_path=train_uri,
    s3_output_path=bias_report_output_path,
    label='Target',
    headers=training_data.columns.to_list(),
    dataset_type='text/csv')

model_config = clarify.ModelConfig(
    model_name=model_name,
    instance_type='ml.c5.xlarge',
    instance_count=1,
    accept_type='text/csv')

predictions_config = clarify.ModelPredictedLabelConfig(probability_threshold=0.8)

bias_config = clarify.BiasConfig(
    label_values_or_threshold=[1],
    facet_name='Sex',
    facet_values_or_threshold=[0])
```

Use `BiasConfig` to provide information on which columns contain the facets (sensitive groups, Sex), what the sensitive features (facet_values_or_threshold) might be, and what the desirable outcomes are (label_values_or_threshold).

You can run both the pretraining and posttraining analysis in the processing job at the same time with `run_bias()`.
clarify_processor.run_bias(
    data_config=bias_data_config,
    bias_config=bias_config,
    model_config=model_config,
    model.predicted_label_config=predictions_config,
    pre_training_methods='all',
    post_training_methods='all')

View the results in Studio or download them from the bias_report_output_path S3 bucket.

Run the Clarify Processing Job with Spark

Apache Spark is a unified analytics engine for large-scale data processing. When working with large datasets, you can use the Spark processing capabilities of SageMaker Clarify to enable your Clarify processing jobs to run faster. To use Spark processing for Clarify jobs, set the instance count to a number greater than one. Clarify uses Spark distributed computing when there is more than once instance per Clarify processor.

The following example shows how to use SageMakerClarifyProcessor to create a Clarify processor with 5 instances.

Clarify runs any jobs associated with this processor using Spark distributed processing.

```python
from sagemaker import clarify
clarify_processor = clarify.SageMakerClarifyProcessor(
    role=role,
    instance_count=5,
    instance_type='ml.c5.xlarge',
    max_runtime_in_seconds=1200,
    volume_size_in_gb=100)
```

If you configure a Clarify job to save local SHAP values in the SHAPConfig class, Spark saves the local SHAP value as multiple part files in parallel.

If you add more instances, we recommend that you also increase the number of instances in the model configuration ModelConfig for the shadow endpoint. This is to prevent the processing instances from being bottlenecked by the shadow endpoint. Specifically, we recommend that you use a one-to-one ratio of endpoint to processing instances.

Get the Analysis Results

After the processing job is finished, you can download the output files to inspect or visualize the results in Studio. The output directory contains the following files:

- analysis.json – Bias metrics and SHAP values in JSON format.
- report.ipynb – Static notebook to visualize the bias metrics and SHAP values.
- explanations_shap/out.csv – Local (per-instance) SHAP values for each row in the dataset in the same format as input dataset. On each row, the output file contains SHAP values for each feature and the predicted label.

In the analysis JSON file, the bias metrics and SHAP values are organized into three separate sections.

```json
{
    "explanations": { . . . }
    "pre_training_bias_metrics": { . . . }
    "post_training_bias_metrics": { . . . }
}
```
SHAP values are in the “explanations” section. Values correspond to the global SHAP value for each feature column.

```
"explanations": {
  "kernel_shap": {
    "label0": {
      "global_shap_values": {
        "feature_0": 0.022486410860333206,
        "feature_1": 0.007381025261958729,
        "feature_2": 0.006843906804137847
      },
      "expected_value": 0.508233428001
    }
  }
}
```

The bias metrics are in the pretraining and posttraining bias metrics sections.

```
{
  "post_training_bias_metrics": {
    "label": "target",
    "label_value_or_threshold": "1",
    "facets": {
      "feature_2": [
        {
          "value_or_threshold": "1",
          "metrics": [
            {
              "name": "DI",
              "description": "Disparate Impact (DI)",
              "value": 0.711340206185567
            },
            {
              "name": "DCR",
              "description": "Difference in Conditional Rejections (DCR)",
              "value": -0.34782608695652184
            }
          ]
        }
      ]
    }
  }
}
```

For more information on bias metrics and SHAP values and how to interpret them, see the Amazon AI Fairness and Explainability Whitepaper.

A bar chart of top SHAP values and tables with the bias metrics are provided in the report notebook.

**Detect Posttraining Data and Model Bias with Amazon SageMaker Clarify**

Posttraining bias analysis can help reveal biases that might have emanated from biases in the data, or from biases introduced by the classification and prediction algorithms. These analyses take into consideration the data, including the labels, and the predictions of a model. You assess performance by analyzing predicted labels or by comparing the predictions with the observed target values in the data with respect to groups with different attributes. There are different notions of fairness, each requiring different bias metrics to measure.
There are legal concepts of fairness that might not be easy to capture because they are hard to detect. For example, the US concept of disparate impact that occurs when a group, referred to as a less favored facet \( d \), experiences an adverse effect even when the approach taken appears to be fair. This type of bias might not be due to a machine learning model, but might still be detectable by posttraining bias analysis.

Amazon SageMaker Clarify tries to ensure a consistent use of terminology. For a list of terms and their definitions, see Amazon SageMaker Clarify Terms for Bias and Fairness (p. 799).

For additional information about posttraining bias metrics, see Learn How Amazon SageMaker Clarify Helps Detect Bias and Fairness Measures for Machine Learning in Finance.

Sample Notebooks

Amazon SageMaker Clarify provides the following sample notebook for posttraining bias detection:

- **Amazon SageMaker Clarify Processing** – Use SageMaker Clarify to create a processing job for the detecting bias and explaining model predictions with feature attributions. Examples include using CSV and JSON Lines data formats, bringing your own container, and running processing jobs with Spark.

This notebook has been verified to run in Amazon SageMaker Studio only. If you need instructions on how to open a notebook in Amazon SageMaker Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133). If you're prompted to choose a kernel, choose Python 3 (Data Science).

Measure Posttraining Data and Model Bias

Amazon SageMaker Clarify provides eleven posttraining data and model bias metrics to help quantify various conceptions of fairness. These concepts cannot all be satisfied simultaneously and the selection depends on specifics of the cases involving potential bias being analyzed. Most of these metrics are a combination of the numbers taken from the binary classification confusion matrices for the different demographic groups. Because fairness and bias can be defined by a wide range of metrics, human judgment is required to understand and choose which metrics are relevant to the individual use case, and customers should consult with appropriate stakeholders to determine the appropriate measure of fairness for their application.

We use the following notation to discuss the bias metrics. The conceptual model described here is for binary classification, where events are labeled as having only two possible outcomes in their sample space, referred to as positive (with value 1) and negative (with value 0). This framework is usually extensible to multiclassification in a straightforward way or to cases involving continuous valued outcomes when needed. In the binary classification case, positive and negative labels are assigned to outcomes recorded in a raw dataset for a favored facet \( a \) and for a disfavored facet \( d \). These labels \( y \) are referred to as observed labels to distinguish them from the predicted labels \( y' \) that are assigned by a machine learning model during the training or inferences stages of the ML life cycle. These labels are used to define probability distributions \( P_a(y) \) and \( P_d(y) \) for their respective facet outcomes.

- **labels:**
  - \( y \) represents the \( n \) observed labels for event outcomes in a training dataset.
  - \( y' \) represents the predicted labels for the \( n \) observed labels in the dataset by a trained model.

- **outcomes:**
  - A positive outcome (with value 1) for a sample, such as an application acceptance.
    - \( n(1) \) is the number of observed labels for positive outcomes (acceptances).
    - \( n'(1) \) is the number of predicted labels for positive outcomes (acceptances).
  - A negative outcome (with value 0) for a sample, such as an application rejection.
    - \( n(0) \) is the number of observed labels for negative outcomes (rejections).
• \( n^{(0)} \) is the number of predicted labels for negative outcomes (rejections).

• Facet values:
  - facet \( a \) – The feature value that defines a demographic that bias favors.
    - \( n_a \) is the number of observed labels for the favored facet value: \( n_a = n_a^{(1)} + n_a^{(0)} \) the sum of the positive and negative observed labels for the value facet \( a \).
    - \( n'_a \) is the number of predicted labels for the favored facet value: \( n'_a = n'_a^{(1)} + n'_a^{(0)} \) the sum of the positive and negative predicted outcome labels for the facet value \( a \). Note that \( n'_a = n_a \).
  - facet \( d \) – The feature value that defines a demographic that bias disfavors.
    - \( n_d \) is the number of observed labels for the disfavored facet value: \( n_d = n_d^{(1)} + n_d^{(0)} \) the sum of the positive and negative observed labels for the facet value \( d \).
    - \( n'_d \) is the number of predicted labels for the disfavored facet value: \( n'_d = n'_d^{(1)} + n'_d^{(0)} \) the sum of the positive and negative predicted labels for the facet value \( d \). Note that \( n'_d = n_d \).

• Probability distributions for outcomes of the labeled facet data outcomes:
  - \( P_a(y) \) is the probability distribution of the observed labels for facet \( a \). For binary labeled data, this distribution is given by the ratio of the number of samples in facet \( a \) labeled with positive outcomes to the total number, \( P_a(y^1) = n_a^{(1)}/n_a \), and the ratio of the number of samples with negative outcomes to the total number, \( P_a(y^0) = n_a^{(0)}/n_a \).
  - \( P_d(y) \) is the probability distribution of the observed labels for facet \( d \). For binary labeled data, this distribution is given by the number of samples in facet \( d \) labeled with positive outcomes to the total number, \( P_d(y^1) = n_d^{(1)}/n_d \), and the ratio of the number of samples with negative outcomes to the total number, \( P_d(y^0) = n_d^{(0)}/n_d \).

The following table contains a cheat sheet for quick guidance and links to the posttraining bias metrics.

### Posttraining bias metrics

<table>
<thead>
<tr>
<th>Posttraining bias metric</th>
<th>Description</th>
<th>Example question</th>
<th>Interpreting metric values</th>
</tr>
</thead>
</table>
| Difference in Positive Proportions in Predicted Labels (DPPL) (p. 2640) | Measures the difference in the proportion of positive predictions between the favored facet \( a \) and the disfavored facet \( d \). | Has there been an imbalance across demographic groups in the predicted positive outcomes that might indicate bias? | Range for normalized binary & multicategory facet labels: [-1, +1] Range for continuous labels: (-\( \infty \), +\( \infty \)) Interpretation:  
  - Positive values indicate that the favored facet \( a \) has a higher proportion of predicted positive outcomes.  
  - Values near zero indicate a more equal proportion of predicted positive outcomes between facets.  
  - Negative values indicate the disfavored facet \( d \) has a higher proportion of predicted negative outcomes. |
<table>
<thead>
<tr>
<th>Posttraining bias metric</th>
<th>Description</th>
<th>Example question</th>
<th>Interpreting metric values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Disparate Impact (DI) (p. 2641)</td>
<td>Measures the ratio of proportions of the predicted labels for the favored facet $a$ and the disfavored facet $d$.</td>
<td>Has there been an imbalance across demographic groups in the predicted positive outcomes that might indicate bias?</td>
<td>Range for normalized binary, multicategory facet, and continuous labels: $[0, \infty)$  &lt;br&gt; Interpretation:  &lt;br&gt; • Values less than 1 indicate the favored facet $a$ has a higher proportion of predicted positive outcomes.  &lt;br&gt; • A value of 1 indicates that we have demographic parity.  &lt;br&gt; • Values greater than 1 indicate the disfavored facet $d$ has a higher proportion of predicted positive outcomes.</td>
</tr>
<tr>
<td>Conditional Demographic Disparity in Predicted Labels (CDDPL) (p. 2650)</td>
<td>Measures the disparity of predicted labels between the facets as a whole, but also by subgroups.</td>
<td>Do some demographic groups have a larger proportion of rejections for loan application outcomes than their proportion of acceptances?</td>
<td>The range of CDDPL values for binary, multicategory, and continuous outcomes: $[-1, +1]$  &lt;br&gt; • Positive values indicate outcomes where facet $d$ is rejected more than accepted.  &lt;br&gt; • Near zero indicates no demographic disparity on average.  &lt;br&gt; • Negative values indicate outcomes where facet $a$ is rejected more than accepted.</td>
</tr>
<tr>
<td>Posttraining bias metric</td>
<td>Description</td>
<td>Example question</td>
<td>Interpreting metric values</td>
</tr>
<tr>
<td>-----------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Counterfactual Fliptest (FT) (p. 2651)</td>
<td>Examine each member of facet (d) and assess whether similar members of facet (a) have different model predictions.</td>
<td>Is one group of a specific-age demographic matched closely on all features with a different age group, yet paid more on average?</td>
<td>The range for binary and multicategory facet labels is ([-1, +1]).</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Positive values occur when the number of unfavorable counterfactual fliptest decisions for the disfavored facet (d) exceeds the favorable ones.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Values near zero occur when the number of unfavorable and favorable counterfactual fliptest decisions balance out.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>• Negative values occur when the number of unfavorable counterfactual fliptest decisions for the disfavored facet (d) is less than the favorable ones.</td>
</tr>
<tr>
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<tr>
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</tr>
</tbody>
</table>
| Accuracy Difference (AD) (p. 2648) | Measures the difference between the prediction accuracy for the favored and disfavored facets. | Does the model predict labels as accurately for applications across all demographic groups? | The range for binary and multicategory facet labels is [-1, +1].
<p>|   |   |   | • Positive values indicate that facet (d) suffers more from some combination of false positives (Type I errors) or false negatives (Type II errors). This means there is a potential bias against the disfavored facet (d). |
|   |   |   | • Values near zero occur when the prediction accuracy for facet (a) is similar to that for facet (d). |
|   |   |   | • Negative values indicate that facet (a) suffers more from some combination of false positives (Type I errors) or false negatives (Type II errors). This means there is a bias against the favored facet (a). |</p>
<table>
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</table>
| Recall Difference (RD) (p. 2645) | Compares the recall of the model for the favored and disfavored facets. | Is there an age-based bias in lending due to a model having higher recall for one age group as compared to another? | Range for binary and multicategory classification: [-1, +1].  
- Positive values suggest that the model finds more of the true positives for facet $a$ and is biased against the disfavored facet $d$.  
- Values near zero suggest that the model finds about the same number of true positives in both facets and is not biased.  
- Negative values suggest that the model finds more of the true positives for facet $d$ and is biased against the favored facet $a$. |
| Difference in Conditional Acceptance (DCAcc) (p. 2642) | Compares the observed labels to the labels predicted by a model. Assesses whether this is the same across facets for predicted positive outcomes (acceptances). | When comparing one age group to another, are loans accepted more frequently, or less often than predicted (based on qualifications)? | The range for binary, multicategory facet, and continuous labels: $(-\infty, +\infty)$.  
- Positive values indicate a possible bias against the qualified applicants from the disfavored facet $d$.  
- Values near zero indicate that qualified applicants from both facets are being accepted in a similar way.  
- Negative values indicate a possible bias against the qualified applicants from the favored facet $a$. |
<table>
<thead>
<tr>
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</tr>
</thead>
</table>
| **Difference in Acceptance Rates (DAR) (p. 2646)** | Measures the difference in the ratios of the observed positive outcomes (TP) to the predicted positives (TP + FP) between the favored and disfavored facets. | Does the model have equal precision when predicting loan acceptances for qualified applicants across all age groups? | The range for binary, multicategory facet, and continuous labels is [−1, +1].
  - Positive values indicate a possible bias against facet \(d\) caused by the occurrence of relatively more false positives in the disfavored facet \(d\).
  - Values near zero indicate the observed labels for positive outcomes (acceptances) are being predicted with equal precision for both facets by the model.
  - Negative values indicate a possible bias against facet \(a\) caused by the occurrence of relatively more false positives in the favored facet \(a\). |
<table>
<thead>
<tr>
<th>Posttraining bias metric</th>
<th>Description</th>
<th>Example question</th>
<th>Interpreting metric values</th>
</tr>
</thead>
</table>
| **Specificity difference (SD)** (p. 2644) | Compares the specificity of the model between favored and disfavored facets. | Is there an age-based bias in lending because the model predicts a higher specificity for one age group as compared to another? | Range for binary and multicategory classification: $[-1, +1]$.  
  * Positive values suggest that the model finds less false positives for facet $d$ and is biased against the disfavored facet $d$.  
  * Values near zero suggest that the model finds a similar number of false positives in both facets and is not biased.  
  * Negative values suggest that the model finds less false positives for facet $a$ and is biased against the favored facet $a$. |
| **Difference in Conditional Rejection (DCR)** (p. 2643) | Compares the observed labels to the labels predicted by a model and assesses whether this is the same across facets for negative outcomes (rejections). | Are there more or less rejections for loan applications than predicted for one age group as compared to another based on qualifications? | The range for binary, multicategory facet, and continuous labels: $(-\infty, +\infty)$.  
  * Positive values indicate a possible bias against the qualified applicants from the disfavored facet $d$.  
  * Values near zero indicate that qualified applicants from both facets are being rejected in a similar way.  
  * Negative values indicate a possible bias against the qualified applicants from the favored facet $a$. |
<table>
<thead>
<tr>
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<th>Description</th>
<th>Example question</th>
<th>Interpreting metric values</th>
</tr>
</thead>
</table>
| **Difference in Rejection Rates (DRR) (p. 2647)** | Measures the difference in the ratios of the observed negative outcomes (TN) to the predicted negatives (TN + FN) between the disfavored and favored facets. | Does the model have equal precision when predicting loan rejections for unqualified applicants across all age groups? | The range for binary, multicategory facet, and continuous labels is \([-1, +1]\).  
- Positive values indicate a possible bias caused by the occurrence of relatively more false negatives in the favored facet.  
- Values near zero indicate that negative outcomes (rejections) are being predicted with equal precision for both facets.  
- Negative values indicate a possible bias caused by the occurrence of relatively more false negatives in the disfavored facet. |
| **Treatment Equality (TE) (p. 2649)** | Measures the difference in the ratio of false positives to false negatives between the favored and disfavored facets. | In loan applications, is the relative ratio of false positives to false negatives the same across all age demographics? | The range for binary and multicategory facet labels: \((-\infty, +\infty)\).  
- Positive values occur when the ratio of false positives to false negatives for facet is greater than that for facet.  
- Values near zero occur when the ratio of false positives to false negatives for facet is similar to that for facet.  
- Negative values occur when the ratio of false positives to false negatives for facet is less than that for facet. |
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<thead>
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<tr>
<td>Generalized entropy (GE) (p. 2652)</td>
<td>Measures the inequality in benefits b assigned to each input by the model predictions.</td>
<td>Of two candidate models for loan application classification, does one lead to a more uneven distribution of desired outcomes than the other?</td>
<td>The range for binary and multiclass labels: (0, 0.5). GE is undefined when the model predicts only false negatives.</td>
</tr>
</tbody>
</table>
  - Zero values occur when all predictions are correct or all predictions are false positives.
  - Positive values indicate inequality in benefits; 0.5 corresponds to the largest inequality.

For additional information about posttraining bias metrics, see A Family of Fairness Measures for Machine Learning in Finance.

Topics

- Difference in Positive Proportions in Predicted Labels (DPPL) (p. 2640)
- Disparate Impact (DI) (p. 2641)
- Difference in Conditional Acceptance (DCAcc) (p. 2642)
- Difference in Conditional Rejection (DCR) (p. 2643)
- Specificity difference (SD) (p. 2644)
- Recall Difference (RD) (p. 2645)
- Difference in Acceptance Rates (DAR) (p. 2646)
- Difference in Rejection Rates (DRR) (p. 2647)
- Accuracy Difference (AD) (p. 2648)
- Treatment Equality (TE) (p. 2649)
- Conditional Demographic Disparity in Predicted Labels (CDDPL) (p. 2650)
- Counterfactual Flipped Test (FT) (p. 2651)
- Generalized entropy (GE) (p. 2652)

Difference in Positive Proportions in Predicted Labels (DPPL)

The difference in positive proportions in predicted labels (DPPL) metric determines whether the model predicts outcomes differently for each facet. It is defined as the difference between the proportion of positive predictions (y' = 1) for facet a and the proportion of positive predictions (y' = 1) for facet d. For example, if the model predictions grant loans to 60% of a middle-aged group (facet a) and 50% of other age groups (facet d), it might be biased against facet d. In this example, you need to determine whether the 10% difference is material to a case for bias. A comparison of DPL with DPPL assesses whether bias initially present in the dataset increases or decreases in the model predictions after training.

The formula for the difference in proportions of predicted labels:

\[ \text{DPPL} = q'_a - q'_d \]
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Where:

- \( q'_a = n'_a(1)/n_a \) is the predicted proportion of facet \( a \) who get a positive outcome of value 1. In our example, the proportion of a middle-aged facet predicted to get granted a loan. Here \( n'_a(1) \) represents the number of members of facet \( a \) who get a positive predicted outcome of value 1 and \( n_a \) the is number of members of facet \( a \).
- \( q'_d = n'_d(1)/n_d \) is the predicted proportion of facet \( d \) who get a positive outcome of value 1. In our example, a facet of older and younger people predicted to get granted a loan. Here \( n'_d(1) \) represents the number of members of facet \( d \) who get a positive predicted outcome and \( n_d \) the is number of members of facet \( d \).

If DPPL is close enough to 0, it means that posttraining demographic parity has been achieved.

For binary and multicategory facet labels, the normalized DPL values range over the interval \([-1, 1]\). For continuous labels, the values vary over the interval \((-\infty, +\infty)\).

- Positive DPPL values indicate that facet \( a \) has a higher proportion of predicted positive outcomes when compared with facet \( d \).
  - This is referred to as positive bias.
- Values of DPPL near zero indicate a more equal proportion of predicted positive outcomes between facets \( a \) and \( d \) and a value of zero indicates perfect demographic parity.
- Negative DPPL values indicate that facet \( d \) has a higher proportion of predicted positive outcomes when compared with facet \( a \). This is referred to as negative bias.

**Disparate Impact (DI)**

The difference in positive proportions in the predicted labels metric can be assessed in the form of a ratio.

The comparison of positive proportions in predicted labels metric can be assessed in the form of a ratio instead of as a difference, as it is with the Difference in Positive Proportions in Predicted Labels (DPPL) (p. 2640). The disparate impact (DI) metric is defined as the ratio of the proportion of positive predictions \( (y' = 1) \) for facet \( d \) over the proportion of positive predictions \( (y' = 1) \) for facet \( a \). For example, if the model predictions grant loans to 60% of a middle-aged group (facet \( a \)) and 50% other age groups (facet \( d \)), then \( DI = .5/.6 = 0.8 \), which indicates a positive bias and an adverse impact on the other aged group represented by facet \( d \).

The formula for the ratio of proportions of the predicted labels:

\[ DI = q'_d/q'_a \]

Where:

- \( q'_a = n'_a(1)/n_a \) is the predicted proportion of facet \( a \) who get a positive outcome of value 1. In our example, the proportion of a middle-aged facet predicted to get granted a loan. Here \( n'_a(1) \) represents the number of members of facet \( a \) who get a positive predicted outcome and \( n_a \) the is number of members of facet \( a \).
- \( q'_d = n'_d(1)/n_d \) is the predicted proportion of facet \( d \) a who get a positive outcome of value 1. In our example, a facet of older and younger people predicted to get granted a loan. Here \( n'_d(1) \) represents the number of members of facet \( d \) who get a positive predicted outcome and \( n_d \) the is number of members of facet \( d \).

For binary, multicategory facet, and continuous labels, the DI values range over the interval \([0, \infty)\).
• Values less than 1 indicate that facet \( a \) has a higher proportion of predicted positive outcomes than facet \( d \). This is referred to as positive bias.

• A value of 1 indicates demographic parity.

• Values greater than 1 indicate that facet \( d \) has a higher proportion of predicted positive outcomes than facet \( a \). This is referred to as negative bias.

**Difference in Conditional Acceptance (DCAcc)**

This metric compares the observed labels to the labels predicted by the model and assesses whether this is the same across facets for predicted positive outcomes. This metric comes close to mimicking human bias in that it quantifies how many more positive outcomes a model predicted (labels \( y' \)) for a certain facet as compared to what was observed in the training dataset (labels \( y \)). For example, if there were more acceptances (a positive outcome) observed in the training dataset for loan applications for a middle-aged group (facet \( a \)) than predicted by the model based on qualifications as compared to the facet containing other age groups (facet \( d \)), this might indicate potential bias in the way loans were approved favoring the middle-aged group.

The formula for the difference in conditional acceptance:

\[
DCAcc = c_a - c_d
\]

Where:

• \( c_a = n_a^{(1)}/n_a^{(1)} \) is the ratio of the observed number of positive outcomes of value 1 (acceptances) of facet \( a \) to the predicted number of positive outcome (acceptances) for facet \( a \).

• \( c_d = n_d^{(1)}/n_d^{(1)} \) is the ratio of the observed number of positive outcomes of value 1 (acceptances) of facet \( d \) to the predicted number of predicted positive outcomes (acceptances) for facet \( d \).

The DCAcc metric can capture both positive and negative biases that reveal preferential treatment based on qualifications. Consider the following instances of age-based bias on loan acceptances.

**Example 1: Positive bias**

Suppose we have dataset of 100 middle-aged people (facet \( a \)) and 50 people from other age groups (facet \( d \)) who applied for loans, where the model recommended that 60 from facet \( a \) and 30 from facet \( d \) be given loans. So the predicted proportions are unbiased with respect to the DPPL metric, but the observed labels show that 70 from facet \( a \) and 20 from facet \( d \) were granted loans. In other words, the model granted loans to 17% fewer from the middle aged facet than the observed labels in the training data suggested (70/60 = 1.17) and granted loans to 33% more from other age groups than the observed labels suggested (20/30 = 0.67). The calculation of the DCAcc value gives the following:

\[
DCAcc = 70/60 - 20/30 = 1/2
\]

The positive value indicates that there is a potential bias against the middle-aged facet \( a \) with a lower acceptance rate as compared with the other facet \( d \) than the observed data (taken as unbiased) indicate is the case.

**Example 2: Negative bias**

Suppose we have dataset of 100 middle-aged people (facet \( a \)) and 50 people from other age groups (facet \( d \)) who applied for loans, where the model recommended that 60 from facet \( a \) and 30 from facet \( d \) be given loans. So the predicted proportions are unbiased with respect to the DPPL metric, but the observed labels show that 50 from facet \( a \) and 40 from facet \( d \) were granted loans. In other words, the model granted loans to 17% fewer from the middle aged facet than the observed labels in the training data suggested (50/60 = 0.83), and granted loans to 33% more from other age groups than the observed labels suggested (40/30 = 1.33). The calculation of the DCAcc value gives the following:
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\[ \text{DCAcc} = \frac{50}{60} - \frac{40}{30} = -\frac{1}{2} \]

The negative value indicates that there is a potential bias against facet \( d \) with a lower acceptance rate as compared with the middle-aged facet \( a \) than the observed data (taken as unbiased) indicate is the case.

Note that you can use DCAcc to help you detect potential (unintentional) biases by humans overseeing the model predictions in a human-in-the-loop setting. Assume, for example, that the predictions \( y' \) by the model were unbiased, but the eventual decision is made by a human (possibly with access to additional features) who can alter the model predictions to generate a new and final version of \( y' \). The additional processing by the human may unintentionally deny loans to a disproportionate number from one facet. DCAcc can help detect such potential biases.

The range of values for differences in conditional acceptance for binary, multicategory facet, and continuous labels is \((-\infty, +\infty)\).

- Positive values occur when the ratio of the observed number of acceptances compared to predicted acceptances for facet \( a \) is higher than the same ratio for facet \( d \). These values indicate a possible bias against the qualified applicants from facet \( a \). The larger the difference of the ratios, the more extreme the apparent bias.
- Values near zero occur when the ratio of the observed number of acceptances compared to predicted acceptances for facet \( a \) is similar to the ratio for facet \( d \). These values indicate that predicted acceptance rates are consistent with the observed values in the labeled data and that qualified applicants from both facets are being accepted in a similar way.
- Negative values occur when the ratio of the observed number of acceptances compared to predicted acceptances for facet \( d \) is less than that ratio for facet \( a \). These values indicate a possible bias against the qualified applicants from facet \( d \). The more negative the difference in the ratios, the more extreme the apparent bias.

**Difference in Conditional Rejection (DCR)**

This metric compares the observed labels to the labels predicted by the model and assesses whether this is the same across facets for negative outcomes (rejections). This metric comes close to mimicking human bias, in that it quantifies how many more negative outcomes a model granted (predicted labels \( y' \)) to a certain facet as compared to what was suggested by the labels in the training dataset (observed labels \( y \)). For example, if there were more observed rejections (a negative outcome) for loan applications for a middle-aged group (facet \( a \)) than predicted by the model based on qualifications as compared to the facet containing other age groups (facet \( d \)), this might indicate potential bias in the way loans were rejected that favored the middle-aged group over other groups.

The formula for the difference in conditional acceptance:

\[ \text{DCR} = r_d - r_a \]

Where:

- \( r_d = \frac{n_d^{(0)}}{n_d^{(0)}} \) is the ratio of the observed number of negative outcomes of value 0 (rejections) of facet \( d \) to the predicted number of negative outcome (rejections) for facet \( d \).
- \( r_a = \frac{n_a^{(0)}}{n_a^{(0)}} \) is the ratio of the observed number of negative outcomes of value 0 (rejections) of facet \( a \) to the predicted number of negative outcome of value 0 (rejections) for facet \( a \).

The DCR metric can capture both positive and negative biases that reveal preferential treatment based on qualifications. Consider the following instances of age-based bias on loan rejections.

**Example 1: Positive bias**

Suppose we have dataset of 100 middle-aged people (facet \( a \)) and 50 people from other age groups (facet \( d \)) who applied for loans, where the model recommended that 60 from facet \( a \) and 30 from facet
be rejected for loans. So the predicted proportions are unbiased by the DPPL metric, but the observed labels show that 50 from facet a and 40 from facet d were rejected. In other words, the model rejected 17% more loans from the middle aged facet than the observed labels in the training data suggested (50/60 = 0.83), and rejected 33% fewer loans from other age groups than the observed labels suggested (40/30 = 1.33). The DCR value quantifies this difference in the ratio of observed to predicted rejection rates between the facets. The positive value indicates that there is a potential bias favoring the middle aged group with lower rejection rates as compared with other groups than the observed data (taken as unbiased) indicate is the case.

\[
DCR = \frac{40}{30} - \frac{50}{60} = 1/2
\]

**Example 2: Negative bias**

Suppose we have dataset of 100 middle-aged people (facet a) and 50 people from other age groups (facet d) who applied for loans, where the model recommended that 60 from facet a and 30 from facet d be rejected for loans. So the predicted proportions are unbiased by the DPPL metric, but the observed labels show that 70 from facet a and 20 from facet d were rejected. In other words, the model rejected 17% fewer loans from the middle aged facet than the observed labels in the training data suggested (70/60 = 1.17), and rejected 33% more loans from other age groups than the observed labels suggested (20/30 = 0.67). The negative value indicates that there is a potential bias favoring facet a with lower rejection rates as compared with the middle-aged facet a than the observed data (taken as unbiased) indicate is the case.

\[
DCR = \frac{20}{30} - \frac{70}{60} = -1/2
\]

The range of values for differences in conditional rejection for binary, multicategory facet, and continuous labels is (-\infty, +\infty).

- Positive values occur when the ratio of the observed number of rejections compared to predicted rejections for facet d is greater than that ratio for facet a. These values indicate a possible bias against the qualified applicants from facet a. The larger the value of DCR metric, the more extreme the apparent bias.

- Values near zero occur when the ratio of the observed number of rejections compared to predicted acceptances for facet a is similar to the ratio for facet d. These values indicate that predicted rejections rates are consistent with the observed values in the labeled data and that the qualified applicants from both facets are being rejected in a similar way.

- Negative values occur when the ratio of the observed number of rejections compared to predicted rejections for facet d is less than that ratio facet a. These values indicate a possible bias against the qualified applicants from facet d. The larger magnitude of the negative DCR metric, the more extreme the apparent bias.

**Specificity difference (SD)**

The specificity difference (SD) is the difference in specificity between the favored facet a and disfavored facet d. Specificity measures how often the model correctly predicts a negative outcome (y'=0). Any difference in these specificities is a potential form of bias.

Specificity is perfect for a facet if all of the y=0 cases are correctly predicted for that facet. Specificity is greater when the model minimizes false positives, known as a Type I error. For example, the difference between a low specificity for lending to facet a, and high specificity for lending to facet d, is a measure of bias against facet d.

The following formula is for the difference in the specificity for facets a and d.

\[
SD = \frac{TN_d}{TN_d + FP_d} - \frac{TN_a}{TN_a + FP_a} = TNR_d - TNR_a
\]

The following variables used to calculated SD are defined as follows:
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- $TN_d$ are the true negatives predicted for facet $d$.
- $FP_d$ are the false positives predicted for facet $d$.
- $TN_a$ are the true negatives predicted for facet $a$.
- $FP_a$ are the false positives predicted for facet $a$.
- $TNR_a = \frac{TN_a}{TN_a + FP_a}$ is the true negative rate, also known as the specificity, for facet $a$.
- $TNR_d = \frac{TN_d}{TN_d + FP_d}$ is the true negative rate, also known as the specificity, for facet $d$.

For example, consider the following confusion matrices for facets $a$ and $d$.

**Confusion matrix for the favored facet $a$**

<table>
<thead>
<tr>
<th>Class $a$ predictions</th>
<th>Actual outcome 0</th>
<th>Actual outcome 1</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>20</td>
<td>5</td>
<td>25</td>
</tr>
<tr>
<td>1</td>
<td>10</td>
<td>65</td>
<td>75</td>
</tr>
<tr>
<td>Total</td>
<td>30</td>
<td>70</td>
<td>100</td>
</tr>
</tbody>
</table>

**Confusion matrix for the disfavored facet $d$**

<table>
<thead>
<tr>
<th>Class $d$ predictions</th>
<th>Actual outcome 0</th>
<th>Actual outcome 1</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>18</td>
<td>7</td>
<td>25</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>20</td>
<td>25</td>
</tr>
<tr>
<td>Total</td>
<td>23</td>
<td>27</td>
<td>50</td>
</tr>
</tbody>
</table>

The value of the specificity difference is $SD = \frac{18}{18+5} - \frac{20}{20+10} = 0.7826 - 0.6667 = 0.1159$, which indicates a bias against facet $d$.

The range of values for the specificity difference between facets $a$ and $d$ for binary and multiclass classification is $[-1, +1]$. This metric is not available for the case of continuous labels. Here is what different values of SD imply:

- Positive values are obtained when there is higher specificity for facet $d$ than for facet $a$. This suggests that the model finds less false positives for facet $d$ than for facet $a$. A positive value indicates bias against facet $d$.
- Values near zero indicate that the specificity for facets that are being compared is similar. This suggests that the model finds a similar number of false positives in both of these facets and is not biased.
- Negative values are obtained when there is higher specificity for facet $a$ than for facet $d$. This suggests that the model finds more false positives for facet $a$ than for facet $d$. A negative value indicates bias against facet $a$.

**Recall Difference (RD)**

The recall difference (RD) metric is the difference in recall of the model between the favored facet $a$ and disfavored facet $d$. Any difference in these recalls is a potential form of bias. Recall is the true positive rate (TPR), which measures how often the model correctly predicts the cases that should receive a positive outcome. Recall is perfect for a facet if all of the $y=1$ cases are correctly predicted as $y'=1$ for that facet. Recall is greater when the model minimizes false negatives known as the Type II error. For example, how many of the people in two different groups (facets $a$ and $d$) that should qualify for loans...
are detected correctly by the model? If the recall rate is high for lending to facet \( a \), but low for lending to facet \( d \), the difference provides a measure of this bias against the group belonging to facet \( d \).

The formula for difference in the recall rates for facets \( a \) and \( d \):

\[
RD = \frac{TP_a}{TP_a + FN_a} - \frac{TP_d}{TP_d + FN_d} = TPR_a - TPR_d
\]

Where:

- \( TP_a \) are the true positives predicted for facet \( a \).
- \( FN_a \) are the false negatives predicted for facet \( a \).
- \( TP_d \) are the true positives predicted for facet \( d \).
- \( FN_d \) are the false negatives predicted for facet \( d \).
- \( TPR_a = \frac{TP_a}{TP_a + FN_a} \) is the recall for facet \( a \) or its true positive rate.
- \( TPR_d = \frac{TP_d}{TP_d + FN_d} \) is the recall for facet \( d \) or its true positive rate.

For example, consider the following confusion matrices for facets \( a \) and \( d \).

### Confusion Matrix for the Favored Facet \( a \)

<table>
<thead>
<tr>
<th>Class ( a ) predictions</th>
<th>Actual outcome 0</th>
<th>Actual outcome 1</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>20</td>
<td>5</td>
<td>25</td>
</tr>
<tr>
<td>1</td>
<td>10</td>
<td>65</td>
<td>75</td>
</tr>
<tr>
<td>Total</td>
<td>30</td>
<td>70</td>
<td>100</td>
</tr>
</tbody>
</table>

### Confusion Matrix for the Disfavored Facet \( d \)

<table>
<thead>
<tr>
<th>Class ( d ) predictions</th>
<th>Actual outcome 0</th>
<th>Actual outcome 1</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>18</td>
<td>7</td>
<td>25</td>
</tr>
<tr>
<td>1</td>
<td>5</td>
<td>20</td>
<td>25</td>
</tr>
<tr>
<td>Total</td>
<td>23</td>
<td>27</td>
<td>50</td>
</tr>
</tbody>
</table>

The value of the recall difference is \( RD = \frac{65}{70} - \frac{20}{27} = 0.93 - 0.74 = 0.19 \) which indicates a bias against facet \( d \).

The range of values for the recall difference between facets \( a \) and \( d \) for binary and multicategory classification is [-1, +1]. This metric is not available for the case of continuous labels.

- Positive values are obtained when there is higher recall for facet \( a \) than for facet \( d \). This suggests that the model finds more of the true positives for facet \( a \) than for facet \( d \), which is a form of bias.
- Values near zero indicate that the recall for facets being compared is similar. This suggests that the model finds about the same number of true positives in both of these facets and is not biased.
- Negative values are obtained when there is higher recall for facet \( d \) than for facet \( a \). This suggests that the model finds more of the true positives for facet \( d \) than for facet \( a \), which is a form of bias.

### Difference in Acceptance Rates (DAR)

The difference in acceptance rates (DAR) metric is the difference in the ratios of the true positive (TP) predictions to the observed positives (TP + FP) for facets \( a \) and \( d \). This metric measures the difference
in the precision of the model for predicting acceptances from these two facets. Precision measures the fraction of qualified candidates from the pool of qualified candidates that are identified as such by the model. If the model precision for predicting qualified applicants diverges between the facets, this is a bias and its magnitude is measured by the DAR.

The formula for difference in acceptance rates between facets $a$ and $d$:

$$\text{DAR} = \frac{TP_a}{TP_a + FP_a} - \frac{TP_d}{TP_d + FP_d}$$

Where:

- $TP_a$ are the true positives predicted for facet $a$.
- $FP_a$ are the false positives predicted for facet $a$.
- $TP_d$ are the true positives predicted for facet $d$.
- $FP_d$ are the false positives predicted for facet $d$.

For example, suppose the model accepts 70 middle-aged applicants (facet $a$) for a loan (predicted positive labels) of whom only 35 are actually accepted (observed positive labels). Also suppose the model accepts 100 applicants from other age demographics (facet $d$) for a loan (predicted positive labels) of whom only 40 are actually accepted (observed positive labels). Then $\text{DAR} = \frac{35}{70} - \frac{40}{100} = 0.10$, which indicates a potential bias against qualified people from the second age group (facet $d$).

The range of values for DAR for binary, multicategory facet, and continuous labels is $[-1, +1]$.

- Positive values occur when the ratio of the predicted positives (acceptances) to the observed positive outcomes (qualified applicants) for facet $a$ is larger than the same ratio for facet $d$. These values indicate a possible bias against the disfavored facet $d$ caused by the occurrence of relatively more false positives in facet $d$. The larger the difference in the ratios, the more extreme the apparent bias.
- Values near zero occur when the ratio of the predicted positives (acceptances) to the observed positive outcomes (qualified applicants) for facets $a$ and $d$ have similar values indicating the observed labels for positive outcomes are being predicted with equal precision by the model.
- Negative values occur when the ratio of the predicted positives (acceptances) to the observed positive outcomes (qualified applicants) for facet $d$ is larger than the ratio facet $a$. These values indicate a possible bias against the favored facet $a$ caused by the occurrence of relatively more false positives in facet $a$. The more negative the difference in the ratios, the more extreme the apparent bias.

**Difference in Rejection Rates (DRR)**

The difference in rejection rates (DRR) metric is the difference in the ratios of the true negative (TN) predictions to the observed negatives (TN + FN) for facets $a$ and $d$. This metric measures the difference in the precision of the model for predicting rejections from these two facets. Precision measures the fraction of unqualified candidates from the pool of unqualified candidates that are identified as such by the model. If the model precision for predicting unqualified applicants diverges between the facets, this is a bias and its magnitude is measured by the DRR.

The formula for difference in rejection rates between facets $a$ and $d$:

$$\text{DRR} = \frac{TN_d}{TN_d + FN_d} - \frac{TN_a}{TN_a + FN_a}$$

Where:

- $TN_d$ are the true negatives predicted for facet $d$.
- $FN_d$ are the false negatives predicted for facet $d$.
- $TP_a$ are the true negatives predicted for facet $a$. 

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• FNₐ are the false negatives predicted for facet a.

For example, suppose the model rejects 100 middle-aged applicants (facet a) for a loan (predicted negative labels) of whom 80 are actually unqualified (observed negative labels). Also suppose the model rejects 50 applicants from other age demographics (facet d) for a loan (predicted negative labels) of whom only 40 are actually unqualified (observed negative labels). Then DRR = 40/50 - 80/100 = 0, so no bias is indicated.

The range of values for DRR for binary, multicategory facet, and continuous labels is [-1, +1].

• Positive values occur when the ratio of the predicted negatives (rejections) to the observed negative outcomes (unqualified applicants) for facet d is larger than the same ratio for facet a. These values indicate a possible bias against the favored facet a caused by the occurrence of relatively more false negatives in facet a. The larger the difference in the ratios, the more extreme the apparent bias.

• Values near zero occur when the ratio of the predicted negatives (rejections) to the observed negative outcomes (unqualified applicants) for facets a and d have similar values, indicating the observed labels for negative outcomes are being predicted with equal precision by the model.

• Negative values occur when the ratio of the predicted negatives (rejections) to the observed negative outcomes (unqualified applicants) for facet a is larger than the ratio facet d. These values indicate a possible bias against the disfavored facet d caused by the occurrence of relatively more false positives in facet d. The more negative the difference in the ratios, the more extreme the apparent bias.

**Accuracy Difference (AD)**

Accuracy difference (AD) metric is the difference between the prediction accuracy for different facets. This metric determines whether the classification by the model is more accurate for one facet than the other. AD indicates whether one facet incurs a greater proportion of Type I and Type II errors. But it cannot differentiate between Type I and Type II errors. For example, the model may have equal accuracy for different age demographics, but the errors may be mostly false positives (Type I errors) for one age-based group and mostly false negatives (Type II errors) for the other.

Also, if loan approvals are made with much higher accuracy for a middle-aged demographic (facet a) than for another age-based demographic (facet d), either a greater proportion of qualified applicants in the second group are denied a loan (FN) or a greater proportion of unqualified applicants from that group get a loan (FP) or both. This can lead to within group unfairness for the second group, even if the proportion of loans granted is nearly the same for both age-based groups, which is indicated by a DPPL value that is close to zero.

The formula for AD metric is the difference between the prediction accuracy for facet a, ACCₐ, minus that for facet d, ACCₐ:

\[ AD = ACCₐ - ACC₉ \]

Where:

• ACCₐ = (TPₐ + TNₐ)/(TPₐ + TNₐ + FPₐ + FNₐ)
  - TPₐ are the true positives predicted for facet a
  - TNₐ are the true negatives predicted for facet a
  - FPₐ are the false positives predicted for facet a
  - FNₐ are the false negatives predicted for facet a
• ACC₉ = (TP₉ + TN₉)/(TP₉ + TN₉ + FP₉ + FN₉)
  - TP₉ are the true positives predicted for facet d
  - TN₉ are the true negatives predicted for facet d
  - FP₉ are the false positives predicted for facet d
  - FN₉ are the false negatives predicted for facet d
Detect Posttraining Data and Model Bias

- FN<sub>d</sub> are the false negatives predicted for facet d

For example, suppose a model approves loans to 70 applicants from facet a of 100 and rejected the other 30. 10 should not have been offered the loan (FP<sub>a</sub>) and 60 were approved that should have been (TP<sub>a</sub>). 20 of the rejections should have been approved (FN<sub>a</sub>) and 10 were correctly rejected (TN<sub>a</sub>). The accuracy for facet a is as follows:

\[ ACC_a = \frac{(60 + 10)}{(60 + 10 + 20 + 10)} = 0.7 \]

Next, suppose a model approves loans to 50 applicants from facet d of 100 and rejected the other 50. 10 should not have been offered the loan (FP<sub>d</sub>) and 40 were approved that should have been (TP<sub>d</sub>). 40 of the rejections should have been approved (FN<sub>d</sub>) and 10 were correctly rejected (TN<sub>d</sub>). The accuracy for facet d is determined as follows:

\[ ACC_d = \frac{(40 + 10)}{(40 + 10 + 40 + 10)} = 0.5 \]

The accuracy difference is thus \( AD = ACC_a - ACC_d = 0.7 - 0.5 = 0.2 \). This indicates there is a bias against facet d as the metric is positive.

The range of values for AD for binary and multicategory facet labels is [-1, +1].

- Positive values occur when the prediction accuracy for facet a is greater than that for facet d. It means that facet d suffers more from some combination of false positives (Type I errors) or false negatives (Type II errors). This means there is a potential bias against the disfavored facet d.
- Values near zero occur when the prediction accuracy for facet a is similar to that for facet d.
- Negative values occur when the prediction accuracy for facet d is greater than that for facet a. It means that facet a suffers more from some combination of false positives (Type I errors) or false negatives (Type II errors). This means the is a bias against the favored facet a.

**Treatment Equality (TE)**

The treatment equality (TE) is the difference in the ratio of false negatives to false positives between facets a and d. The main idea of this metric is to assess whether, even if the accuracy across groups is the same, is it the case that errors are more harmful to one group than another? Error rate comes from the total of false positives and false negatives, but the breakdown of these two maybe very different across facets. TE measures whether errors are compensating in the similar or different ways across facets.

The formula for the treatment equality:

\[ TE = \frac{FN_d}{FP_d} - \frac{FN_a}{FP_a} \]

Where:

- FN<sub>d</sub> are the false negatives predicted for facet d.
- FP<sub>d</sub> are the false positives predicted for facet d.
- FN<sub>a</sub> are the false negatives predicted for facet a.
- FP<sub>a</sub> are the false positives predicted for facet a.

Note the metric becomes unbounded if FP<sub>a</sub> or FP<sub>d</sub> is zero.

For example, suppose that there are 100 loan applicants from facet a and 50 from facet d. For facet a, 8 were wrongly denied a loan (FN<sub>a</sub>) and another 6 were wrongly approved (FP<sub>d</sub>). The remaining predictions were true, so TP<sub>a</sub> + TN<sub>a</sub> = 86. For facet d, 5 were wrongly denied (FN<sub>d</sub>) and 2 were wrongly approved (FP<sub>d</sub>). The remaining predictions were true, so TP<sub>d</sub> + TN<sub>d</sub> = 43. The ratio of false negatives to false
positives equals $8/6 = 1.33$ for facet $a$ and $5/2 = 2.5$ for facet $d$. Hence $TE = 2.5 - 1.33 = 1.167$, even though both facets have the same accuracy:

$$\text{ACC}_a = \frac{86}{86+8+6} = 0.86$$
$$\text{ACC}_d = \frac{43}{43+5+2} = 0.86$$

The range of values for differences in conditional rejection for binary and multcategory facet labels is $(-\infty, +\infty)$. The TE metric is not defined for continuous labels. The interpretation of this metric depends on the relative important of false positives (Type I error) and false negatives (Type II error).

- Positive values occur when the ratio of false negatives to false positives for facet $d$ is greater than that for facet $a$.
- Values near zero occur when the ratio of false negatives to false positives for facet $a$ is similar to that for facet $d$.
- Negative values occur when the ratio of false negatives to false positives for facet $d$ is less than that for facet $a$.

**Note**

A previous version stated that the Treatment Equality metric is computed as $FP_a / FN_a - FP_d / FN_d$ instead of $FN_d / FP_d - FN_a / FP_a$. While either of the versions can be used. For more information, see Fairness measures for Machine Learning in Finance.

**Conditional Demographic Disparity in Predicted Labels (CDDPL)**

The demographic disparity metric (DDPL) determines whether facet $d$ has a larger proportion of the predicted rejected labels than of the predicted accepted labels. It enables a comparison of difference in predicted rejection proportion and predicted acceptance proportion across facets. This metric is exactly the same as the pretraining CDD metric except that it is computed off the predicted labels instead of the observed ones. This metric lies in the range $(-1,+1)$.

The formula for the demographic disparity predictions for labels of facet $d$ is as follows:

$$\text{DDPL}_d = n'_d^{(0)}/n'_d^{(0)} - n'_d^{(1)}/n'_d^{(1)} = P_d^R(y'^0) - P_d^A(y'^1)$$

Where:

- $n'_d^{(0)} = n'_a^{(0)} + n'_d^{(0)}$ is the number of predicted rejected labels for facets $a$ and $d$.
- $n'_d^{(1)} = n'_a^{(1)} + n'_d^{(1)}$ is the number of predicted accepted labels for facets $a$ and $d$.
- $P_d^R(y'^0)$ is the proportion of predicted rejected labels (value 0) in facet $d$.
- $P_d^A(y'^1)$ is the proportion of predicted accepted labels (value 1) in facet $d$.

A conditional demographic disparity in predicted labels (CDDPL) metric that conditions DDPL on attributes that define a strata of subgroups on the dataset is needed to rule out Simpson’s paradox. The regrouping can provide insights into the cause of apparent demographic disparities for less favored facets. The classic case arose in the case of Berkeley admissions where men were accepted at a higher rate overall than women. But when departmental subgroups were examined, women were shown to have higher admission rates than men by department. The explanation was that women had applied to departments with lower acceptance rates than men had. Examining the subgroup acceptance rates revealed that women were actually accepted at a higher rate than men for the departments with lower acceptance rates.

The CDDPL metric gives a single measure for all of the disparities found in the subgroups defined by an attribute of a dataset by averaging them. It is defined as the weighted average of demographic disparities in predicted labels (DDPL) for each of the subgroups, with each subgroup disparity weighted
in proportion to the number of observations in contains. The formula for the conditional demographic disparity in predicted labels is as follows:

\[ CDDPL = \frac{1}{n} \sum_i n_i \cdot DDPL_i \]

Where:
- \( \sum_i n_i = n \) is the total number of observations and \( n_i \) is the number of observations for each subgroup.
- \( DDPL_i = n_i^{(0)}/n^{(0)} - n_i^{(1)}/n^{(1)} = P_i^R(y^{(0)}) - P_i^A(y^{(1)}) \) is the demographic disparity in predicted labels for the subgroup.

So the demographic disparity for a subgroup in predicted labels (DDPL_i) are the difference between the proportion of predicted rejected labels and the proportion of predicted accepted labels for each subgroup.

The range of DDPL values for binary, multicategory, and continuous outcomes is \([-1, +1]\).

- \(+1\): when there are no predicted rejection labels for facet \( a \) or subgroup and no predicted acceptances for facet \( d \) or subgroup.
- Positive values indicate there is a demographic disparity in predicted labels as facet \( d \) or subgroup has a larger proportion of the predicted rejected labels than of the predicted accepted labels. The higher the value the greater the disparity.
- Values near zero indicate there is no demographic disparity on average.
- Negative values indicate there is a demographic disparity in predicted labels as facet \( a \) or subgroup has a larger proportion of the predicted rejected labels than of the predicted accepted labels. The lower the value the greater the disparity.
- \(-1\): when there are no predicted rejection labels for facet \( d \) or subgroup and no predicted acceptances for facet \( a \) or subgroup.

**Counterfactual Fliptest (FT)**

The fliptest is an approach that looks at each member of facet \( d \) and assesses whether similar members of facet \( a \) have different model predictions. The members of facet \( a \) are chosen to be k-nearest neighbors of the observation from facet \( d \). We assess how many nearest neighbors of the opposite group receive a different prediction, where the flipped prediction can go from positive to negative and vice versa.

The formula for the counterfactual fliptest is the difference in the cardinality of two sets divided by the number of members of facet \( d \):

\[ FT = (F^* - F^-)/n_d \]

Where:
- \( F^* \) is the number of disfavored facet \( d \) members with an unfavorable outcome whose nearest neighbors in favored facet \( a \) received a favorable outcome.
- \( F^- \) is the number of disfavored facet \( d \) members with a favorable outcome whose nearest neighbors in favored facet \( a \) received an unfavorable outcome.
- \( n_d \) is the sample size of facet \( d \).

The range of values for the counterfactual fliptest for binary and multicategory facet labels is \([-1, +1]\). For continuous labels, we set a threshold to collapse the labels to binary.

- Positive values occur when the number of unfavorable counterfactual fliptest decisions for the disfavored facet \( d \) exceeds the favorable ones.
Values near zero occur when the number of unfavorable and favorable counterfactual flip test decisions balance out.

Negative values occur when the number of unfavorable counterfactual flip test decisions for the disfavored facet $d$ is less than the favorable ones.

**Generalized entropy (GE)**

The generalized entropy index (GE) measures the inequality in benefit $b$ for the predicted label compared to the observed label. A benefit occurs when a false positive is predicted. A false positive occurs when a negative observation ($y=0$) has a positive prediction ($y'=1$). A benefit also occurs when the observed and predicted labels are the same, also known as a true positive and true negative. No benefit occurs when a false negative is predicted. A false negative occurs when a positive observation ($y=1$) is predicted to have a negative outcome ($y'=0$). The benefit $b$ is defined, as follows.

$$b = y' - y + 1$$

Using this definition, a false positive receives a benefit $b$ of 2, and a false negative receives a benefit of 0. Both a true positive and a true negative receive a benefit of 1.

The GE metric is computed following the Generalized Entropy Index (GE) with the weight $\alpha$ set to 2. This weight controls the sensitivity to different benefit values. A smaller $\alpha$ means an increased sensitivity to smaller values.

$$GE = \frac{1}{2n} \sum_{i=1}^{n} \left( \frac{b_i}{b'} \right)^2 - 1$$

The following variables used to calculate GE are defined as follows:

- $b_i$ is the benefit received by the $i^{th}$ data point.
- $b'$ is the mean of all benefits.

GE can range from 0 to 0.5, where values of zero indicate no inequality in benefits across all data points. This occurs either when all inputs are correctly predicted or when all the predictions are false positives. GE is undefined when all predictions are false negatives.

**Note**

The metric GE does not depend on a facet value being either favored or disfavored.

**Amazon SageMaker Clarify Model Explainability**

Amazon SageMaker Clarify provides tools to help explain how machine learning (ML) models make predictions. These tools can help ML modelers and developers and other internal stakeholders understand model characteristics as a whole prior to deployment and to debug predictions provided by the model after it’s deployed. Transparency about how ML models arrive at their predictions is also critical to consumers and regulators. They need to trust the model predictions if they are going to accept the decisions based on them. SageMaker Clarify uses a model-agnostic feature attribution approach. You can use this to understand why a model made a prediction after training, and to provide per-instance explanation during inference. The implementation includes a scalable and efficient implementation of SHAP. This is based on the concept of a Shapley value, from the field of cooperative game theory, that assigns each feature an importance value for a particular prediction.

Clarify produces partial dependence plots (PDPs) that show the marginal effect features have on the predicted outcome of a machine learning model. Partial dependence helps explain target response given a set of input features. It also supports both computer vision (CV) and natural language processing (NLP) explainability using the same Shapley Values (SHAP) algorithm as used for tabular data explanations.
What is the function of an explanation in the machine learning context? An explanation can be thought of as the answer to a Why question that helps humans understand the cause of a prediction. In the context of an ML model, you might be interested in answering questions such as:

- Why did the model predict a negative outcome such as a loan rejection for a given applicant?
- How does the model make predictions?
- Why did the model make an incorrect prediction?
- Which features have the largest influence on the behavior of the model?

You can use explanations for auditing and meeting regulatory requirements, building trust in the model and supporting human decision-making, and debugging and improving model performance.

The need to satisfy the demands for human understanding about the nature and outcomes of ML inference is key to the sort of explanation needed. Research from philosophy and cognitive science disciplines has shown that people care especially about contrastive explanations, or explanations of why an event X happened instead of some other event Y that did not occur. Here, X could be an unexpected or surprising event that happened and Y corresponds to an expectation based on their existing mental model referred to as a baseline. Note that for the same event X, different people might seek different explanations depending on their point of view or mental model Y. In the context of explainable AI, you can think of X as the example being explained and Y as a baseline that is typically chosen to represent an uninformative or average example in the dataset. Sometimes, for example in the case of ML modeling of images, the baseline might be implicit, where an image whose pixels are all the same color can serves as a baseline.

Sample Notebooks

Amazon SageMaker Clarify provides the following sample notebook for model explainability:

- Amazon SageMaker Clarify Processing – Use SageMaker Clarify to create a processing job for the detecting bias and explaining model predictions with feature attributions. Examples include using CSV and JSONLines data formats, bringing your own container, and running processing jobs with Spark.
- Explaining Image Classification with SageMaker Clarify – SageMaker Clarify provides you with insights into how your computer vision models classify images.
- Explaining object detection models with SageMaker Clarify – SageMaker Clarify provides you with insights into how your computer vision models detect objects.

This notebook has been verified to run in Amazon SageMaker Studio only. If you need instructions on how to open a notebook in Amazon SageMaker Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133). If you're prompted to choose a kernel, choose Python 3 (Data Science).

Topics

- Feature Attributions that Use Shapley Values (p. 2653)
- SHAP Baselines for Explainability (p. 2654)
- Partial Dependence Plots: Analysis Configuration and Output (p. 2655)
- SageMaker Clarify Computer Vision (p. 2657)
- Create Feature Attribute Baselines and Explainability Reports (p. 2658)
- Explainability Reports for NLP Models (p. 2659)

Feature Attributions that Use Shapley Values

SageMaker Clarify provides feature attributions based on the concept of Shapley value. You can use Shapley values to determine the contribution that each feature made to model predictions. These
attributions can be provided for specific predictions and at a global level for the model as a whole. For example, if you used an ML model for college admissions, the explanations could help determine whether the GPA or the SAT score was the feature most responsible for the model’s predictions, and then you can determine how responsible each feature was for determining an admission decision about a particular student.

SageMaker Clarify has taken the concept of Shapley values from game theory and deployed it in a machine learning context. The Shapley value provides a way to quantify the contribution of each player to a game, and hence the means to distribute the total gain generated by a game to its players based on their contributions. In this machine learning context, SageMaker Clarify treats the prediction of the model on a given instance as the game and the features included in the model as the players. For a first approximation, you might be tempted to determine the marginal contribution or effect of each feature by quantifying the result of either dropping that feature from the model or dropping all other features from the model. However, this approach does not take into account that features included in a model are often not independent from each other. For example, if two features are highly correlated, dropping either one of the features might not alter the model prediction significantly.

To address these potential dependencies, the Shapley value requires that the outcome of each possible combination (or coalition) of features must be considered to determine the importance of each feature. Given \(d\) features, there are \(2^d\) such possible feature combinations, each corresponding to a potential model. To determine the attribution for a given feature \(f\), consider the marginal contribution of including \(f\) in all feature combinations (and associated models) that do not contain \(f\), and take the average. It can be shown that Shapley value is the unique way of assigning the contribution or importance of each feature that satisfies certain desirable properties. In particular, the sum of Shapley values of each feature corresponds to the difference between the predictions of the model and a dummy model with no features. However, even for reasonable values of \(d\), say 50 features, it is computationally prohibitive and impractical to train \(2^d\) possible models. As a result, SageMaker Clarify needs to make use of various approximation techniques. For this purpose, SageMaker Clarify uses SHapley Additive exPlanations (SHAP), which incorporates such approximations and devised a scalable and efficient implementation of the Kernel SHAP algorithm through additional optimizations.

For additional information on Shapley values, see A Unified Approach to Interpreting Model Predictions.

**SHAP Baselines for Explainability**

Explanations are typically contrastive (that is, they account for deviations from a baseline). As a result, for the same model prediction, you can expect to get different explanations with respect to different baselines. Therefore, your choice of a baseline is crucial. In an ML context, the baseline corresponds to a hypothetical instance that can be either uninformative or informative. During the computation of Shapley values, SageMaker Clarify generates several new instances between the baseline and the given instance, in which the absence of a feature, is modeled by setting the feature value to that of the baseline and the presence of a feature is modeled by setting the feature value to that of the given instance. Thus, the absence of all features corresponds to the baseline and the presence of all features corresponds to the given instance.

How can you choose good baselines? Often it is desirable to select a baseline with very low information content. For example, you can construct an average instance from the training dataset by taking either the median or average for numerical features and the mode for categorical features. For the college admissions example, you might be interested in explaining why a particular applicant was accepted as compared to a baseline acceptances based on an average applicant. If not provided, a baseline is calculated automatically by SageMaker Clarify using K-means or K-prototypes in the input dataset.

Alternatively, you can choose to generate explanations with respect to informative baselines. For the college admissions scenario, you might want to explain why a particular applicant was rejected when compared with other applicants from similar demographic backgrounds. In this case, you can choose a baseline that represents the applicants of interest, namely those from a similar demographic background. Thus, you can use informative baselines to concentrate the analysis on the specific aspects
of a particular model prediction. You can isolate the features for assessment by setting demographic attributes and other features that you can’t act on to the same value as in the given instance.

## Partial Dependence Plots: Analysis Configuration and Output

Partial dependence plots (PDP) show the dependence of the predicted target response on a set of input features of interest. These are marginalized over the values of all other input features and are referred to as the *complement features*. Intuitively, you can interpret the partial dependence as the target response, which is expected as a function of each input feature of interest.

### Topics
- Partial dependence plots analysis configuration
- Partial dependence plots analysis output

### Partial dependence plots analysis configuration

To create a partial dependence plot (PDP), Amazon SageMaker Clarify initially looks for the feature columns specified in a JSON array of the `analysis_config.json`. The other parameters that configure the analysis of a processing job must be provided in this JSON file. For more information about configuring PDPs and other aspects of an analysis, see [Configure the Analysis](p. 2620).

The following code contains an example of a JSON "pdp" object in the "methods" object of an `analysis_config.json` configuration file.

```json
{
    "dataset_type":...
    "baseline": [[..]]
    .
    "methods": {
        "shap": {
            "baseline": "...
            "num_samples": 100
        },
        "pdp": {
            "features": ["Age", "MaturityMonths"] // The features for which we need to plot PDP.
            "grid_resolution": 20, //Required for numerical columns only.
            "top_k_features": 10, //Specifies how many of the top features must be used for PDP plots. The default is 10.
        }
    }
    .
    .
}
```

**Note**

If "features" is not mentioned in the "pdp" object but "shap" config is provided, SageMaker Clarify takes top ten features from the global SHAP results to plot the PDP visualizations.

### Partial dependence plots analysis output

The following code shows an example of the partial dependence plot (PDP) schema returned in the `analysis.json` result file. The "pdp" section in this analysis output file contains the information required
to generate the PDP plots. Each dictionary in the list contains the specification for the PDP of the feature specified by the `feature_name`.

The `data_type` indicates whether the data is numerical or categorical. The `feature_values` field contains the values present in the feature. If the `data_type` inferred by Clarify is categorical, `feature_values` contain all the unique values that the feature could assume. If the `data_type` inferred by Clarify is numerical, it contains a list of the central values of each of the `grid_resolution` number of buckets generated by Clarify.

If the partial dependence plots are computed for a particular feature, the `feature_values`, `model_predictions`, and `data_distributions` fields are replaced by the `error` field which contains an error message.

```json
{
    "version": "1.0",
    "explanations": {
        "kernel_shap": {
            ...
        },
        "pdp": [
            {
                "feature_name": "Age",
                "data_type": "numerical",
                "feature_values": [
                    20.4,
                    23.2,
                    26.0,
                    28.799999999999997,
                    31.599999999999998,
                    34.4,
                    70.8,
                    73.6
                ],
                "model_predictions": [
                    0.6830344458296895,
                    0.6812452118471265,
                    0.6908621763065458,
                    0.7008252082392573,
                    0.733054383918643,
                    0.7332442337575274,
                    0.7337257475035403,
                    0.7395857129991055
                ],
                "data_distribution": [0.13, 0.25, 0.15, 0.35, 0.35, 0.17]
            },
            {
                "feature_name": "text_column",
                "data_type": "free_text",
                "error": "Detected data type is not supported for PDP. PDP can only be computed for numerical or categorical columns"
            }
        ]
    }
}
```
This PDP schema generates the following partial dependence plot for the Age feature. The PDP plots the `feature_values` along the x-axis. The y-axis contains the values in `model_predictions` field. Each list in the `model_predictions` field corresponds to one class in the output from the model.

You can view the plot in the report.pdf file in the analysis output path that you provided.

**SageMaker Clarify Computer Vision**

Amazon SageMaker Clarify generates heat maps for images that highlight features under analysis. In particular, the heat maps provide insights into how your computer vision models classify the images and how they detect objects in those images.

**Topics**
- Explain Image Classification with Amazon SageMaker Clarify (p. 2657)
- Explain Object Detection with Amazon SageMaker Clarify (p. 2658)

**Explain Image Classification with Amazon SageMaker Clarify**

SageMaker Clarify processing jobs provides support for explaining images using the KernelSHAP algorithm. This algorithm treats the image as a collection of super pixels. Given a dataset consisting of images, the processing job outputs a dataset of images where each image shows the heat map of the relevant super pixels.

For a sample notebook that uses SageMaker Clarify to classify images and explain its classification, see Explaining Image Classification with SageMaker Clarify.
Explain Object Detection with Amazon SageMaker Clarify

Amazon SageMaker Clarify can detect and classify objects in an image and then provide an explanation for the detection predicted. The objects are first categorized into one of the classes in a specified collection. SageMaker Clarify produces a confidence score for each object that it belongs to the class and the coordinates of a bounding box that delimits the object. For each detected object identified with sufficient probability, SageMaker Clarify extracts features using the Simple Linear Iterative Clustering (SLIC) method from scikit-learn library for image segmentation.

SageMaker Clarify can then provide an explanation for the detection of an object in the image scene. It uses Shapley values to determine the contribution that each feature has made to a model prediction. It produces a heat map that shows how important each of the features in the image scene were for its detection of the object. The context of an object is often very important for the correct identification of an object, so it is important not to just use the cropped image for classification.

For a sample notebook that uses SageMaker Clarify to detect objects in an image and explain its predictions, see Explaining object detection models with Amazon SageMaker Clarify.

Create Feature Attribute Baselines and Explainability Reports

For an example notebook with instructions on how to run a SageMaker Clarify processing job in Studio that creates explanations for its predictions relative to a baseline, see Explainability and bias detection with Amazon SageMaker Clarify.

If you need instructions on how to open a notebook in Amazon SageMaker Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133). The following code examples are taken from the example notebook listed previously. This section discusses the code related to the use of Shapley values to provide reports that compare the relative contributions each feature made the predictions.

Use SHAPConfig to create the baseline. In this example, the mean_abs is the mean of absolute SHAP values for all instances, specified as the baseline. You use DataConfig to configure the target variable, data input and output paths, and their formats.

```python
shap_config = clarify.SHAPConfig(baseline=[test_features.iloc[0].values.tolist()],
                                  num_samples=15,
                                  agg_method='mean_abs')

explainability_output_path = 's3://{}/{}/clarify-explainability'.format(bucket, prefix)

explainability_data_config = clarify.DataConfig(s3_data_input_path=train_uri,
                                                s3_output_path=explainability_output_path,
                                                label='Target',
                                                headers=training_data.columns.to_list(),
                                                dataset_type='text/csv')
```

**Note**
Kernel SHAP in SageMaker Clarify supports omitting the “baseline” parameter. In this case, a baseline based on clustering the input dataset is generated automatically.

Then run the explainability job.

```python
clarify_processor.run_explainability(data_config=explainability_data_config,
                                      model_config=model_config,
                                      explainability_config=shap_config)
```

To view Partial Dependence plots (PDP), use explainability_config=PDP_config.
You can select both types of reports with explainability_config=[PDP_config, shap_config].
View the results in Studio or download them from the explainability_output_path S3 bucket.
Explainability Reports for NLP Models

Amazon SageMaker Clarify supports explanations for natural language processing (NLP) models. NLP models help you understand which sections of text are most important for the predictions made by your model. This functionality can be used to explain either an individual local prediction or the model's expected predictions for overall global explanations. You can define the length of the text segment (tokens, phrases, sentences, paragraphs) to understand and visualize a model's behavior at multiple levels of granularity.

SageMaker Clarify NLP explainability is compatible with classification and regression models. You can also use Clarify to explain your model's behavior on multi-modal datasets that contain text, categorical, or numerical features. NLP explainability for multi-modal datasets can help you understand how important each feature is to the model's output. SageMaker Clarify supports 62 languages and can handle text which includes multiple languages.

To obtain feature importance for parts of an input text, create a `TextConfig` specifying the granularity of the parts of the text and the language. Clarify then breaks the text down into tokens, sentences, or paragraphs depending on your choice of granularity. It replaces subsets of these parts with the values from the baseline. The baseline defaults to empty strings, meaning SageMaker Clarify drops parts of the input text. SageMaker Clarify then replaces tokens (sentences and paragraphs, respectively) to determine how these replacements affect the model's prediction, in order to assess their importance.

```python
from sagemaker import clarify
text_config = clarify.TextConfig(
    # Specify the language of your text or use "multi-language" for multi-language.
    language="english",
    # Choose the granularity of your explanations as tokens, sentences or paragraphs.
    granularity="token"
)
shap_config = clarify.SHAPConfig(
    # For now, we don't support global aggregation,
    # so make sure you retrieve local explanations.
    save_local_shap_values=True,
    text_config=text_config,
    # Determine with what to replace tokens/sentences/paragraphs (based on your choice of granularity) with.
    baseline=["<UNK>"],
    # You can further specify num_samples and agg_method.
)
```

The remainder of the explainability job is coded as usual.

```python
explainability_output_path = 's3://{}/clarify-explainability'.format(bucket, prefix)
explainability_data_config = clarify.DataConfig(
    s3_data_input_path=train_uri,
    s3_output_path=explainability_output_path,
    # With text data sometimes detection of headers fails,
    # so we recommend explicitly setting it in the config.
    headers=["text"],
    dataset_type="text/csv")
model_config = clarify.ModelConfig(
    model_name=model_name,
    # Specialized hardware is well-suited for NLP models.
    instance_type="ml.p2.xlarge",
    instance_count=1)
clarify_processor = clarify.SageMakerClarifyProcessor(
    role=role, instance_count=1, instance_type="ml.m5.xlarge", sagemaker_session=session
```
clarify_processor.run_explainability(
    data_config=explainability_data_config,
    model_config=model_config,
    explainability_config=shap_config)

View the local explanations in the explainability_output_path S3 bucket. SageMaker Clarify does not aggregate the importance of individual tokens/sentences/paragraphs.

Extensions:

- **Multi-modal data** - If your data contains more than text, such as categorical or numeric features, you can add more columns in your header and baseline to accommodate those features.

- **JSON** - If the model input or output data is in JSON Lines format, specify the dataset_type in the DataConfig or the accept_type and content_type in the ModelConfig.

- **Multi-class model output** - If your model does multi-class or multi-label predictions, SageMaker Clarify computes the importance for each class.

- **Model output** - Some model outputs contain more than a single score. A prediction of three examples returns a matrix of shape [3, 1] such as [[0.1], [-1.1], [10.2], [0.0], [3.2]]. You can specify model_scores in run_explainability. For example, if your model predicts probabilities of five classes and additionally outputs the winning class, ["c1", [0.1, 0.4, 0.3, 0.2]], then you can set model_scores=1.

Tips for fast results:

- During the development phase, work with a small subset of examples for quick iterations.

- To scale up for deployment, increase the instance_count for the processing job and the predictor. This instructs SageMaker Clarify to partition the data and work with multiple machines in parallel. For parallel processing, we recommend using the parquet data format because Spark can struggle with special characters in CSV files.

- Choose an appropriate instance_type for your model. GPU instances are often suitable for NLP models.

- To save unnecessary computation, consider truncating your text. Many models work with a maximum text length. By applying the truncation in a preprocessing step, SageMaker Clarify does not waste resources determining the feature importance for the parts of text that are disregarded by the model.

## Troubleshoot SageMaker Clarify Processing Jobs

If you encounter failures with SageMaker Clarify processing jobs, consult the following scenarios to help identify the issue.

**Note**
The failure reason and exit message are intended to contain descriptive messages and exceptions, if encountered, during the run. One common reason is invalid or missing parameters. If you encounter unclear, confusing, or misleading messages or are unable to find a solution, submit feedback.

**Topics**

- Processing job fails to finish (p. 2661)
- Processing job finishes without results and you get a CloudWatch warning message (p. 2661)
- Error message for invalid analysis configuration (p. 2661)
- Bias metric computation fails for several or all metrics (p. 2661)
Troubleshoot Jobs

- Mismatch between analysis config and dataset/model input/output (p. 2662)
- Model returns 500 Internal Server Error or container falls back to per-record predictions due to model error (p. 2662)
- Execution role is invalid (p. 2662)
- Failed to download data (p. 2662)
- Could not connect to SageMaker (p. 2662)

Processing job fails to finish

If the processing job fails to finish, you can try the following:

- Inspect the job logs directly in the notebook where you ran the job in. The job logs are located in the output of the notebook cell where you initiated the run.
- Inspect the job logs in CloudWatch.
- Add the following line in your notebook to describe the last processing job and look for the failure reason and exit message:
  ```python
clarify_processor.jobs[-1].describe()
```
- Execute the following AWS CLI command to describe the processing job and look for the failure reason and exit message:
  ```
aws sagemaker describe-processing-job --processing-job-name <processing-job-id>
```

Processing job finishes without results and you get a CloudWatch warning message

If the processing job finishes but no results are found and a warning message is found in the CloudWatch logs that says “Signal 15 received, cleaning up”, this is an indication that the job was stopped either due to a customer request that called the StopProcessingJob API or that the job ran out of time allotted for its completion. In the later case, check the maximum runtime in the job configuration (max_runtime_in_seconds) and increase it as needed.

Error message for invalid analysis configuration

- If you get the error message "Unable to load analysis configuration as JSON.", this means that the analysis configuration input file for the processing job does not contain a valid JSON object. Check the validity of the JSON object using a JSON linter.
- If you get the error message "Analysis configuration schema validation error.", this means that the analysis configuration input file for the processing job contains unknown fields or invalid types for some field values. Review the configuration parameters in the file and cross-check them with the parameters listed in the configuration specification file.

Bias metric computation fails for several or all metrics

If you receive one of the following error messages "No Label values are present in the predicted Label Column, Positive Predicted Index Series contains all False values." or "Predicted Label Column series data type is not the same as Label Column series.", try the following:

- Check that the correct dataset is being used.
- Check whether the dataset size is too small; whether, for example, it contains only a few rows. This may cause the model outputs to have the same value or the data type is inferred incorrectly.
• Check if the label or facet is treated as continuous or categorical. SageMaker Clarify uses heuristics to determine the **DataType**. For post-training bias metrics, the data type returned by the model may not match what is in the dataset or SageMaker Clarify may not be able to transform it correctly.
  • In the bias report, you should see a single value for categorical columns or an interval for continuous columns.
  • For example, if a column has values 0.0 and 1.0 as floats, it will be treated as continuous even if there are too few unique values.

**Mismatch between analysis config and dataset/model input/output**

• Check that the baseline format in the analysis config is the same as dataset format.
  • If you receive the error message "Could not convert string to float.", check that the format is correctly specified. It could also indicate that the model predictions have a different format than the label column or it could indicate that the configuration for the label or probabilities is incorrect.
  • If you receive the error message "Unable to locate the facet." or "Headers must contain label." or "Headers in config do not match with the number of columns in the dataset." or "Feature names not found.", check that the headers match the columns.
  • If you receive the error message "Data must contain features.", check the content template for JSON Lines and compare it with the dataset sample if available.

**Model returns 500 Internal Server Error or container falls back to per-record predictions due to model error**

If you receive the error message "Fallback to per-record prediction because of model error.", this could indicate that model cannot handle the batch size, or be throttled, or just does not accept the input passed by the container due to serialization problems. You should review the CloudWatch logs for the SageMaker endpoint and look for error messages or tracebacks. For model throttling cases, it may help to use a different instance type or increasing the number of instances for the endpoint.

**Execution role is invalid**

This indicates that the role provided is incorrect or missing required permissions. Check the role and its permissions that were used to configure the processing job and verify the permission and trust policy for the role.

**Failed to download data**

This indicates that job inputs could not be downloaded for the job to start. Check the bucket name and permissions for the dataset and the configuration inputs.

**Could not connect to SageMaker**

This indicates that the job could not reach SageMaker service endpoints. Check the network configuration settings for the processing job and verify VPC configuration.

### Train Using a Heterogeneous Cluster

Using the heterogeneous cluster feature of SageMaker Training, you can run a training job with multiple types of ML instances for a better resource scaling and utilization for different ML training tasks and
purposes. For example, if your training job on a cluster with GPU instances suffers low GPU utilization and CPU bottleneck problems due to CPU-intensive tasks, using a heterogeneous cluster can help offload CPU-intensive tasks by adding more cost-efficient CPU instance groups, resolve such bottleneck problems, and achieve a better GPU utilization.

**Note**
This feature is available in the SageMaker Python SDK v2.98.0 and later.

**Note**
This feature is available through the SageMaker PyTorch and TensorFlow framework estimator classes. Supported frameworks are PyTorch v1.10 or later and TensorFlow v2.6 or later.

**Topics**
- How to Configure a Heterogeneous Cluster (p. 2663)
- Distributed Training with a Heterogeneous Cluster (p. 2666)
- Modify Your Training Script to Assign Instance Groups (p. 2668)
- Considerations (p. 2670)
- Examples, Blogs, and Case Studies (p. 2670)

# How to Configure a Heterogeneous Cluster

This section provides instructions on how to run a training job using a heterogeneous cluster that consists of multiple instance types.

**Topics**
- Using the SageMaker Python SDK (p. 2663)
- Using the Low-Level SageMaker APIs (p. 2666)

## Using the SageMaker Python SDK

Follow instructions on how to configure instance groups for a heterogeneous cluster using the SageMaker Python SDK.

1. To configure instance groups of a heterogeneous cluster for a training job, use the `sagemaker.instance_group.InstanceGroup` class. You can specify a custom name for each instance group, the instance type, and the number of instances for each instance group. For more information, see `sagemaker.instance_group.InstanceGroup` in the *SageMaker Python SDK documentation*.

   **Note**
   For more information about available instance types and the maximum number of instance groups that you can configure in a heterogeneous cluster, see the `InstanceGroup` API reference.

   The following code example shows how to set up two instance groups that consists of two `ml.c5.18xlarge` CPU-only instances named `instance_group_1` and one `ml.p3dn.24xlarge` GPU instance named `instance_group_2`, as shown in the following diagram.
The preceding diagram shows a conceptual example of how pre-training processes, such as data preprocessing, can be assigned to the CPU instance group and stream the preprocessed data to the GPU instance group.

```python
from sagemaker.instance_group import InstanceGroup

instance_group_1 = InstanceGroup(
    "instance_group_1", "ml.c5.18xlarge", 2
)

instance_group_2 = InstanceGroup(
    "instance_group_2", "ml.p3dn.24xlarge", 1
)
```

2. Using the instance group objects, set up training input channels and assign instance groups to the channels through the `instance_group_names` argument of the `sagemaker.inputs.TrainingInput` class. The `instance_group_names` argument accepts a list of strings of instance group names.
The following example shows how to set two training input channels and assign the instance groups created in the example of the previous step. You can also specify Amazon S3 bucket paths to the s3_data argument for the instance groups to process data for your usage purposes.

```python
from sagemaker.inputs import TrainingInput

training_input_channel_1 = TrainingInput(
    s3_data_type='S3Prefix', # Available Options: S3Prefix | ManifestFile | AugmentedManifestFile
    s3_data='s3://your-training-data-storage/folder1',
    distribution='FullyReplicated', # Available Options: FullyReplicated | ShardedByS3Key
    input_mode='File', # Available Options: File | Pipe | FastFile
    instance_groups=['instance_group_1'])

training_input_channel_2 = TrainingInput(
    s3_data_type='S3Prefix',
    s3_data='s3://your-training-data-storage/folder2',
    distribution='FullyReplicated',
    input_mode='File',
    instance_groups=['instance_group_2'])
```

For more information about the arguments of TrainingInput, see the following links.

- The `sagemaker.inputs.TrainingInput` class in the SageMaker Python SDK documentation
- The `S3DataSource` API in the SageMaker API Reference

3. Configure a SageMaker estimator with the instance_groups argument as shown in the following code example. The instance_groups argument accepts a list of InstanceGroup objects.

PyTorch

```python
from sagemaker.pytorch import PyTorch

estimator = PyTorch(
    ...,
    entry_point='my-training-script.py',
    framework_version='x.y.z', # 1.10.0 or later
    py_version='pyxy',
    job_name='my-training-job-with-heterogeneous-cluster',
    instance_groups=['instance_group_1', 'instance_group_2'])
```

TensorFlow

```python
from sagemaker.tensorflow import TensorFlow

estimator = TensorFlow(
    ...,
    entry_point='my-training-script.py',
    framework_version='x.y.z', # 2.6.0 or later
    py_version='pyxy',
    job_name='my-training-job-with-heterogeneous-cluster',
    instance_groups=['instance_group_1', 'instance_group_2'])
```

**Note**

The instance_type and instance_count argument pair and the instance_groups argument of the SageMaker estimator class are mutually exclusive. For homogeneous cluster
training, use the `instance_type` and `instance_count` argument pair. For heterogeneous cluster training, use `instance_groups`.

**Note**
To find a complete list of available framework containers, framework versions, and Python versions, see SageMaker Framework Containers in the AWS Deep Learning Container GitHub repository.

4. Configure the `estimator.fit` method with the training input channels configured with the instance groups and start the training job.

```python
estimator.fit(
    inputs={
        'training': training_input_channel_1,
        'dummy-input-channel': training_input_channel_2
    }
)
```

**Using the Low-Level SageMaker APIs**

If you use the AWS Command Line Interface or AWS SDK for Python (Boto3) and want to use low-level SageMaker APIs for submitting a training job request with a heterogeneous cluster, see the following API references.

- `CreateTrainingJob`
- `ResourceConfig`
- `InstanceGroup`
- `S3DataSource`

**Distributed Training with a Heterogeneous Cluster**

Through the `distribution` argument of the SageMaker estimator class, you can assign a specific instance group to run distributed training. For example, assume that you have the following two instance groups and want to run multi-GPU training on one of them.

```python
from sagemaker.instance_group import InstanceGroup

instance_group_1 = InstanceGroup("instance_group_1", "ml.c5.18xlarge", 1)
instance_group_2 = InstanceGroup("instance_group_2", "ml.p3dn.24xlarge", 2)
```

You can set the distributed training configuration for one of the instance groups. For example, the following code examples show how to assign `training_group_2` with two `ml.p3dn.24xlarge` instances to the distributed training configuration.

**Note**
Currently, only one instance group of a heterogeneous cluster can be specified to the distribution configuration.

**With MPI**

PyTorch

```python
from sagemaker.pytorch import PyTorch

estimator = PyTorch(
```
instance_groups=[instance_group_1, instance_group_2],
distribution={
    "mpi": {
        "enabled": True, "processes_per_host": 8
    },
    "instance_groups": [instance_group_2]
}
)

### TensorFlow

from sagemaker.tensorflow import TensorFlow

estimator = TensorFlow(
    ...
    instance_groups=[instance_group_1, instance_group_2],
    distribution={
        "mpi": {
            "enabled": True, "processes_per_host": 8
        },
        "instance_groups": [instance_group_2]
    }
)

### With the SageMaker data parallel library

**PyTorch**

from sagemaker.pytorch import PyTorch

estimator = PyTorch(
    ...
    instance_groups=[instance_group_1, instance_group_2],
    distribution={
        "smdistributed": {
            "dataparallel": {
                "enabled": True
            }
        },
        "instance_groups": [instance_group_2]
    }
)

### TensorFlow

from sagemaker.tensorflow import TensorFlow

estimator = TensorFlow(
    ...
    instance_groups=[instance_group_1, instance_group_2],
    distribution={
        "smdistributed": {
            "dataparallel": {
                "enabled": True
            }
        },
        "instance_groups": [instance_group_2]
    }
)
Note
When using the SageMaker data parallel library, make sure the instance group consists of the supported instance types by the library.

For more information about the SageMaker data parallel library, see SageMaker Data Parallel Training.

With the SageMaker model parallel library

PyTorch

```python
from sagemaker.pytorch import PyTorch

estimator = PyTorch(
    ...
    instance_groups=[instance_group_1, instance_group_2],
    distribution={
        "smdistributed": {
            "modelparallel": {
                "enabled": True,
                "parameters": {
                    # SageMaker model parallel parameters
                }
            }
        }
    },
    "instance_groups": [instance_group_2]
)
```

TensorFlow

```python
from sagemaker.tensorflow import TensorFlow

estimator = TensorFlow(
    ...
    instance_groups=[instance_group_1, instance_group_2],
    distribution={
        "smdistributed": {
            "modelparallel": {
                "enabled": True,
                "parameters": {
                    # SageMaker model parallel parameters
                }
            }
        }
    },
    "instance_groups": [instance_group_2]
)
```

For more information about the SageMaker model parallel library, see SageMaker Model Parallel Training.

Modify Your Training Script to Assign Instance Groups

With the heterogeneous cluster configuration in the previous sections, you have prepared the SageMaker training environment and instances for your training job. To further assign the instance groups to certain training and data processing tasks, the next step is to modify your training script. By default, the training job simply makes training script replicas for all nodes regardless the size of the instance, and this might lead to performance loss.
For example, if you mix CPU instances and GPU instances in a heterogeneous cluster while passing a deep neural network training script to the `entry_point` argument of the SageMaker estimator, the entry_point script is replicated to each instance. This means that, without proper task assignments, CPU instances also run the entire script and start the training job that’s designed for distributed training on GPU instances. Therefore, you must make changes in specific processing functions that you want to offload and run on the CPU instances. You can use the SageMaker environment variables to retrieve the information of the heterogeneous cluster and let specific processes to run accordingly.

**Query instance group information during the initialization phase of a SageMaker training job**

When your training job starts, your training script reads SageMaker training environment information that includes heterogeneous cluster configuration. The configuration contains information such as the current instance groups, the current hosts in each group, and in which group the current host resides.

You can retrieve instance group information in the following ways.

**(Recommended) Reading instance group information with the SageMaker training toolkit**

Use the environment Python module that the SageMaker training toolkit library provides. The toolkit library is preinstalled in the SageMaker framework containers for TensorFlow and PyTorch, so you don’t need an additional installation step when using the prebuilt containers. This is the recommended way to retrieve the SageMaker environment variables with fewer code changes in your training script.

```python
from sagemaker_training import environment
env = environment.Environment()
```

Environment variables related to general SageMaker training and heterogeneous clusters:

- `env.is_hetero` – Returns a Boolean result whether a heterogeneous cluster is configured or not.
- `env.current_host` – Returns the current host.
- `env.current_instance_type` – Returns the type of instance of the current host.
- `env.current_instance_group` – Returns the name of the current instance group.
- `env.current_instance_group_hosts` – Returns a list of hosts in current instance group.
- `env.instance_groups` – Returns a list of instance group names used for training.
- `env.instance_groups_dict` – Returns the entire heterogeneous cluster configuration of the training job.
- `env.distribution_instance_groups` – Returns a list of instance groups assigned to the distribution parameter of the SageMaker estimator class.
- `env.distribution_hosts` – Returns a list of hosts belonging to the instance groups assigned to the distribution parameter of the SageMaker estimator class.

For example, consider the following example of a heterogeneous cluster that consists of two instance groups.

```python
from sagemaker.instance_group import InstanceGroup
instance_group_1 = InstanceGroup(    "instance_group_1", "ml.c5.18xlarge", 1)
instance_group_2 = InstanceGroup(    "instance_group_2", "ml.p3dn.24xlarge", 2)
```
The output of `env.instance_groups_dict` of the example heterogeneous cluster should be similar to the following.

```json
{
    "instance_group_1": {
        "hosts": ["algo-2" ],
        "instance_group_name": "instance_group_1",
        "instance_type": "ml.c5.18xlarge"
    },
    "instance_group_2": {
        "hosts": ["algo-3", "algo-1" ],
        "instance_group_name": "instance_group_2",
        "instance_type": "ml.p3dn.24xlarge"
    }
}
```

(Optional) Reading instance group information from the resource configuration JSON file

If you prefer to retrieve the environment variables in JSON format, you can directly use the resource configuration JSON file. The JSON file in a SageMaker training instance is located at `/opt/ml/input/config/resourceconfig.json` by default.

```python
file_path = '/opt/ml/input/config/resourceconfig.json'
config = read_file_as_json(file_path)
print(json.dumps(config, indent=4, sort_keys=True))
```

Considerations

Consider the following items when using the heterogeneous cluster feature.

- All instance groups share the same Docker image and training script. Therefore, your training script should be modified to detect which instance group it belongs to and fork execution accordingly.

- The heterogeneous cluster feature is not supported in SageMaker local mode.

- The Amazon CloudWatch log streams of a heterogeneous cluster training job are not grouped by instance groups. You need to figure out from the logs which nodes are in which group.

- The heterogeneous cluster feature is available through the SageMaker PyTorch and TensorFlow framework estimator classes. Supported frameworks are PyTorch v1.10 or later and TensorFlow v2.6 or later. To find a complete list of available framework containers, framework versions, and Python versions, see SageMaker Framework Containers in the AWS Deep Learning Container GitHub repository.

- A distributed training strategy can be applied only to one instance group.

Examples, Blogs, and Case Studies

The following blog discusses case studies about using the SageMaker heterogeneous cluster training.

- Improve price performance of your model training using Amazon SageMaker heterogeneous clusters (Oct 27, 2022)
Train Using SageMaker Managed Warm Pools

SageMaker Managed Warm Pools let you retain and reuse provisioned infrastructure after the completion of a training job to reduce latency for repetitive workloads, such as iterative experimentation or running many jobs consecutively. Subsequent training jobs that match specified parameters run on the retained warm pool infrastructure, which speeds up start times by reducing the time spent provisioning resources.

**Important**
SageMaker Managed Warm Pools are a billable resource. For more information, see Billing (p. 2673).

**Topics**
- How it works (p. 2671)
- Warm pool resource limits (p. 2673)
- How to use SageMaker Managed Warm Pools (p. 2673)
- Considerations (p. 2677)

**How it works**

To use SageMaker Managed Warm Pools and reduce latency between similar consecutive training jobs, create a training job that specifies a `KeepAlivePeriodInSeconds` value in its `ResourceConfig`. This value represents the duration of time in seconds to retain configured resources in a warm pool for subsequent training jobs.

**Topics**
- Warm pool lifecycle (p. 2671)
- Warm pool creation (p. 2672)
- Matching training jobs (p. 2672)
- Maximum warm pool duration (p. 2672)
- Billing (p. 2673)

**Warm pool lifecycle**

1. Create an initial training job with a `KeepAlivePeriodInSeconds` value greater than 0. When you run this first training job, this “cold-starts” a cluster with typical startup times.
2. When the first training job completes, the provisioned resources are kept alive in a warm pool for the period specified in the `KeepAlivePeriodInseconds` value. As long as the cluster is healthy and the warm pool is within the specified `KeepAlivePeriodInseconds` value, then the warm pool status is Available.
3. The warm pool stays Available until it either identifies a matching training job for reuse or it exceeds the specified `KeepAlivePeriodInseconds` and is terminated. The maximum length of time allowed for the `KeepAlivePeriodInseconds` is 3600 seconds (60 minutes). If the warm pool status is Terminated, then this is the end of the warm pool lifecycle.
4. If the warm pool identifies a second training job with matching specifications such as instance count or instance type, then the warm pool moves from the first training job to the second training job for reuse. The status of the first training job warm pool becomes Reused. This is the end of the warm pool lifecycle for the first training job.
5. The status of the second training job that reused the warm pool becomes InUse. After the second training job completes, the warm pool is Available for the `KeepAlivePeriodInseconds` duration.
specified in the second training job. A warm pool can continue moving to subsequent matching training jobs for a maximum of 7 days.

6. If the warm pool is no longer available to reuse, the warm pool status is Terminated. Warm pools are no longer available if they are terminated by a user, for a patch update, or for exceeding the specified KeepAlivePeriodInSeconds.

For more information on warm pool status options, see WarmPoolStatus in the Amazon SageMaker API Reference.

**Warm pool creation**

If an initial training job successfully completes and has a KeepAlivePeriodInSeconds value greater than 0, this creates a warm pool. If you stop a training job after a cluster is already launched, a warm pool is still retained. If the training job fails due to an algorithm or client error, a warm pool is still retained. If the training job fails for any other reason that might compromise the health of the cluster, then the warm pool is not created.

To verify successful warm pool creation, check the warm pool status of your training job. If a warm pool successfully provisions, the warm pool status is Available. If a warm pool fails to provision, the warm pool status is Terminated.

**Matching training jobs**

For a warm pool to persist, it must find a matching training job within the time specified in the KeepAlivePeriodInSeconds value. The next training job is a match if the following values are identical:

- RoleArn
- ResourceConfig values:
  - InstanceCount
  - InstanceType
  - VolumeKmsKeyId
  - VolumeSizeInGB
- VpcConfig values:
  - SecurityGroupIds
  - Subnets
  - EnableInterContainerTrafficEncryption
  - EnableNetworkIsolation

All of these values must be the same for a warm pool to move to a subsequent training job for reuse.

**Maximum warm pool duration**

The maximum KeepAlivePeriodInSeconds for a single training job is 3600 seconds (60 minutes) and the maximum length of time that a warm pool cluster can continue running consecutive training jobs is 7 days.

Each subsequent training job must also specify a KeepAlivePeriodInSeconds value. When the warm pool moves to the next training job, it inherits the new KeepAlivePeriodInSeconds value specified in that training job's ResourceConfig. In this way, you can keep a warm pool moving from training job to training job for a maximum of 7 days.
If no `KeepAlivePeriodInSeconds` is specified, then the warm pool spins down after the training job completes.

**Billing**

SageMaker Managed Warm Pools are a billable resource. Retrieve the warm pool status for your training job to check the billable time for your warm pools. You can check the warm pool status either through the Using the Amazon SageMaker console (p. 2676) or directly through the `DescribeTrainingJob` API command. For more information, see `WarmPoolStatus` in the Amazon SageMaker API Reference.

**Warm pool resource limits**

To get started, you must first request a service limit increase for SageMaker Managed Warm Pools. The default resource limit for warm pools is 0.

If a training job is created with `KeepAlivePeriodInSeconds` specified, but you did not request a warm pool limit increase, then a warm pool is not retained after the completion of the training job. A warm pool is only created if your warm pool limit has sufficient resources. After a warm pool is created, the resources are released when they move to a matching training job or if the `KeepAlivePeriodInSeconds` expires (if the warm pool status is Reused or Terminated).

**Request a warm pool quota increase**

Request a warm pool quota increase using the AWS Service Quotas console.

**Note**

All warm pool instance usage counts toward your SageMaker training resource limit. Increasing your warm pool resource limit does not increase your instance limit, but allocates a subset of your resource limit to warm pool training.

1. Open the AWS Service Quotas console.
2. On the left-hand navigation panel, choose **AWS services**.
3. Search for and choose **Amazon SageMaker**.
4. Search for the keyword **warm pool** to see all available warm pool service quotas.
5. Find the instance type for which you want to increase your warm pool quota, select the warm pool service quota for that instance type, and choose **Request quota increase**.
6. Enter your requested instance limit number under **Change quota value**. The new value must be greater than the current **Applied quota value**.
7. Choose **Request**.

There is a limit on the number of instances that you can retain for each warm pool, which is determined by instance type. You can check your resource limits in the AWS Service Quotas console or directly using the `list-service-quotas` AWS CLI command. For more information on AWS Service Quotas, see Requesting a quota increase in the Service Quotas User Guide.

You can also use AWS Support Center to request a warm pool quota increase. For a list of available instance types according to Region, see Amazon SageMaker Pricing and choose Training in the On-Demand Pricing table.

**How to use SageMaker Managed Warm Pools**

You can use SageMaker Managed Warm Pools through the SageMaker Python SDK, the Amazon SageMaker console, or through the low-level APIs. Administrators can optionally use the `sagemaker:KeepAlivePeriod` condition key to further restrict the `KeepAlivePeriodInSeconds` limits for certain users or groups.
Using the SageMaker Python SDK

Create, update, or terminate warm pools using the SageMaker Python SDK.

**Note**
This feature is available in the SageMaker Python SDK v2.110.0 and later.

### Create a warm pool

To create a warm pool, use the SageMaker Python SDK to create an estimator with a `keep_alive_period_in_seconds` value greater than 0 and call `fit()`. When the training job completes, a warm pool is retained. For more information on training scripts and estimators, see [Train a Model with the SageMaker Python SDK](#). If your script does not create a warm pool, see [Warm pool creation](#) for possible explanations.

```python
import sagemaker
from sagemaker import get_execution_role
from sagemaker.tensorflow import TensorFlow

# Creates a SageMaker session and gets execution role
session = sagemaker.Session()
role = get_execution_role()

# Creates an example estimator
estimator = TensorFlow(
    entry_point='my-training-script.py',
    source_dir='code',
    role=role,
    model_dir='model_dir',
    framework_version='x.y.z',
    py_version='pyxy',
    job_name='my-training-job-1',
    instance_type='instance_type',
    instance_count=1,
    volume_size=250,
    hyperparameters={
        "batch-size": 512,
        "epochs": 1,
        "learning-rate": 1e-3,
        "beta_1": 0.9,
        "beta_2": 0.999,
    },
    keep_alive_period_in_seconds=1800,
)

# Starts a SageMaker training job and waits until completion
```
Next, create a second matching training job. In this example, we create my-training-job-2, which has all of the necessary attributes to match with my-training-job-1, but has a different hyperparameter for experimentation. The second training job reuses the warm pool and starts up faster than the first training job. For more information on which attributes need to match, see Matching training jobs (p. 2672).

# Creates an example estimator
estimator = TensorFlow(...
    entry_point='my-training-script.py',
    source_dir='code',
    role=role,
    model_dir='model_dir',
    framework_version='x.y.z',
    py_version='pyxy',
    job_name='my-training-job-2',
    instance_type='instance_type',
    instance_count=1,
    volume_size=250,
    hyperparameters={
        "batch-size": 512,
        "epochs": 2,
        "learning-rate": 1e-3,
        "beta_1": 0.9,
        "beta_2": 0.999,
    },
    keep_alive_period_in_seconds=1800,
)

# Starts a SageMaker training job and waits until completion
estimator.fit('s3://my_bucket/my_training_data/')

Check the warm pool status of both training jobs to confirm that the warm pool is Reused for my-training-job-1 and InUse for my-training-job-2.

**Note**

Training job names have date/time suffixes. The example training job names my-training-job-1 and my-training-job-2 should be replaced with actual training job names. You can use the estimator.latest_training_job.job_name command to fetch the actual training job name.

session.describe_training_job('my-training-job-1')
session.describe_training_job('my-training-job-2')

The result of describe_training_job provides all details about a given training job. Find the WarmPoolStatus attribute to check information about a training job's warm pool. Your output should look similar to the following example:

# Warm pool status for training-job-1
...
'WarmPoolStatus': {'Status': 'Reused',
    'ResourceRetainedBillableTimeInSeconds': 1000,
    'ReusedByName': my-training-job-2}
...

# Warm pool status for training-job-2
...
'WarmPoolStatus': {'Status': 'InUse'}
Update a warm pool

When the training job is complete and the warm pool status is Available, then you can update the KeepAlivePeriodInSeconds value.

```python
session.update_training_job(job_name, resource_config={"KeepAlivePeriodInSeconds":3600})
```

Terminate a warm pool

To manually terminate a warm pool, set the KeepAlivePeriodInSeconds value to 0.

```python
session.update_training_job(job_name, resource_config={"KeepAlivePeriodInSeconds":0})
```

The warm pool automatically terminates when it exceeds the designated KeepAlivePeriodInSeconds value or if there is a patch update for the cluster.

Using the Amazon SageMaker console

You cannot create or update a warm pool through the console, but you can use the console to check the warm pool status and billable time of specific training jobs. You can also use the console to see which matching training job reused the warm pool.

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/ and choose **Training jobs** from the navigation pane. The warm pool status of each training job is visible in the **Warm pool status** column.
2. Select a training job ID for more information.
3. Scroll down to the **Warm pool status** section to find the warm pool status, the time left if the warm pool status is Available, the warm pool billable seconds, and the name of the training job that reused the warm pool if the warm pool status is Reused.

Using the low-level SageMaker APIs

Use SageMaker Managed Warm Pools with either the SageMaker API or the AWS CLI.

**SageMaker API**

Set up SageMaker Managed Warm Pools using the SageMaker API with the following commands:

- `CreateTrainingJob`
- `UpdateTrainingJob`
- `ListTrainingJobs`
- `DescribeTrainingJob`

**AWS CLI**

Set up SageMaker Managed Warm Pools using the AWS CLI with the following commands:

- `create-training-job`
- `update-training-job`
- `list-training-jobs`
- `describe-training-job`
IAM condition key

Administrators can optionally use the `sagemaker:KeepAlivePeriod` condition key to further restrict the `KeepAlivePeriodInSeconds` limits for certain users or groups. SageMaker Managed Warm Pools are limited to a `KeepAlivePeriodInSeconds` value of 3600 seconds (60 minutes), but administrators can lower this limit if needed.

```
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "EnforceKeepAlivePeriodLimit",
            "Effect": "Allow",
            "Action": [
                "sagemaker:CreateTrainingJob"
            ],
            "Resource": "*",
            "Condition": {
                "NumericLessThanIfExists": {
                    "sagemaker:KeepAlivePeriod": 1800
                }
            }
        }
    ]
}
```

For more information, see [Condition keys for Amazon SageMaker](https://docs.aws.amazon.com/sagemaker/latest/dg/service-authorization-reference.html) in the *Service Authorization Reference*.

Considerations

Consider the following items when using SageMaker Managed Warm Pools.

- SageMaker Managed Warm Pools cannot be used with heterogeneous cluster training.
- SageMaker Managed Warm Pools cannot be used with spot instances.
- SageMaker Managed Warm Pools are limited to a `KeepAlivePeriodInSeconds` value of 3600 seconds (60 minutes).
- If a warm pool continues to successfully match training jobs within the specified `KeepAlivePeriodInSeconds` value, the cluster can only continue running for a maximum of 7 days.

Incremental Training in Amazon SageMaker

Over time, you might find that a model generates inference that are not as good as they were in the past. With incremental training, you can use the artifacts from an existing model and use an expanded dataset to train a new model. Incremental training saves both time and resources.

Use incremental training to:

- Train a new model using an expanded dataset that contains an underlying pattern that was not accounted for in the previous training and which resulted in poor model performance.
- Use the model artifacts or a portion of the model artifacts from a popular publicly available model in a training job. You don't need to train a new model from scratch.
- Resume a training job that was stopped.
- Train several variants of a model, either with different hyperparameter settings or using different datasets.
For more information about training jobs, see Train a Model with Amazon SageMaker (p. 9).

You can train incrementally using the SageMaker console or the Amazon SageMaker Python SDK.

**Important**
Only three built-in algorithms currently support incremental training: **Object Detection** - MXNet (p. 2196), **Image Classification** - MXNet (p. 2172), and **Semantic Segmentation Algorithm** (p. 2215).

**Topics**
- Perform Incremental Training (Console) (p. 2678)
- Perform Incremental Training (API) (p. 2680)

**Perform Incremental Training (Console)**

To complete this procedure, you need:

- The Amazon Simple Storage Service (Amazon S3) bucket URI where you've stored the training data.
- The S3 bucket URI where you want to store the output of the job.
- The Amazon Elastic Container Registry path where the training code is stored. For more information, see Docker Registry Paths and Example Code (p. 1105).
- The URL of the S3 bucket where you've stored the model artifacts that you want to use in incremental training. To find the URL for the model artifacts, see the details page of the training job used to create the model. To find the details page, in the SageMaker console, choose **Inference**, choose **Models**, and then choose the model.

To restart a stopped training job, use the URL to the model artifacts that are stored in the details page as you would with a model or a completed training job.

**To perform incremental training (console)**

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the navigation pane, choose **Training**, then choose **Training jobs**.
3. Choose **Create training job**.
4. Provide a name for the training job. The name must be unique within an AWS Region in an AWS account. The training job name must have 1 to 63 characters. Valid characters: a-z, A-Z, 0-9, and . : + = @ _ % - (hyphen).
5. Choose the algorithm that you want to use. For information about algorithms, see Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096).
6. (Optional) For **Resource configuration**, either leave the default values or increase the resource consumption to reduce computation time.
   a. (Optional) For **Instance type**, choose the ML compute instance type that you want to use. In most cases, ml.m4.xlarge is sufficient.
   b. For **Instance count**, use the default, 1.
   c. (Optional) For **Additional volume per instance (GB)**, choose the size of the ML storage volume that you want to provision. In most cases, you can use the default, 1. If you are using a large dataset, use a larger size.
7. Provide information about the input data for the training dataset.
   a. For **Channel name**, either leave the default (train) or enter a more meaningful name for the training dataset, such as expanded-training-dataset.
b. For **InputMode**, choose **File**. For incremental training, you need to use file input mode.

c. For **S3 data distribution type**, choose **FullyReplicated**. This causes each ML compute instance to use a full replicate of the expanded dataset when training incrementally.

d. If the expanded dataset is uncompressed, set the **Compression type** to **None**. If the expanded dataset is compressed using Gzip, set it to **Gzip**.

e. (Optional) If you are using File input mode, leave **Content type** empty. For Pipe input mode, specify the appropriate MIME type. **Content type** is the multipurpose internet mail extension (MIME) type of the data.

f. For **Record wrapper**, if the dataset is saved in RecordIO format, choose **RecordIO**. If your dataset is not saved as a RecordIO formatted file, choose **None**.

g. For **S3 data type**, if the dataset is stored as a single file, choose **S3Prefix**. If the dataset is stored as several files in a folder, choose **Manifest**.

h. For **S3 location**, provide the URL to the path where you stored the expanded dataset.

i. Choose **Done**.

8. To use model artifacts in a training job, you need to add a new channel and provide the needed information about the model artifacts.

a. For **Input data configuration**, choose **Add channel**.

b. For **Channel name**, enter **model** to identify this channel as the source of the model artifacts.

c. For **InputMode**, choose **File**. Model artifacts are stored as files.

d. For **S3 data distribution type**, choose **FullyReplicated**. This indicates that each ML compute instance should use all of the model artifacts for training.

e. For **Compression type**, choose **None** because we are using a model for the channel.

f. Leave **Content type** empty. Content type is the multipurpose internet mail extension (MIME) type of the data. For model artifacts, we leave it empty.

g. Set **Record wrapper** to **None** because model artifacts are not stored in RecordIO format.

h. For **S3 data type**, if you are using a built-in algorithm or an algorithm that stores the model as a single file, choose **S3Prefix**. If you are using an algorithm that stores the model as several files, choose **Manifest**.

i. For **S3 location**, provide the URL to the path where you stored the model artifacts. Typically, the model is stored with the name **model.tar.gz**. To find the URL for the model artifacts, in the navigation pane, choose **Inference**, then choose **Models**. From the list of models, choose a model to display its details page. The URL for the model artifacts is listed under **Primary container**.

j. Choose **Done**.

9. For **Output data configuration**, provide the following information:

a. For **S3 location**, type the path to the S3 bucket where you want to store the output data.

b. (Optional) For **Encryption key**, you can add your AWS Key Management Service (AWS KMS) encryption key to encrypt the output data at rest. Provide the key ID or its Amazon Resource Number (ARN). For more information, see [KMS-Managed Encryption Keys](https://docs.aws.amazon.com/kms/latest/developerguide/).

10. (Optional) For **Tags**, add one or more tags to the training job. A tag is metadata that you can define and assign to AWS resources. In this case, you can use tags to help you manage your training jobs. A tag consists of a key and a value, which you define. For example, you might want to create a tag with **Project** as a key and a value referring to a project that is related to the training job, such as **Home value forecasts**.

11. Choose **Create training job**. SageMaker creates and runs training job.

After the training job has completed, the newly trained model artifacts are stored under the **S3 output path** that you provided in the **Output data configuration** field. To deploy the model to get predictions, see [Step 5: Deploy the Model to Amazon EC2](p. 85).
Perform Incremental Training (API)

This example shows how to use SageMaker APIs to train a model using the SageMaker image classification algorithm and the Caltech 256 Image Dataset, then train a new model using the first one. It uses Amazon S3 for input and output sources. Please see the incremental training sample notebook for more details on using incremental training.

**Note**
In this example we used the original datasets in the incremental training, however you can use different datasets, such as ones that contain newly added samples. Upload the new datasets to S3 and make adjustments to the `data_channels` variable used to train the new model.

Get an AWS Identity and Access Management (IAM) role that grants required permissions and initialize environment variables:

```python
import sagemaker
from sagemaker import get_execution_role

role = get_execution_role()
print(role)

sess = sagemaker.Session()

bucket=sess.default_bucket()
print(bucket)

prefix = 'ic-incr-training'
```

Get the training image for the image classification algorithm:

```python
from sagemaker.amazon.amazon_estimator import get_image_uri

training_image = get_image_uri(sess.boto_region_name, 'image-classification',
                    repo_version="latest")

#Display the training image
print (training_image)
```

Download the training and validation datasets, then upload them to Amazon Simple Storage Service (Amazon S3):

```python
import os
import urllib.request
import boto3

# Define a download function
def download(url):
    filename = url.split('/')[-1]
    if not os.path.exists(filename):
        urllib.request.urlretrieve(url, filename)

# Download the caltech-256 training and validation datasets
download('http://data.mxnet.io/data/caltech-256/caltech-256-60-train.rec')
download('http://data.mxnet.io/data/caltech-256/caltech-256-60-val.rec')

# Create four channels: train, validation, train_lst, and validation_lst
s3train = 's3://{}/{}/train/'.format(bucket, prefix)
s3validation = 's3://{}/{}/validation/'.format(bucket, prefix)

# Upload the first files to the train and validation channels
!aws s3 cp caltech-256-60-train.rec $s3train --quiet
!aws s3 cp caltech-256-60-val.rec $s3validation --quiet
```
Define the training hyperparameters:

```python
# Define hyperparameters for the estimator
hyperparams = {
    "num_layers": "18",
    "resize": "32",
    "num_training_samples": "50000",
    "num_classes": "10",
    "image_shape": "3,28,28",
    "mini_batch_size": "128",
    "epochs": "3",
    "learning_rate": "0.1",
    "lr_scheduler_step": "2,3",
    "lr_scheduler_factor": "0.1",
    "augmentation_type": "crop_color",
    "optimizer": "sgd",
    "momentum": "0.9",
    "weight_decay": "0.0001",
    "beta_1": "0.9",
    "beta_2": "0.999",
    "gamma": "0.9",
    "eps": "1e-8",
    "top_k": "5",
    "checkpoint_frequency": "1",
    "use_pretrained_model": "0",
    "model_prefix": ""
}
```

Create an estimator object and train the first model using the training and validation datasets:

```python
# Fit the base estimator
s3_output_location = 's3://{}/{}{}/output'.format(bucket, prefix)
ic = sagemaker.estimator.Estimator(training_image,
    role,
    instance_count=1,
    instance_type='ml.p2.xlarge',
    volume_size=50,
    max_run=360000,
    input_mode='File',
    output_path=s3_output_location,
    sagemaker_session=sess,
    hyperparameters=hyperparams)
train_data = sagemaker.inputs.TrainingInput(s3train, distribution='FullyReplicated',
    content_type='application/x-recordio',
    s3_data_type='S3Prefix')
validation_data = sagemaker.inputs.TrainingInput(s3validation,
    distribution='FullyReplicated',
    content_type='application/x-recordio',
    s3_data_type='S3Prefix')
data_channels = {'train': train_data, 'validation': validation_data}
ic.fit(inputs=data_channels, logs=True)
```

To use the model to incrementally train another model, create a new estimator object and use the model artifacts (i.e., model_data, in this example) for the model_uri input argument:

```python
# Given the base estimator, create a new one for incremental training
incr_ic = sagemaker.estimator.Estimator(training_image,
    role,
    instance_count=1,
    instance_type='ml.p2.xlarge',
    volume_size=50,
    model_data=ic.model_data,
    model_uri=ic.model_uri)
```

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Amazon SageMaker Training Storage Folders for Training Datasets, Checkpoints, Model Artifacts, and Outputs

This page provides a high-level summary of how the SageMaker training platform manages storage paths for training datasets, model artifacts, checkpoints, and outputs between AWS cloud storage and training jobs in SageMaker. Throughout this guide, you learn to identify the default paths set by the SageMaker platform and how the data channels can be streamlined with your data sources in Amazon S3, FSx for Lustre, and Amazon EFS. For more information about various data channel input modes and storage options, see Access Training Data (p. 2686).

Topics
- Overview (p. 2682)
- SageMaker Environment Variables and Default Paths for Training Storage Folders (p. 2684)
- Tips and Considerations for Setting Up Storage Paths (p. 2685)

Overview

The following diagram shows the simplest example of how SageMaker manages input and output folders when you run a training job using the SageMaker Python SDK Estimator class and its fit method. It's based on using file mode as the data access strategy and Amazon S3 as the data source for the training input channels.
This figure shows an overview of how SageMaker pairs storage paths between an Amazon S3 bucket as the data source and the SageMaker training instance based on how the paths are specified in a SageMaker estimator class. More information about the paths, how they read from or write to the paths, and purposes of the paths are described in the following section the section called “SageMaker Environment Variables and Default Paths for Training Storage Folders” (p. 2684).

For more information and examples of how SageMaker manages data source, input modes, and local paths in SageMaker training instances, see *Access Training Data*.

**SageMaker Environment Variables and Default Paths for Training Storage Folders**

The following table summarizes input and output paths for training datasets, checkpoints, model artifacts, and outputs, managed by the SageMaker training platform.

<table>
<thead>
<tr>
<th>Local path in SageMaker training instance</th>
<th>SageMaker environment variable</th>
<th>Purpose</th>
<th>Read from S3 during start</th>
<th>Read from S3 during Spot-restart</th>
<th>Writes to S3 during training</th>
<th>Writes to S3 when job is terminated</th>
</tr>
</thead>
<tbody>
<tr>
<td>/opt/ml/input/data/channel_name</td>
<td>SM_CHANNEL_&lt;channel_name&gt;</td>
<td>Reading training data from the input channels specified through the SageMaker Python SDK Estimator class or the CreateTrainingJob API operation. For more information about how to specify it in your training script using the SageMaker Python SDK, see Prepare a Training script.</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>/opt/ml/output</td>
<td>SM_OUTPUT_DIR</td>
<td>Saving outputs such as loss, accuracy, intermediate layers, weights, gradients, bias, and TensorBoard-compatible outputs. You can also save any arbitrary output you’d like using this path. Note that this is a different path from the one for storing the final model artifact /opt/ml/model/.</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>/opt/ml/model</td>
<td>SM_MODEL_DIR</td>
<td>Storing the final model artifact. This is also the path from where the model artifact is deployed for Real-time</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>
Tips and Considerations for Setting Up Storage Paths

Consider the following items when setting up storage paths for training jobs in SageMaker.

- If you want to store training artifacts for distributed training in the `/opt/ml/output/` directory, you must properly assign subfolders or unique file names for the artifacts through your model definition or training script. If the subfolders and file names are not properly configured, all of the distributed training workers might write outputs to the same file name in the same output folder in Amazon S3.

- If you use a custom training container, make sure you install the SageMaker Training Toolkit that helps set up the environment for SageMaker training jobs. Otherwise, you must specify the environment variables explicitly in your Dockerfile. For more information, see Create a container with your own algorithms and models.

---

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<th>Writes to S3 when job is terminated</th>
</tr>
</thead>
<tbody>
<tr>
<td>/opt/ml/checkpoints(^4)</td>
<td></td>
<td>Saving model checkpoints (the state of model) to resume training from a certain point, and recover from unexpected or Managed Spot Training interruptions.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>/opt/ml/code</td>
<td>SAGEMAKER_SUBMIT_DIRECTORY</td>
<td>Copying training scripts, additional libraries, and dependencies.</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>/tmp</td>
<td></td>
<td>Reading or writing to /tmp as a scratch space.</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
</tbody>
</table>

\(^1\) channel\(_\)name is the place to specify user-defined channel names for training data inputs. Each training job can contain several data input channels. You can specify up to 20 training input channels per training job. Note that the data downloading time from the data channels is counted to the billable time. For more information about data input paths, see How Amazon SageMaker Provides Training Information. Also, there are three types of data input modes that SageMaker supports: file, FastFile, and pipe mode. To learn more about the data input modes for training in SageMaker, see Access Training Data.

\(^2\) SageMaker compresses and writes training artifacts to TAR files (\(\text{tar.gz}\)). Compression and uploading time is counted to the billable time. For more information, see How Amazon SageMaker Processes Training Output.

\(^3\) SageMaker compresses and writes the final model artifact to a TAR file (\(\text{tar.gz}\)). Compression and uploading time is counted to the billable time. For more information, see How Amazon SageMaker Processes Training Output.

\(^4\) Sync with Amazon S3 during training. Write as is without compressing to TAR files. For more information, see Use Checkpoints in Amazon SageMaker.
When using an ML instance with NVMe SSD volumes, SageMaker doesn’t provision Amazon EBS gp2 storage. Available storage is fixed to the NVMe-type instance's storage capacity. SageMaker configures storage paths for training datasets, checkpoints, model artifacts, and outputs to use the entire capacity of the instance storage. For example, ML instance families with the NVMe-type instance storage include ml.p4d, ml.g4dn, and ml.g5. When using an ML instance with the EBS-only storage option and without instance storage, you must define the size of EBS volume through the volume_size parameter in the SageMaker estimator class (or VolumeSizeInGB if you are using the ResourceConfig API). For example, ML instance families that use EBS volumes include ml.c5 and ml.p2. To look up instance types and their instance storage types and volumes, see Amazon EC2 Instance Types.

The default paths for SageMaker training jobs are mounted to Amazon EBS volumes or NVMe SSD volumes of the ML instance. When you adapt your training script to SageMaker, make sure that you use the default paths listed in the previous topic about the section called “SageMaker Environment Variables and Default Paths for Training Storage Folders” (p. 2684). We recommend that you use the /tmp directory as a scratch space for temporarily storing any large objects during training. This means that you must not use directories that are mounted to small disk space allocated for system, such as /user and /home, to avoid out-of-space errors.

To learn more, see the AWS machine learning blog Choose the best data source for your Amazon SageMaker training job that further discusses case studies and performance benchmarks of data sources and input modes.

### Access Training Data

When you create a training job, you specify the location of a training dataset and an input mode for accessing the dataset. For data location, Amazon SageMaker supports Amazon Simple Storage Service (Amazon S3), Amazon Elastic File System (Amazon EFS), and Amazon FSx for Lustre. The input modes determine whether to stream data files of the dataset in real time or download the whole dataset at the start of the training job.

### SageMaker Input Modes and AWS Cloud Storage

This section summarizes SageMaker input modes for Amazon S3 and file systems in Amazon EFS and Amazon FSx for Lustre.
• **File mode** presents a file system view of the dataset to the training container. This is the default input mode if you don't explicitly specify one of the other two options. If you use file mode, SageMaker downloads the training data from the storage location to a local directory in the Docker container. Training starts after the full dataset has been downloaded. In file mode, the training instance must have enough storage space to fit the entire dataset. File mode download speed depends on the size of the dataset, the average size of files, and the number of files. You can configure the dataset for file mode by providing either an Amazon S3 prefix, manifest file, or augmented manifest file. You should use an S3 prefix when all your dataset files are located within a common S3 prefix. File mode is compatible with SageMaker local mode (starting a SageMaker training container interactively in seconds). For distributed training, you can shard the dataset across multiple instances with the `ShardedByS3Key` option.

• **Fast file mode** provides file system access to an Amazon S3 data source while leveraging the performance advantage of pipe mode. At the start of training, fast file mode identifies the data files but does not download them. Training can start without waiting for the entire dataset to download. This means that the training startup takes less time when there are fewer files in the Amazon S3 prefix provided.

In contrast to pipe mode, fast file mode works with random access to the data. However, it works best when data is read sequentially. Fast file mode doesn't support augmented manifest files.

Fast file mode exposes S3 objects using a POSIX-compliant file system interface, as if the files are available on the local disk of your training instance. It streams S3 content on demand as your training script consumes data. This means that your dataset no longer needs to fit into the training instance storage space as a whole, and you don't need to wait for the entire dataset to be downloaded to the training instance before training starts. Fast file currently supports S3 prefixes only (it does not support manifest and augmented manifest). Fast file mode is compatible with SageMaker local mode.

• **Pipe mode** streams data directly from an Amazon S3 data source. Streaming can provide faster start times and better throughput than file mode.

When you stream the data directly, you can reduce the size of the Amazon EBS volumes used by the training instance. Pipe mode needs only enough disk space to store the final model artifacts.

It is another streaming mode that is largely replaced by the newer and simpler-to-use fast file mode. In pipe mode, data is pre-fetched from Amazon S3 at high concurrency and throughput, and streamed into a named pipe, which also known as a First-In-First-Out (FIFO) pipe for its behavior. Each pipe may only be read by a single process. A SageMaker specific extension to TensorFlow conveniently integrates Pipe mode into the native TensorFlow data loader for streaming text, TFRecords, or RecordIO file formats. Pipe mode also supports managed sharding and shuffling of data.

• **Amazon FSx for Lustre** – FSx for Lustre can scale to hundreds of gigabytes of throughput and millions of IOPS with low-latency file retrieval. When starting a training job, SageMaker mounts the FSx for Lustre file system to the training instance file system, then starts your training script. Mounting itself is a relatively fast operation that doesn't depend on the size of the dataset stored in FSx for Lustre.

To access FSx for Lustre, your training job must connect to an Amazon Virtual Private Cloud (VPC), which requires DevOps setup and involvement. To avoid data transfer costs, the file system uses a single Availability Zone, and you need to specify a VPC subnet which maps to this Availability Zone ID when running the training job.

• **Amazon EFS** – To use Amazon EFS as a data source, the data must already reside in Amazon EFS prior to training. SageMaker mounts the specified Amazon EFS file system to the training instance, then starts your training script. Your training job must connect to a VPC to access Amazon EFS.

**Tip**
To learn more about how to specify your VPC configuration to SageMaker estimators, see Use File Systems as Training Inputs in the *SageMaker Python SDK documentation.*
Choosing Data Input Mode Using the SageMaker Python SDK

SageMaker Python SDK provides the generic `Estimator` class and its variations for ML frameworks for launching training jobs. You can specify one of the data input modes while configuring the SageMaker `Estimator` class or the `Estimator.fit` method. The following code templates show the two ways to specify input modes.

**To specify the input mode using the Estimator class**

```python
class Estimator:
    def __init__(self, checkpoint_s3_uri='s3://my-bucket/checkpoint-destination/',
                 output_path='s3://my-bucket/output-path/',
                 base_job_name='job-name',
                 input_mode='File',
                 ...):
        # Run the training job
        self.fit(inputs=TrainingInput(s3_data='s3://my-bucket/my-data/train'))
```

For more information, see the `sagemaker.estimator.Estimator` class in the *SageMaker Python SDK documentation*.

**To specify the input mode through the Estimator fit method**

```python
class Estimator:
    def fit(self, inputs):
        # Run the training job
        self.fit(inputs=TrainingInput(s3_data='s3://my-bucket/my-data/train',
                                      input_mode='File'))
```

For more information, see the `sagemaker.estimator.Estimator.fit` class method and the `sagemaker.inputs.TrainingInput` class in the *SageMaker Python SDK documentation*.

**Tip**
To learn more about how to configure Amazon FSx for Lustre or Amazon EFS with your VPC configuration using the SageMaker Python SDK estimators, see *Use File Systems as Training Inputs* in the *SageMaker Python SDK documentation*.

**Tip**
The data input mode integrations with Amazon S3, Amazon EFS, and FSx for Lustre are recommended ways to optimally configure data source for the best practices. You can
strategically improve data loading performance using the SageMaker managed storage options and input modes, but it's not strictly constrained. You can write your own data reading logic directly in your training container. For example, you can set to read from a different data source, write your own S3 data loader class, or use third-party frameworks' data loading functions within your training script. However, you must make sure that you specify the right paths that SageMaker can recognize.

**Tip**
If you use a custom training container, make sure you install the SageMaker training toolkit that helps set up the environment for SageMaker training jobs. Otherwise, you must specify the environment variables explicitly in your Dockerfile. For more information, see Create a container with your own algorithms and models.

For more information about how to set the data input modes using the low-level SageMaker APIs, see How Amazon SageMaker Provides Training Information (p. 3185), the CreateTrainingJob API, and the TrainingInputMode in AlgorithmSpecification.

**Configure Data Input Channel to Use Amazon FSx for Lustre**

Learn how to use Amazon FSx for Lustre as your data source for higher throughput and faster training by reducing the time for data loading.

**Sync Amazon S3 and Amazon FSx for Lustre**

To link your Amazon S3 to Amazon FSx for Lustre and upload your training datasets, do the following.

1. Prepare your dataset and upload to an Amazon S3 bucket. For example, assume that the Amazon S3 paths for a train dataset and a test dataset are in the following format.

   ```
   s3://my-bucket/data/train
   s3://my-bucket/data/test
   ```

2. To create an FSx for Lustre file system linked with the Amazon S3 bucket with the training data, follow the steps at Linking your file system to an Amazon S3 bucket in the Amazon FSx for Lustre User Guide. Make sure that you add an endpoint to your VPC allowing Amazon S3 access. For more information, see the section called “Create an Amazon S3 VPC Endpoint” (p. 3648). When you specify **Data repository path**, provide the Amazon S3 bucket URI of the folder that contains your datasets. For example, based on the example S3 paths in step 1, the data repository path should be the following.

   ```
   s3://my-bucket/data
   ```

3. After the FSx for Lustre file system is created, check the configuration information by running the following commands.

   ```
   aws fsx describe-file-systems && \
   aws fsx describe-data-repository-association
   ```

   These commands return FileSystemId, MountName, FileSystemPath, and DataRepositoryPath. For example, the outputs should look like the following.

   ```
   # Output of aws fsx describe-file-systems
   "FileSystemId": "fs-0123456789abcdef0"
   "MountName": "1234abcd"
   # Output of aws fsx describe-data-repository-association
   ```
"FileSystemPath": "/ns1",
"DataRepositoryPath": "s3://my-bucket/data/"

After the sync between Amazon S3 and Amazon FSx has completed, your datasets are saved in Amazon FSx in the following directories.

/ns1/train  # synced with s3://my-bucket/data/train
/ns1/test   # synced with s3://my-bucket/data/test

Set the Amazon FSx file system path as the data input channel for SageMaker training

The following procedures walk you through the process of setting the Amazon FSx file system as the data source for SageMaker training jobs.

Using the SageMaker Python SDK

To properly set the Amazon FSx file system as the data source, configure the SageMaker estimator classes and FileSystemInput using the following instruction.

1. Configure a FileSystemInput class object.

```python
from sagemaker.inputs import FileSystemInput
train_fs = FileSystemInput(
    file_system_id="fs-0123456789abcdef0",
    file_system_type="FSxLustre",
    directory_path="/1234abcd/ns1/",
    file_system_access_mode="ro",
)
```

**Tip**
When you specify `directory_path`, make sure that you provide the Amazon FSx file system path starting with MountName.

2. Configure a SageMaker estimator with the VPC configuration used for the Amazon FSx file system.

```python
from sagemaker.estimator import Estimator
estimator = Estimator(
    ...
    role="your-iam-role-with-access-to-your-fsx",
    subnets=["subnet-id"],  # Should be the same as the subnet used for Amazon FSx
    security_group_ids="security-group-id"
)
```

3. Launch the training job by running the estimator.fit method with the Amazon FSx file system.

```python
estimator.fit(train_fs)
```

To find more code examples, see Use File Systems as Training Inputs in the SageMaker Python SDK documentation.

Using the SageMaker CreateTrainingJob API

As part of the CreateTrainingJob request JSON, configure InputDataConfig as follows.

```json
"InputDataConfig": {
    "FileSystemInputConfig": {
        "FileSystemUri": "s3://my-bucket/data/",
        "FileMode": "ro",
        "MountName": "/ns1/"
    }
}
```
Amazon SageMaker Developer Guide
Best Practices for Choosing Data Source and Input Mode

"InputDataConfig": [
  {
    "ChannelName": "string",
    "DataSource": {
      "FileSystemDataSource": {
        "DirectoryPath": "/1234abcd/ns1/",
        "FileSystemAccessMode": "ro",
        "FileSystemId": "fs-0123456789abcdef0",
        "FileSystemType": "FSxLustre"
      }
    }
  }
],

Tip
When you specify DirectoryPath, make sure that you provide the Amazon FSx file system path starting with MountName.

Tips and Considerations When Configuring FSx for Lustre

1. When you use EFA-enabled instances such as P4d and P3dn, make sure that you set appropriate inbound and output rules in the security group. Specially, opening up these ports is necessary for SageMaker to access the Amazon FSx file system in the training job. To learn more, see File System Access Control with Amazon VPC.

2. Make sure the IAM Role used to launch the SageMaker training job has access to Amazon FSx.

Best Practices for Choosing Data Source and Input Mode

The best data source for your training job depends on workload characteristics such as the size of the dataset, the file format, the average size of files, the training duration, a sequential or random data loader read pattern, and how fast your model can consume the training data. The following best practices provide guidelines to get started with the most suitable input mode and data storage for your use case.
When to use Amazon EFS

If your dataset is stored in Amazon Elastic File System, you might have a preprocessing or annotations application that uses Amazon EFS for storage. You can run a training job configured with a data channel that points to the Amazon EFS file system. For more information, see Speed up training on Amazon SageMaker using Amazon FSx for Lustre and Amazon EFS file systems. If you cannot achieve better performance, check your optimization options following the Amazon Elastic File System performance guide or consider using different input modes or data storage.

Use file mode for small datasets

If the dataset is stored in Amazon Simple Storage Service and its overall volume is relatively small (for example, less than 50-100 GB), try using file mode. The overhead of downloading a 50 GB dataset can vary based on the total number of files. For example, it takes about 5 minutes if a dataset is chunked into 100 MB shards. Whether this startup overhead is acceptable primarily depends on the overall duration of your training job, because a longer training phase means a proportionally smaller download phase.

Serializing many small files

If your dataset size is small (less than 50-100 GB), but is made up of many small files (less than 50 MB per file), the file mode download overhead grows, because each file needs to be downloaded individually from Amazon Simple Storage Service to the training instance volume. To reduce this overhead and data traversal time in general, consider serializing groups of such small files into fewer larger file containers (such as 150 MB per file) by using file formats, such as TFRecord for TensorFlow, WebDataset for PyTorch, and RecordIO for MXNet.

When to use fast file mode

For larger datasets with larger files (more than 50 MB per file), the first option is to try fast file mode, which is more straightforward to use than FSx for Lustre because it doesn't require creating a file system, or connecting to a VPC. Fast file mode is ideal for large file containers (more than 150 MB), and might also do well with files more than 50 MB. Because fast file mode provides a POSIX interface, it supports random reads (reading non-sequential byte-ranges). However, this is not the ideal use case, and your throughput might be lower than with the sequential reads. However, if you have a relatively large and computationally intensive ML model, fast file mode might still be able to saturate the effective bandwidth of the training pipeline and not result in an IO bottleneck. You'll need to experiment and see. To switch from file mode to fast file mode (and back), just add (or remove) the input_mode='FastFile' parameter while defining your input channel using the SageMaker Python SDK:

```python
sagemaker.inputs.TrainingInput(S3_INPUT_FOLDER, input_mode = 'FastFile')
```

When to use Amazon FSx for Lustre

If your dataset is too large for file mode, has many small files that you can't serialize easily, or uses a random read access pattern, FSx for Lustre is a good option to consider. Its file system scales to hundreds of gigabytes per second (GB/s) of throughput and millions of IOPs, which is ideal when you have many small files. However, note that there might be the cold start issue due to lazy loading and the overhead of setting up and initializing the FSx for Lustre file system.
Tip
To learn more, see Choose the best data source for your Amazon SageMaker training job. This AWS machine learning blog further discusses case studies and performance benchmark of data sources and input modes.

Managed Spot Training in Amazon SageMaker

Amazon SageMaker makes it easy to train machine learning models using managed Amazon EC2 Spot instances. Managed spot training can optimize the cost of training models up to 90% over on-demand instances. SageMaker manages the Spot interruptions on your behalf.

Managed Spot Training uses Amazon EC2 Spot instance to run training jobs instead of on-demand instances. You can specify which training jobs use spot instances and a stopping condition that specifies how long SageMaker waits for a job to run using Amazon EC2 Spot instances. Metrics and logs generated during training runs are available in CloudWatch.

Amazon SageMaker automatic model tuning, also known as hyperparameter tuning, can use managed spot training. For more information on automatic model tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

Spot instances can be interrupted, causing jobs to take longer to start or finish. You can configure your managed spot training job to use checkpoints. SageMaker copies checkpoint data from a local path to Amazon S3. When the job is restarted, SageMaker copies the data from Amazon S3 back into the local path. The training job can then resume from the last checkpoint instead of restarting. For more information about checkpointing, see Use Checkpoints in Amazon SageMaker (p. 2696).

Note
Unless your training job will complete quickly, we recommend you use checkpointing with managed spot training. SageMaker built-in algorithms and marketplace algorithms that do not checkpoint are currently limited to a MaxWaitTimeInSeconds of 3600 seconds (60 minutes).

Topics
- Using Managed Spot Training (p. 2695)
- Managed Spot Training Lifecycle (p. 2696)

Using Managed Spot Training

To use managed spot training, create a training job. Set EnableManagedSpotTraining to True and specify the MaxWaitTimeInSeconds. MaxWaitTimeInSeconds must be larger than MaxRuntimeInSeconds. For more information about creating a training job, see DescribeTrainingJob.

You can calculate the savings from using managed spot training using the formula \((1 - \frac{\text{BillableTimeInSeconds}}{\text{TrainingTimeInSeconds}}) \times 100\). For example, if BillableTimeInSeconds is 100 and TrainingTimeInSeconds is 500, the savings is 80%.

To learn how to run training jobs on Amazon SageMaker spot instances and how managed spot training works and reduces the billable time, see the following example notebooks:

- Managed Spot Training with TensorFlow
- Managed Spot Training with XGBoost
- Managed Spot Training with MXNet
- Amazon SageMaker Managed Spot Training Examples GitHub repository
Managed Spot Training Lifecycle

You can monitor a training job using TrainingJobStatus and SecondaryStatus returned by DescribeTrainingJob. The list below shows how TrainingJobStatus and SecondaryStatus values change depending on the training scenario:

- **Spot instances acquired with no interruption during training**
  1. InProgress → Starting → Downloading → Training → Uploading

- **Spot instances interrupted once. Later, enough spot instances were acquired to finish the training job.**
  1. InProgress → Starting → Downloading → Training → Interrupted → Starting → Downloading → Training → Uploading

- **Spot instances interrupted twice and MaxWaitTimeInSeconds exceeded.**
  1. InProgress → Starting → Downloading → Training → Interrupted → Starting → Downloading → Training → Interrupted → Training → Interrupted → Downloading → Training → Interrupted → Training → Training
  2. Stopping: Stopping
  3. Stopped: MaxWaitTimeExceeded

- **Spot instances were never launched.**
  1. InProgress: Starting
  2. Stopping: Stopping
  3. Stopped: MaxWaitTimeExceeded

Use Checkpoints in Amazon SageMaker

Use checkpoints in Amazon SageMaker to save the state of machine learning (ML) models during training. Checkpoints are snapshots of the model and can be configured by the callback functions of ML frameworks. You can use the saved checkpoints to restart a training job from the last saved checkpoint.

The SageMaker training mechanism uses training containers on Amazon EC2 instances, and the checkpoint files are saved under a local directory of the containers (the default is /opt/ml/checkpoints). SageMaker provides the functionality to copy the checkpoints from the local path to Amazon S3 and automatically syncs the checkpoints in that directory with Amazon S3. Existing checkpoints in S3 are written to the SageMaker container at the start of the job, enabling jobs to resume from a checkpoint. Checkpoints added to the S3 folder after the job has started are not copied to the training container. SageMaker also writes new checkpoints from the container to S3 during training. If a checkpoint is deleted in the SageMaker container, it will also be deleted in the S3 folder.

Using checkpoints, you can do the following:

- Save your model snapshots under training due to an unexpected interruption to the training job or instance.
- Resume training the model in the future from a checkpoint.
- Analyze the model at intermediate stages of training.
- Use checkpoints with SageMaker managed spot training to save on training costs.

If you are using checkpoints with SageMaker managed spot training, SageMaker manages checkpointing your model training on a spot instance and resuming the training job on the next spot instance. With SageMaker managed spot training, you can significantly reduce the billable time for training ML models. For more information, see Managed Spot Training in Amazon SageMaker (p. 2695).
Checkpoints for Frameworks and Algorithms in SageMaker

Use checkpoints to save snapshots of ML models built on your preferred frameworks within SageMaker.

SageMaker frameworks and algorithms that support checkpointing

SageMaker supports checkpointing for AWS Deep Learning Containers and a subset of built-in algorithms without requiring training script changes. SageMaker saves the checkpoints to the default local path `/opt/ml/checkpoints` and copies them to Amazon S3.

- Deep Learning Containers: TensorFlow, PyTorch, MXNet, and HuggingFace
  
  **Note**
  
  If you are using the HuggingFace framework estimator, you need to specify a checkpoint output path through hyperparameters. For more information, see Run training on Amazon SageMaker in the HuggingFace documentation.

- Built-in algorithms: Image Classification, Object Detection, Semantic Segmentation, and XGBoost (0.90-1 or later)
  
  **Note**
  
  If you are using the XGBoost algorithm in framework mode (script mode), you need to bring an XGBoost training script with checkpointing that's manually configured. For more information about the XGBoost training methods to save model snapshots, see Training XGBoost in the XGBoost Python SDK documentation.

If a pre-built algorithm that does not support checkpointing is used in a managed spot training job, SageMaker does not allow a maximum wait time greater than an hour for the job in order to limit wasted training time from interrupts.

For custom training containers and other frameworks

If you are using your own training containers, training scripts, or other frameworks not listed in the previous section, you must properly set up your training script using callbacks or training APIs to save checkpoints to the local path (`/opt/ml/checkpoints`) and load from the local path in your training script. SageMaker estimators can sync up with the local path and save the checkpoints to Amazon S3.

Enable Checkpointing

After you enable checkpointing, SageMaker saves checkpoints to Amazon S3 and syncs your training job with the checkpoint S3 bucket.
The following example shows how to configure checkpoint paths when you construct a SageMaker estimator. To enable checkpointing, add the `checkpoint_s3_uri` and `checkpoint_local_path` parameters to your estimator.

The following example template shows how to create a generic SageMaker estimator and enable checkpointing. You can use this template for the supported algorithms by specifying the `image_uri` parameter. To find Docker image URIs for algorithms with checkpointing supported by SageMaker, see Docker Registry Paths and Example Code (p. 1105). You can also replace `estimator` and `Estimator` with other SageMaker frameworks' estimator parent classes and estimator classes, such as TensorFlow, PyTorch, MXNet, HuggingFace and XGBoost.

```python
import sagemaker
from sagemaker.estimator import Estimator

bucket=sagemaker.Session().default_bucket()
base_job_name="sagemaker-checkpoint-test"
checkpoint_in_bucket="checkpoints"

# The S3 URI to store the checkpoints
checkpoint_s3_bucket="s3://{}/{}/{}".format(bucket, base_job_name, checkpoint_in_bucket)

# The local path where the model will save its checkpoints in the training container
checkpoint_local_path="/opt/ml/checkpoints"

estimator = Estimator(
    ...
    image_uri="<ecr_path>/<algorithm-name>:<tag>" # Specify to use built-in algorithms
    output_path=bucket,
    base_job_name=base_job_name,

    # Parameters required to enable checkpointing
    checkpoint_s3_uri=checkpoint_s3_bucket,
    checkpoint_local_path=checkpoint_local_path
)
```

The following two parameters specify paths for checkpointing:

- `checkpoint_local_path` – Specify the local path where the model saves the checkpoints periodically in a training container. The default path is set to `'/opt/ml/checkpoints'`. If you are using other frameworks or bringing your own training container, ensure that your training script's checkpoint configuration specifies the path to `'/opt/ml/checkpoints'`.

**Note**

We recommend specifying the local paths as `'/opt/ml/checkpoints'` to be consistent with the default SageMaker checkpoint settings. If you prefer to specify your own local
path, make sure you match the checkpoint saving path in your training script and the checkpoint_local_path parameter of the SageMaker estimators.

- checkpoint_s3_uri – The URI to an S3 bucket where the checkpoints are stored in real time.

To find a complete list of SageMaker estimator parameters, see the Estimator API in the Amazon SageMaker Python SDK documentation.

**Browse Checkpoint Files**

Locate checkpoint files using the SageMaker Python SDK and the Amazon S3 console.

**To find the checkpoint files programmatically**

To retrieve the S3 bucket URI where the checkpoints are saved, check the following estimator attribute:

```
estimator.checkpoint_s3_uri
```

This returns the Amazon S3 output path for checkpoints configured while requesting the CreateTrainingJob request. To find the saved checkpoint files using the Amazon S3 console, use the following procedure.

**To find the checkpoint files from the Amazon S3 console**

2. In the left navigation pane, choose Training jobs.
3. Choose the link to the training job with checkpointing enabled to open Job settings.
4. On the Job settings page of the training job, locate the Checkpoint configuration section.

<table>
<thead>
<tr>
<th>Checkpoint configuration</th>
</tr>
</thead>
<tbody>
<tr>
<td>S3 output path</td>
</tr>
<tr>
<td>s3://path-to-your-checkpoint</td>
</tr>
<tr>
<td>Local path</td>
</tr>
<tr>
<td>/opt/ml/ checkpoints/</td>
</tr>
</tbody>
</table>

5. Use the link to the S3 bucket to access the checkpoint files.

**Resume Training From a Checkpoint**

To resume a training job from a checkpoint, run a new estimator with the same checkpoint_s3_uri that you created in the Enable Checkpointing (p. 2697) section. Once the training has resumed, the checkpoints from this S3 bucket are restored to checkpoint_local_path in each instance of the new training job. Ensure that the S3 bucket is in the same Region as that of the current SageMaker session.
Considerations for Checkpointing

Consider the following when using checkpoints in SageMaker.

- To avoid overwrites in distributed training with multiple instances, you must manually configure the checkpoint file names and paths in your training script. The high-level SageMaker checkpoint configuration specifies a single Amazon S3 location without additional suffixes or prefixes to tag checkpoints from multiple instances.
- The SageMaker Python SDK does not support high-level configuration for checkpointing frequency. To control the checkpointing frequency, modify your training script using the framework's model save functions or checkpoint callbacks.
- If you use SageMaker checkpoints with SageMaker Debugger and SageMaker distributed and are facing issues, see the following pages for troubleshooting and considerations.
  - Considerations for Amazon SageMaker Debugger (p. 2432)
  - Data Parallel Troubleshooting (p. 2505)
  - Model Parallel Troubleshooting (p. 2569)

Provide Dataset Metadata to Training Jobs with an Augmented Manifest File

To include metadata with your dataset in a training job, use an augmented manifest file. When using an augmented manifest file, your dataset must be stored in Amazon Simple Storage Service (Amazon S3), and you must configure your training job to use the dataset stored there. You specify the location and format of this dataset for one or more Channel. Augmented manifests can only support Pipe input mode. See the section, InputMode in Channel to learn more about pipe input mode.

When specifying a channel's parameters, you specify a path to the file, called a S3Uri. Amazon SageMaker interprets this URI based on the specified S3DataType in S3DataSource. The AugmentedManifestFile option defines a manifest format that includes metadata with the input data. Using an augmented manifest file is an alternative to preprocessing when you have labeled data. For training jobs using labeled data, you typically need to preprocess the dataset to combine input data with metadata before training. If your training dataset is large, preprocessing can be time consuming and expensive.

Augmented Manifest File Format

An augmented manifest file must be formatted in JSON Lines format. In JSON Lines format, each line in the file is a complete JSON object followed by a newline separator.
During training, SageMaker parses each JSON line and sends some or all of its attributes on to the training algorithm. You specify which attribute contents to pass and the order in which to pass them with the AttributeNames parameter of the `CreateTrainingJob` API. The AttributeNames parameter is an ordered list of attribute names that SageMaker looks for in the JSON object to use as training input.

For example, if you list `"line", "book"` for AttributeNames, the input data must include the attribute names of `line` and `book` in the specified order. For this example, the following augmented manifest file content is valid:

```json
[{
    "author": "Herman Melville",
    "line": "Call me Ishmael", 
    "book": "Moby Dick"
},
{
    "line": "It was love at first sight.", 
    "author": "Joseph Heller",
    "book": "Catch-22"
}]
```

SageMaker ignores unlisted attribute names even if they precede, follow, or are in between listed attributes.

When using augmented manifest files, observe the following guidelines:

- The order of the attributes listed in the AttributeNames parameter determines the order of the attributes passed to the algorithm in the training job.
- The listed AttributeNames can be a subset of all of the attributes in the JSON line. SageMaker ignores unlisted attributes in the file.
- You can specify any type of data allowed by the JSON format in AttributeNames, including text, numerical, data arrays, or objects.
- To include an S3 URI as an attribute name, add the suffix `-ref` to it.

If an attribute name contains the suffix `-ref`, the attribute's value must be an S3 URI to a data file that is accessible to the training job. For example, if AttributeNames contains `"image-ref", "is-a-cat"`, the following example shows a valid augmented manifest file:

```json
[{
   "image-ref": "s3://mybucket/sample01/image1.jpg", 
   "is-a-cat": 1
},
{
   "image-ref": "s3://mybucket/sample02/image2.jpg", 
   "is-a-cat": 0
}]
```

In case of the first JSON line of this manifest file, SageMaker retrieves the `image1.jpg` file from `s3://mybucket/sample01/` and the string representation of the `is-a-cat` attribute "1" for image classification.

**Tip**
To create an augmented manifest file, use Amazon SageMaker Ground Truth and create a labeling job. For more information about the output from a labeling job, see Output Data (p. 614).

## Stream Augmented Manifest File Data

Augmented manifest format enables you to do training in Pipe mode using files without needing to create RecordIO files. You need to specify both train and validation channels as values for the `InputDataConfig` parameter of the `CreateTrainingJob` request. Augmented manifest files are supported only for channels using Pipe input mode. For each channel, the data is extracted from its augmented manifest file and streamed (in order) to the algorithm through the channel's named pipe. Pipe mode uses the first in first out (FIFO) method, so records are processed in the order in which they are queued. For information about Pipe input mode, see Input Mode.

Attribute names with a `-ref` suffix point to preformatted binary data. In some cases, the algorithm knows how to parse the data. In other cases, you might need to wrap the data so that records are delimited for the algorithm. If the algorithm is compatible with RecordIO-formatted data, specifying
RecordIO for RecordWrapperType solves this issue. If the algorithm is not compatible with RecordIO format, specify None for RecordWrapperType and make sure that your data is parsed correctly for your algorithm.

Using the ["image-ref", "is-a-cat"] example, if you use RecordIO wrapping, the following stream of data is sent to the queue:

```
recordio_formatted(s3://mybucket/foo/image1.jpg)recordio_formatted("1")recordio_formatted(s3://mybucket/bar/image2.jpg)recordio_formatted("0")
```

Images that are not wrapped with RecordIO format, are streamed with the corresponding is-a-cat attribute value as one record. This can cause a problem because the algorithm might not delimit the images and attributes correctly. For more information about using augmented manifest files for image classification, see Train with Augmented Manifest Image Format.

With augmented manifest files and Pipe mode in general, size limits of the EBS volume do not apply. This includes settings that otherwise must be within the EBS volume size limit such as S3DataDistributionType. For more information about Pipe mode and how to use it, see Using Your Own Training Algorithms - Input Data Configuration.

Use an Augmented Manifest File (Console)

To complete this procedure, you need:

- The URL of the S3 bucket where you've stored the augmented manifest file.
- To store the data that is listed in the augmented manifest file in an S3 bucket.
- The URL of the S3 bucket where you want to store the output of the job.

To use an augmented manifest file in a training job (console)

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the navigation pane, choose Training, then choose Training jobs.
3. Choose Create training job.
4. Provide a name for the training job. The name must be unique within an AWS Region in an AWS account. It can have 1 to 63 characters. Valid characters: a-z, A-Z, 0-9, and . : + = @ _ % - (hyphen).
5. Choose the algorithm that you want to use. For information about supported built-in algorithms, see Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096). If you want to use a custom algorithm, make sure that it is compatible with Pipe mode.
6. (Optional) For Resource configuration, either accept the default values or, to reduce computation time, increase the resource consumption.
   a. (Optional) For Instance type, choose the ML compute instance type that you want to use. In most cases, ml.m4.xlarge is sufficient.
   b. For Instance count, use the default, 1.
   c. (Optional) For Additional volume per instance (GB), choose the size of the ML storage volume that you want to provision. In most cases, you can use the default, 1. If you are using a large dataset, use a larger size.
7. Provide information about the input data for the training dataset.
   a. For Channel name, either accept the default (train) or enter a more meaningful name, such as training-augmented-manifest-file.
   b. For InputMode, choose Pipe.
c. For **S3 data distribution type**, choose **FullyReplicated**. When training incrementally, fully replicating causes each ML compute instance to use a complete copy of the expanded dataset. For neural-based algorithms, such as Neural Topic Model (NTM) Algorithm (p. 2081), choose ShardedByS3Key.

d. If the data specified in the augmented manifest file is uncompressed, set the **Compression type** to None. If the data is compressed using gzip, set it to Gzip.

e. (Optional) For **Content type**, specify the appropriate MIME type. Content type is the multipurpose internet mail extension (MIME) type of the data.

f. For **Record wrapper**, if the dataset specified in the augmented manifest file is saved in RecordIO format, choose **RecordIO**. If your dataset is not saved as a RecordIO-formatted file, choose None.

g. For **S3 data type**, choose **AugmentedManifestFile**.

h. For **S3 location**, provide the path to the bucket where you stored the augmented manifest file.

i. For **AugmentedManifestFile attribute names**, specify the name of an attribute that you want to use. The attribute name must be present within the augmented manifest file, and is case-sensitive.

j. (Optional) To add more attribute names, choose **Add row** and specify another attribute name for each attribute.

k. (Optional) To adjust the order of attribute names, choose the up or down buttons next to the names. When using an augmented manifest file, the order of the specified attribute names is important.

l. Choose **Done**.

8. For **Output data configuration**, provide the following information:

   a. For **S3 location**, type the path to the S3 bucket where you want to store the output data.

   b. (Optional) You can use your AWS Key Management Service (AWS KMS) encryption key to encrypt the output data at rest. For **Encryption key**, provide the key ID or its Amazon Resource Number (ARN). For more information, see KMS-Managed Encryption Keys.

9. (Optional) For **Tags**, add one or more tags to the training job. A tag is metadata that you can define and assign to AWS resources. In this case, you can use tags to help you manage your training jobs. A tag consists of a key and a value, which you define. For example, you might want to create a tag with **Project** as a key and a value that refers to a project that is related to the training job, such as **Home value forecasts**.

10. Choose **Create training job**. SageMaker creates and runs the training job.

After the training job has finished, SageMaker stores the model artifacts in the bucket whose path you provided for **S3 output path** in the **Output data configuration** field. To deploy the model to get predictions, see Step 5: Deploy the Model to Amazon EC2 (p. 85).

### Use an Augmented Manifest File (API)

The following shows how to train a model with an augmented manifest file using the SageMaker high-level Python library:

```python
import sagemaker

# Create a model object set to using "Pipe" mode.
model = sagemaker.estimator.Estimator(
    training_image,
    role,
    instance_count=1,
    instance_type='ml.p3.2xlarge',
    volume_size = 50,
    sagemaker
)  # End import sagemaker
```
Monitor and Analyze Using CloudWatch Metrics

An Amazon SageMaker training job is an iterative process that teaches a model to make predictions by presenting examples from a training dataset. Typically, a training algorithm computes several metrics, such as training error and prediction accuracy. These metrics help diagnose whether the model is learning well and will generalize well for making predictions on unseen data. The training algorithm writes the values of these metrics to logs, which SageMaker monitors and sends to Amazon CloudWatch in real time. To analyze the performance of your training job, you can view graphs of these metrics in CloudWatch. When a training job has completed, you can also get a list of the metric values that it computes in its final iteration by calling the `DescribeTrainingJob` operation.

**Note**

Amazon CloudWatch supports high-resolution custom metrics, and its finest resolution is 1 second. However, the finer the resolution, the shorter the lifespan of the CloudWatch metrics. For the 1-second frequency resolution, the CloudWatch metrics are available for 3 hours. For more information about the resolution and the lifespan of the CloudWatch metrics, see `GetMetricStatistics` in the Amazon CloudWatch API Reference.

**Tip**

If you want to profile your training job with a finer resolution down to 100-millisecond (0.1 second) granularity and store the training metrics indefinitely in Amazon S3 for custom analysis at any time, consider using Amazon SageMaker Debugger. SageMaker Debugger provides built-in rules to automatically detect common training issues; it detects hardware resource utilization issues (such as CPU, GPU, and I/O bottlenecks) and non-converging model issues (such as overfit, vanishing gradients, and exploding tensors). SageMaker Debugger also provides visualizations through Studio and its profiling report. To explore the Debugger visualizations, see SageMaker Debugger Insights Dashboard Walkthrough, Debugger Profiling Report Walkthrough, and Analyze Data Using the SMDebug Client Library.
Defining Training Metrics

SageMaker automatically parses training job logs and sends training metrics to CloudWatch. By default, SageMaker sends system resource utilization metrics listed in SageMaker Jobs and Endpoint Metrics. If you want SageMaker to parse logs and send custom metrics from a training job of your own algorithm to CloudWatch, you need to specify metrics definitions by passing the name of metrics and regular expressions when you configure a SageMaker training job request.

You can specify the metrics that you want to track using the SageMaker console, the SageMaker Python SDK, or the low-level SageMaker API.

If you are using your own algorithm, do the following:

• Make sure that the algorithm writes the metrics that you want to capture to logs.
• Define a regular expression that accurately searches the logs to capture the values of the metrics that you want to send to CloudWatch.

For example, suppose your algorithm emits the following metrics for training error and validation error:

```
Train_error=0.138318;  Valid_error=0.324557;
```

If you want to monitor both of those metrics in CloudWatch, the dictionary for the metric definitions should look like the following example:

```
[
    {
        "Name": "train:error",
        "Regex": "Train_error=(.*?);"
    },
    {
        "Name": "validation:error",
        "Regex": "Valid_error=(.*?);"
    }
]
```

In the regex for the `train:error` metric defined in the preceding example, the first part of the regex finds the exact text "Train_error=" and the expression `(.*?);` captures any characters until the first semicolon character appears. In this expression, the parenthesis tell the regex to capture what is inside them, `.` means any character, `*` means zero or more, and `?` means capture only until the first instance of the `;` character.

Define Metrics Using the SageMaker Python SDK

Define the metrics that you want to send to CloudWatch by specifying a list of metric names and regular expressions as the `metric_definitions` argument when you initialize an `Estimator` object. For example, if you want to monitor both the `train:error` and `validation:error` metrics in CloudWatch, your `Estimator` initialization would look like the following example:

```
import sagemaker

[...
```
Define Training Metrics

```python
from sagemaker.estimator import Estimator
estimator = Estimator(
    image_uri="your-own-image-uri",
    role=sagemaker.get_execution_role(),
    sagemaker_session=sagemaker.Session(),
    instance_count=1,
    instance_type='ml.c4.xlarge',
    metric_definitions=
    [{'Name': 'train:error', 'Regex': 'Train_error=(.*);'},
     {'Name': 'validation:error', 'Regex': 'Valid_error=(.*);'}
    ]
)
```

For more information about training by using Amazon SageMaker Python SDK estimators, see Sagemaker Python SDK on GitHub.

Define Metrics Using the SageMaker Console

If you choose the Your own algorithm container in ECR option as your algorithm source in the SageMaker console when you create a training job, add the metric definitions in the Metrics section. The following screenshot shows how it should look after you add the example metric names and the corresponding regular expressions.

Algorithm options
Use an Amazon SageMaker built-in algorithm, your own algorithm, or a third-party algorithm from AWS Marketplace.

- **Algorithm source**
  - Amazon SageMaker built-in algorithm [Learn more](#)
  - Your own algorithm resource
  - Your own algorithm container in ECR [Learn more](#)
  - An algorithm subscription from AWS Marketplace

Provide container ECR path

Container
The registry path where the training image is stored in Amazon ECR. [Learn more](#)

Input mode
You can provide your training data as a file or pipe.

Metrics
Define the metrics you want to emit to CloudWatch metrics.

<table>
<thead>
<tr>
<th>Metric name</th>
<th>Regex</th>
</tr>
</thead>
<tbody>
<tr>
<td>train:error</td>
<td>Train_error=(.*);</td>
</tr>
<tr>
<td>validation:error</td>
<td>Valid_error=(.*);</td>
</tr>
</tbody>
</table>

Define Metrics Using the Low-level SageMaker API

Define the metrics that you want to send to CloudWatch by specifying a list of metric names and regular expressions in the MetricDefinitions field of the **AlgorithmSpecification** input parameter.
that you pass to the `CreateTrainingJob` operation. For example, if you want to monitor both the `train:error` and `validation:error` metrics in CloudWatch, your `AlgorithmSpecification` would look like the following example:

```json
"AlgorithmSpecification": {
  "TrainingImage": "your-own-image-uri",
  "TrainingInputMode": "File",
  "MetricDefinitions" : [
    {
      "Name": "train:error",
      "Regex": "Train_error=(.*?);"
    },
    {
      "Name": "validation:error",
      "Regex": "Valid_error=(.*?)"
    }
  ]
}
```

For more information about defining and running a training job by using the low-level SageMaker API, see `CreateTrainingJob`.

**Monitoring Training Job Metrics (CloudWatch Console)**

You can monitor the metrics that a training job emits in real time in the CloudWatch console.

**To monitor training job metrics (CloudWatch console)**

2. Choose Metrics, then choose `/aws/sagemaker/TrainingJobs`.
3. Choose TrainingJobName.
4. On the All metrics tab, choose the names of the training metrics that you want to monitor.
5. On the Graphed metrics tab, configure the graph options. For more information about using CloudWatch graphs, see Graph Metrics in the Amazon CloudWatch User Guide.

**Monitoring Training Job Metrics (SageMaker Console)**

You can monitor the metrics that a training job emits in real time by using the SageMaker console.

**To monitor training job metrics (SageMaker console)**

2. Choose Training jobs, then choose the training job whose metrics you want to see.
3. Choose TrainingJobName.
4. In the Monitor section, you can review the graphs of instance utilization and algorithm metrics.
Example: Viewing a Training and Validation Curve

Typically, you split the data on which you train your model into training and validation datasets. You use the training set to train the model parameters that are used to make predictions on the training dataset. Then you test how well the model makes predictions by calculating predictions for the validation set. To analyze the performance of a training job, you commonly plot a training curve against a validation curve.

Viewing a graph that shows the accuracy for both the training and validation sets over time can help you to improve the performance of your model. For example, if training accuracy continues to increase over time, but, at some point, validation accuracy starts to decrease, you are likely overfitting your model. To address this, you can make adjustments to your model, such as increasing regularization.

For this example, you can use the `Image-classification-full-training` example in the Example notebooks section of your SageMaker notebook instance. If you don't have a SageMaker notebook instance, create one by following the instructions at Step 1: Create an Amazon SageMaker Notebook Instance (p. 74). If you prefer, you can follow along with the End-to-End Multiclass Image Classification Example in the example notebook on GitHub. You also need an Amazon S3 bucket to store the training data and for the model output.

To view training and validation error curves

2. Choose Notebooks, and then choose Notebook instances.
3. Choose the notebook instance that you want to use, and then choose Open.
4. On the dashboard for your notebook instance, choose SageMaker Examples.
5. Expand the Introduction to Amazon Algorithms section, and then choose Use next to Image-classification-fulltraining.ipynb.
7. Run all of the cells in the notebook up to the Inference section. You don't need to deploy an endpoint or get inference for this example.
8. After the training job starts, open the CloudWatch console at https://console.aws.amazon.com/cloudwatch.
9. Choose Metrics, then choose /aws/sagemaker/TrainingJobs.
10. Choose TrainingJobName.
11. On the All metrics tab, choose the train:accuracy and validation:accuracy metrics for the training job that you created in the notebook.
12. On the graph, choose an area that the metric's values to zoom in. You should see something like the following example.
Example: Viewing a Training and Validation Curve
Deploy Models for Inference

After you build and train your models, you can deploy them to get predictions in one of two ways:

• To set up a persistent endpoint to get predictions from your models, use Amazon SageMaker hosting services. For an example of how to deploy a model to the SageMaker hosting service, see Create your endpoint and deploy your model (p. 2745).

Or, if you prefer, watch the following video tutorial:

Deploy Your ML Models to Production at Scale with Amazon SageMaker

• To get predictions for an entire dataset, use SageMaker batch transform. For an overview on deploying a model with SageMaker batch transform, see Use Batch Transform (p. 2955).

For an example of how to deploy a model with batch transform, see (Optional) Make Prediction with Batch Transform (p. 86).

Or, if you prefer, watch the following video tutorial:

Deploy Your ML Models to Production at Scale with Amazon SageMaker

Prerequisites

These topics assume that you have built and trained one or more machine learning models and are ready to deploy them. If you are new to SageMaker and have not completed these prerequisite tasks, work through the steps in the Get Started with Amazon SageMaker (p. 33) tutorial to familiarize yourself with an example of how SageMaker manages the data science process and how it handles model deployment. For more information about training a model, see Train Models (p. 1091).

What do you want to do?

SageMaker provides features to manage resources and optimize inference performance when deploying machine learning models. For guidance on using inference pipelines, compiling and deploying models with Neo, Elastic Inference, and automatic model scaling, see the following topics.

• To manage data processing and real-time predictions or to process batch transforms in a pipeline, see Host models along with pre-processing logic as serial inference pipeline behind one endpoint (p. 2789).

• If you want to deploy a model on inf1 instances, see Optimize model performance using Neo (p. 3063).

• To train TensorFlow, Apache MXNet, PyTorch, ONNX, and XGBoost models once and optimize them to deploy on ARM, Intel, and Nvidia processors, see Optimize model performance using Neo (p. 3063).

• To preprocess entire datasets quickly or to get inferences from a trained model for large datasets when you don't need a persistent endpoint, see Use Batch Transform (p. 2955).

• To speed up the throughput and decrease the latency of getting real-time inferences from your deep learning models that are deployed as SageMaker hosted models using a GPU instance for your endpoint, see Use Amazon SageMaker Elastic Inference (EI) (p. 3129).

• To dynamically adjust the number of instances provisioned in response to changes in your workload, see Automatically Scale Amazon SageMaker Models (p. 2803).
To create an endpoint that can host multiple models using a shared serving container, see Host multiple models in one container behind one endpoint (p. 2755).

To test multiple models in production, see Safely update models in production (p. 2819).

Manage Model Deployments

For guidance on managing model deployments, including monitoring, troubleshooting, and best practices, and for information on storage associated with inference hosting instances:

- For tools that can be used to monitor model deployments, see Monitor Amazon SageMaker (p. 3663).
- For troubleshooting model deployments, see Troubleshoot Amazon SageMaker model deployments (p. 2832).
- For model deployment best practices, see Best practices (p. 2826).
- For information about the size of storage volumes provided for different sizes of hosting instances, see Host instance storage volumes (p. 2819).

Deploy Your Own Inference Code

For developers that need more advanced guidance on how to run your own inference code:

- To run your own inference code hosting services, see Use Your Own Inference Code with Hosting Services (p. 3191).
- To run your own inference code for batch transforms, see Use Your Own Inference Code with Batch Transform (p. 3197).

Amazon SageMaker Inference Recommender

Amazon SageMaker Inference Recommender is a new capability of Amazon SageMaker that reduces the time required to get machine learning (ML) models in production by automating load testing and model tuning across SageMaker ML instances. You can use Inference Recommender to deploy your model to a real-time inference endpoint that delivers the best performance at the lowest cost. Inference Recommender helps you select the best instance type and configuration (such as instance count, container parameters, and model optimizations) for your ML models and workloads.

Amazon SageMaker Inference Recommender only charges you for the instances used while your jobs are executing.

How it Works

To use Amazon SageMaker Inference Recommender, you must first register a model to SageMaker model registry with your model artifact and container, use AWS SDK for Python (Boto3) to benchmark different SageMaker endpoint configurations, collect metrics, and visualize metrics across performance and resource utilization to help you decide on which instance type to choose.

How to Get Started

If you are a first-time user of Amazon SageMaker Inference Recommender, we recommend that you do the following:

1. Read through the Prerequisites (p. 2713) section to make sure you have satisfied the requirements to use Amazon SageMaker Inference Recommender.
2. Read through the Recommendation jobs (p. 2719) section to launch your first Inference Recommender recommendation jobs.

3. Explore the introductory Amazon SageMaker Inference Recommender Jupyter notebook example, or review the example notebooks in the following section.

Example notebooks

The following example Jupyter notebooks can help you with the workflows for multiple use cases in Inference Recommender:

- If you want an introductory notebook that benchmarks a TensorFlow model, see the SageMaker Inference Recommender TensorFlow notebook.
- If you want to benchmark a HuggingFace model, see the SageMaker Inference Recommender for HuggingFace notebook.
- If you want to benchmark an XGBoost model, see the SageMaker Inference Recommender XGBoost notebook.
- If you want to review CloudWatch metrics for your Inference Recommender jobs, see the SageMaker Inference Recommender CloudWatch metrics notebook.

Prerequisites

To use Amazon SageMaker Inference Recommender, first make sure you have met the prerequisites listed below. As an example, we show how to use a PyTorch (v1.7.1) ResNet-18 pre-trained model for both types of Amazon SageMaker Inference Recommender recommendation jobs.

Note

- The following code examples use Python. Remove the `!` prefix character if you run any of the following code samples in your terminal or AWS CLI.
- This example uses the conda_pytorch_p36_latest kernel within a Amazon SageMaker Notebook instance. This kernel is provided by SageMaker and uses Python 3.6 and PyTorch 1.7.1. For more information about SageMaker Notebooks, see Use Amazon SageMaker Notebook Instances (p. 291).

1. Create an IAM role for Amazon SageMaker.

   Create an IAM Role for Amazon SageMaker that has the AmazonSageMakerFullAccess IAM managed policy attached.

2. (Optional) Review existing models benchmarked by Inference Recommender.

   Inference Recommender benchmarks models from popular model zoos. Inference Recommender supports your model even if it is not already benchmarked.

   Use ListModelMetaData to get a response object that lists the domain, framework, task, and model name of machine learning models found in common model zoos.

   You use the domain, framework, framework version, task, and model name in later steps to both select an inference Docker image and register your model with SageMaker Model Registry. The following demonstrates how to list model metadata with SDK for Python (Boto3):

```python
import boto3
aws_region="<INSERT>"
sagemaker_client = boto3.client("sagemaker", aws_region)
```
list_model_metadata_response=sagemaker_client.list_model_metadata()

The output includes model summaries (ModelMetadataSummaries) and response metadata (ResponseMetadata) similar to the following:

```python
{
'ModelMetadataSummaries': [[
'Domain': 'NATURAL_LANGUAGE_PROCESSING',
'Framework': 'PYTORCH:1.6.0',
'Model': 'bert-base-cased',
'Task': 'FILL_MASK'
],
[
'Domain': 'NATURAL_LANGUAGE_PROCESSING',
'Framework': 'PYTORCH:1.6.0',
'Model': 'bert-base-uncased',
'Task': 'FILL_MASK'
],
[
'Domain': 'COMPUTER_VISION',
'Framework': 'MXNET:1.8.0',
'Model': 'resnet18v2-gluon',
'Task': 'IMAGE_CLASSIFICATION'
],
[
'Domain': 'COMPUTER_VISION',
'Framework': 'PYTORCH:1.6.0',
'Model': 'resnet152',
'Task': 'IMAGE_CLASSIFICATION'
]],
'ResponseMetadata': {
'HTTPHeaders': {
'content-length': '2345',
'content-type': 'application/x-amz-json-1.1',
'date': 'Tue, 19 Oct 2021 20:52:03 GMT',
'x-amzn-requestid': 'xxxxxxxx-xxxx-xxxx-xxxx-xxxxxxxxxxxxxxx'
},
'HTTPStatusCode': 200,
'RequestId': 'xxxxxxxx-xxxx-xxxx-xxxx-xxxxxxxxxxxxxxx',
'RetryAttempts': 0
}
}
```

For this demo, we use a PyTorch (v1.7.1) ResNet-18 model to perform image classification. The following Python code sample stores the framework, framework version, domain, and task into variables for later use:

```python
# ML framework details
framework = 'PYTORCH'
framework_version = '1.7.1'

# ML model details
ml_domain = 'COMPUTER_VISION'
ml_task = 'IMAGE_CLASSIFICATION'
```

3. **Upload your machine learning model to Amazon S3.**

Use this PyTorch (v1.7.1) ResNet-18 model if you do not have a pre-trained machine learning model:

```python
# Optional: Download a sample PyTorch model
import torch
from torchvision import models, transforms, datasets
```
# Create an example input for tracing
image = torch.zeros([1, 3, 256, 256], dtype=torch.float32)

# Load a pretrained resnet18 model from TorchHub
model = models.resnet18(pretrained=True)

# Tell the model we are using it for evaluation (not training). Note this is required
# for Inferentia compilation.
model.eval()
model_trace = torch.jit.trace(model, image)

# Save your traced model
model_trace.save('model.pth')

Download a sample inference script `inference.py`. Create a code directory and move the
inference script to the code directory.

```bash
# Download the inference script

# move it into a code/ directory
!mkdir code
!mv inference.py code/
```

Amazon SageMaker requires pre-trained machine learning models be packaged as a compressed TAR
file (*.tar.gz). Compress your model to satisfy this requirement:

```bash
!tar -czf test.tar.gz model.pth resnet18.py
```

When your endpoint is provisioned, the files in the archive are extracted to /opt/ml/model/ on the
derived.

After you compress your model and model artifacts as a .tar.gz file, upload them to your Amazon
S3 bucket. The following demonstrates how to upload your model to Amazon S3 using the AWS CLI:

```bash
!aws s3 cp test.tar.gz s3://{your-bucket}/models/
```

4. **Select a prebuilt Docker inference image or create your own Inference Docker Image.**

SageMaker provides containers for its built-in algorithms and prebuilt Docker images for some of
the most common machine learning frameworks, such as Apache MXNet, TensorFlow, PyTorch, and
Chainer. For a full list of the available SageMaker images, see [Available Deep Learning Containers
Images](#).

If none of the existing SageMaker containers meet your needs and you don't have an existing
container of your own, create a new Docker image. See [Use Your Own Inference Code (p. 3191)](#)
for information about how to create your Docker image.

The following demonstrates how to retrieve a PyTorch version 1.7.1 inference image using the
SageMaker Python SDK:

```python
from sagemaker import image_uris

aws_region="<aws_region>"

## Uncomment and replace with your own values if you did not define
## these variables a previous step.
framework = 'PYTORCH'
```
#framework_version = '1.7.1'

# Note: you can use any CPU-based instance here,
# this is just to set the arch as CPU for the Docker image
instance_type = 'ml.m5.2xlarge'

image_uri = image_uris.retrieve(framework,
                          region=aws_region,
                          version=framework_version,
                          py_version='py3',
                          instance_type=instance_type,
                          image_scope='inference')

For a list of available SageMaker Instances, see Amazon SageMaker Pricing.

5. **Create a sample payload archive.**

   Create an archive that contains individual files that the load testing tool can send to your SageMaker endpoints. Your inference code must be able to read the file formats from the sample payload.

   The following downloads a .jpg image that this example uses in a later step for the ResNet-18 model.

   ```bash
   !wget https://cdn.pixabay.com/photo/2020/12/18/05/56/flowers-5841251_1280.jpg
   ```

   Compress the sample payload as a tarball:

   ```bash
   !tar -cvzf payload.tar.gz flowers-5841251_1280.jpg
   ```

   Upload the sample payload to Amazon S3 and note the Amazon S3 URI:

   ```bash
   !aws s3 cp payload.tar.gz s3://{bucket}/models/
   ```

   You need the Amazon S3 URI in a later step, so store it in a variable:

   ```python
   bucket_prefix='models'
bucket = '<your-bucket-name>'  # Provide the name of your S3 bucket
payload_s3_key = f'{bucket_prefix}/payload.tar.gz'
sample_payload_url = f's3://{bucket}/{payload_s3_key}'
   ```

6. **Register your model in the model registry**

   With SageMaker Model Registry, you can catalog models for production, manage model versions, associate metadata (such as training metrics) with a model, manage the approval status of a model, deploy models to production, and automate model deployment with CI/CD.

   When you use SageMaker Model Registry to track and manage your models, they are represented as a versioned model package within model package groups. Unversioned model packages are not part of a model group. Model package groups hold multiple versions or iterations of a model. Though it is not required to create them for every model in the registry, they help organize various models that all have the same purpose and provide automatic versioning.

   To use Amazon SageMaker Inference Recommender, you must have a versioned model package. You can create a versioned model package programmatically with the AWS SDK for Python (Boto3) or with Amazon SageMaker Studio. To create a versioned model package programmatically, first create a model package group with the CreateModelPackageGroup API. Next, create a model package using the CreateModelPackage API. Calling this method makes a versioned model package.
See Create a Model Group (p. 2983) and Register a Model Version (p. 2988) for detailed instructions about how to programmatically and interactively create a model package group and how to create a versioned model package, respectively, with the AWS SDK for Python (Boto3) and Amazon SageMaker Studio.

The following code sample demonstrates how to create a versioned model package using the AWS SDK for Python (Boto3).

Note
Note: You do not need to approve the model package to create an Inference Recommender job.

a. Create a model package group

Create a model package group with the CreateModelPackageGroup API. Provide a name to the model package group for the ModelPackageGroupName and optionally provide a description of the model package in the ModelPackageGroupDescription field.

```python
model_package_group_name = '<INSERT>'
model_package_group_description = '<INSERT>'

model_package_group_input_dict = {
    "ModelPackageGroupName" : model_package_group_name,
    "ModelPackageGroupDescription" : model_package_group_description,
}

model_package_group_response = sagemaker_client.create_model_package_group(**model_package_group_input_dict)
```

See the Amazon SageMaker API Reference Guide for a full list of optional and required arguments you can pass to CreateModelPackageGroup.

Create a Model Package by specifying a Docker image that runs your inference code and the Amazon S3 location of your model artifacts and provide values for InferenceSpecification. InferenceSpecification should contain information about inference jobs that can be run with models based on this Model Package, including the following:

- The Amazon ECR paths of images that run your inference code.
- (Optional) The instance types that the Model Package supports for transform jobs and real-time endpoints used for inference.
- The input and output content formats that the Model Package supports for inference.

In addition, you must specify the following parameters when you create a model package:

- **Domain**: The machine learning domain of your model package and its components. Common machine learning domains include computer vision and natural language processing.
- **Task**: The machine learning task your model package accomplishes. Common machine learning tasks include object detection and image classification. Specify "OTHER" if none of the tasks listed in the API Reference Guide satisfy your use case. See the Task API field descriptions for a list of supported machine learning tasks.
- **SamplePayloadUrl**: The Amazon Simple Storage Service (Amazon S3) path where the sample payload are stored. This path must point to a single gzip compressed tar archive (.tar.gz suffix).
- **Framework**: The machine learning framework of the model package container image.
- **FrameworkVersion**: The framework version of the Model Package Container Image.
If you provide an allow list of instance types to use to generate inferences in real-time for the `SupportedRealtimeInferenceInstanceTypes`, Inference Recommender will limit the search space for instance types during a Default job. Use this parameter if you have budget constraints or know there's a specific set of instance types that can support your model and container image.

In a previous step we downloaded a pre-trained ResNet18 model and stored it in an Amazon S3 bucket in a directory called `models`. We retrieved a PyTorch (v1.7.1) Deep Learning Container inference image and stored the URI in a variable called `image_uri`. We use those variables in the following code sample where we define a dictionary used as input to the CreateModelPackage API.

```python
# Provide the Amazon S3 URI of your compressed tarfile
# so that Model Registry knows where to find your model artifacts
bucket_prefix='models'
bucket = '<your-bucket-name>'
model_s3_key = f'{bucket_prefix}/test.tar.gz'
model_url = f's3://{bucket}/{model_s3_key}'

# Similar open source model to the packaged model
# The name of the ML model as standardized by common model zoos
nearest_model_name = 'resnet18'

# The supported MIME types for input and output data. In this example,
# we are using images as input.
input_content_type='image/jpeg'

# Optional - provide a description of your model.
model_package_description = '<INSERT>'

## Uncomment if you did not store the domain and task in an earlier
## step
# ml_domain = 'COMPUTER_VISION'
# ml_task = 'IMAGE_CLASSIFICATION'

## Uncomment if you did not store the framework and framework version
## in a previous step.
# framework = 'PYTORCH'
# framework_version = '1.7.1'

# Optional: Used for optimizing your model using SageMaker Neo
# PyTorch uses NCHW format for images
data_input_configuration = ‘[[1,3,256,256]]’

# Create a dictionary to use as input for creating a model pacakge group
model_package_input_dict = {
    "ModelPackageName": model_package_group_name,
    "ModelPackageDescription": model_package_description,
    "Domain": ml_domain,
    "Task": ml_task,
    "SamplePayloadUrl": sample_payload_url,
    "InferenceSpecification": {
        "Containers": [
            {
                "Image": image_uri,
                "ModelDataUrl": model_url,
                "Framework": framework.upper(),
                "FrameworkVersion": framework_version,
                "NearestModelName": nearest_model_name,
                "ModelInput": {
                    "DataInputConfig": data_input_configuration
                }
            }
        ]
    }
}
```
Recommendation jobs

Amazon SageMaker Inference Recommender can make two types of recommendations:

1. Instance recommendations (Default job type) run a set of load tests on recommended instance types. You only need to provide a model package Amazon Resource Name (ARN) to launch this type of recommendation job. Instance recommendation jobs complete within 45 minutes.

2. Endpoint recommendations (Advanced job type) are based on a custom load test where you select ML instances, provide a custom traffic pattern, and provide requirements for latency and throughput based on your production requirements. This job takes an average of 2 hours to complete depending on the job duration set and the total number of instance configurations tested.

Both types of recommendations use the same APIs to create, describe, and stop jobs. The output is a list of instance configuration recommendations with associated environment variables, cost, throughput, and latency metrics. Endpoint recommendations also provide an initial instance count which you can use to configure an autoscaling policy. To differentiate between the two types of jobs, specify Default to create preliminary endpoint recommendations and Advanced for custom load testing and endpoint recommendations.

Note

- You do not need to do both types of recommendation jobs in your own workflow. You can do either independently of each other.

Topics

- Get an instance recommendation (p. 2720)
- Get an instance recommendation for an existing endpoint (p. 2726)
- Get compiled recommendations with Neo (p. 2730)
- Interpret recommendation results (p. 2732)
- Run a custom load test (p. 2733)
- Troubleshoot Inference Recommender errors (p. 2742)
Get an instance recommendation

Instance recommendation jobs run a set of load tests on recommended instance types. Inference recommendation jobs use performance metrics that are based on load tests using the sample data you provided during model version registration.

Note
Before you create an Inference Recommender recommendation job, make sure you have satisfied the Prerequisites (p. 2713).

The following demonstrates how to use Amazon SageMaker Inference Recommender to create an instance recommendation based on your model type using the AWS SDK for Python (Boto3), AWS CLI, and Amazon SageMaker Studio.

Create an instance recommendation

Create an instance recommendation programmaticially using AWS SDK for Python (Boto3), with the AWS CLI, or interactively using Studio. Specify a job name for your instance recommendation, an AWS IAM role ARN, an input configuration, and your model package ARN when you registered your model with the model registry.

AWS SDK for Python (Boto3)

Use the CreateInferenceRecommendationsJob API to get an instance endpoint recommendation. Set the JobType field to 'Default' for instance endpoint recommendation jobs. In addition, provide the following:

- The Amazon Resource Name (ARN) of an IAM role that enables Inference Recommender to perform tasks on your behalf. Define this for the RoleArn field.
- The ARN of the versioned model package you created when you registered your model with the model registry. Define this for ModelPackageVersionArn in the InputConfig field.
- Provide a name for your Inference Recommender recommendation job for the JobName field. The Inference Recommender job name must be unique within the AWS Region and within your AWS account.

Import the AWS SDK for Python (Boto3) package and create a SageMaker client object using the client class. If you followed the steps in the Prerequisites section, the model package group ARN was stored in a variable named model_package_arn.

```python
# Create a low-level SageMaker service client.
import boto3
aws_region = '<INSERT>'
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Provide your model package ARN that was created when you registered your
# model with Model Registry
model_package_arn = '<INSERT>'

# Provide a unique job name for SageMaker Inference Recommender job
# job_name = '<INSERT>'

# Inference Recommender job type. Set to Default to get an initial recommendation
# job_type = 'Default'

# Provide an IAM Role that gives SageMaker Inference Recommender permission to
# access AWS services
role_arn = '<arn:aws:iam::<account>::role/*>'

sagemaker_client.create_inference_recommendations_job(
    JobName = job_name,
    # Other parameters...
)
```
Recommendation jobs

```python
JobType = job_type,
RoleArn = role_arn,
InputConfig = {
    'ModelPackageVersionArn': model_package_arn
}
)
```

See the Amazon SageMaker API Reference Guide for a full list of optional and required arguments you can pass to CreateInferenceRecommendationsJob.

AWS CLI

Use the create-inference-recommendations-job API to get an instance endpoint recommendation. Set the job-type field to 'Default' for instance endpoint recommendation jobs. In addition, provide the following:

- The Amazon Resource Name (ARN) of an IAM role that enables Amazon SageMaker Inference Recommender to perform tasks on your behalf. Define this for the role-arn field.
- The ARN of the versioned model package you created when you registered your model with Model Registry. Define this for ModelPackageVersionArn in the input-config field.
- Provide a name for your Inference Recommender recommendation job for the job-name field. The Inference Recommender job name must be unique within the AWS Region and within your AWS account.

```
aws sagemaker create-inference-recommendations-job
--region <region>
--job-name <job_name>
--job-type Default
--role-arn arn:aws:iam::<account:role/>
--input-config "{
    "ModelPackageVersionArn": \"arn:aws:sagemaker::<region:account:role/>\",
}
```

Amazon SageMaker Studio

Create an instance recommendation job in Studio.

1. In the left sidebar of Amazon SageMaker, choose the Components and registries icon.
2. Select Model Registry from the dropdown list to display models you have registered with the model registry.

   The left panel displays a list of model groups. The list includes all the model groups registered with the model registry in your account, including models registered outside of Studio.
3. Select the name of your model group. When you select your model group, the right pane of Studio displays column heads such as Versions and Setting.

   If you have one or more model packages within your model group, you will see a list of those model packages within the Versions column.
4. Choose the Inference recommender column.
5. Choose an IAM role that grants Inference Recommender permission to access AWS services. You can create a role and attach the AmazonSageMakerFullAccess IAM managed policy to accomplish this. Or you can let Studio create a role for you.
6. Choose Get recommendations.

   The instance recommendation can take up to 45 minutes.

   **Warning**
   
   Do not close this tab. If you close this tab, you cancel the instance recommendation job.
Get Your Instance Recommendation Job Results

Collect the results of your instance recommendation job programatically with AWS SDK for Python (Boto3), the AWS CLI, or Studio.

AWS SDK for Python (Boto3)

Once an instance recommendation is complete, you can use DescribeInferenceRecommendationsJob to get the job details and recommended instance types. Provide the job name that you used when you created the instance recommendation job.

```python
job_name='<INSERT>'
response = sagemaker_client.describe_inference_recommendations_job(
    JobName=job_name)
```

Print the response object. The previous code sample stored the response in a variable name response.

```python
print(response['Status'])
```

This returns a JSON response similar to the following:

```json
{
    'JobName': 'job-name',
    'JobDescription': 'job-description',
    'JobType': 'Default',
    'Status': 'COMPLETED',
    'CreationTime': datetime.datetime(2021, 10, 26, 20, 4, 57, 627000, tzinfo=tzlocal()),
    'LastModifiedTime': datetime.datetime(2021, 10, 26, 20, 25, 1, 997000, tzinfo=tzlocal()),
    'InputConfig': {
        'JobDurationInSeconds': 0
    },
    'InferenceRecommendations': [
        {
            'Metrics': {
                'CostPerHour': 0.20399999618530273,
                'CostPerInference': 5.246913588052848e-06,
                'MaximumInvocations': 648,
                'ModelLatency': 263596
            },
            'EndpointConfiguration': {
                'EndpointName': 'endpoint-name',
                'VariantName': 'variant-name',
                'InstanceType': 'ml.c5.xlarge',
                'InitialInstanceCount': 1
            },
            'ModelConfiguration': {
                'Compiled': False,
                'EnvironmentParameters': []
            }
        },
        {
            'Metrics': {
                'CostPerHour': 0.11500000208616257,
                'CostPerInference': 2.92620870823157e-06,
                'MaximumInvocations': 655,
                'ModelLatency': 826019
            }
        }
    ]
}
```
The first few lines provide information about the instance recommendation job itself. This includes the job name, role ARN, and creation and deletion times.

The `InferenceRecommendations` dictionary contains a list of Inference Recommender instance recommendations.

The `EndpointConfiguration` nested dictionary contains the instance type (`InstanceType`) recommendation along with the endpoint and variant name (a deployed AWS machine learning model) that was used during the recommendation job. You can use the endpoint and variant name for monitoring in Amazon CloudWatch Events. See Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663) for more information.

The `Metrics` nested dictionary contains information about the estimated cost per hour (`CostPerHour`) for your real-time endpoint in US dollars, the estimated cost per inference (`CostPerInference`) in US dollars for your real-time endpoint, the expected maximum number of `InvokeEndpoint` requests per minute sent to the endpoint (`MaxInvocations`), and the model latency (`ModelLatency`), which is the interval of time (in milliseconds) that your model took to respond to SageMaker. The model latency includes the local communication times taken to send the request and to fetch the response from the container of a model and the time taken to complete the inference in the container.
AWS CLI

Once an instance recommendation is complete, you can use `describe-inference-recommendations-job` to get the job details and recommended instance types. Provide the job name that you used when you created the instance recommendation job.

```
aws sagemaker describe-inference-recommendations-job
   --job-name <job-name>
   --region <aws-region>
```

The JSON response similar should resemble the following:

```
{
    'JobName': 'job-name',
    'JobDescription': 'job-description',
    'JobType': 'Default',
    'Status': 'COMPLETED',
    'CreationTime': datetime.datetime(2021, 10, 26, 20, 4, 57, 627000, tzinfo=tzlocal()),
    'LastModifiedTime': datetime.datetime(2021, 10, 26, 20, 25, 1, 997000, tzinfo=tzlocal()),
    'InputConfig': {
        'JobDurationInSeconds': 0
    },
    'InferenceRecommendations': [
        {
            'Metrics': {
                'CostPerHour': 0.20399999618530273,
                'CostPerInference': 5.246913588052848e-06,
                'MaximumInvocations': 648,
                'ModelLatency': 263596
            },
            'EndpointConfiguration': {
                'EndpointName': 'endpoint-name',
                'VariantName': 'variant-name',
                'InstanceType': 'ml.c5.xlarge',
                'InitialInstanceCount': 1
            },
            'ModelConfiguration': {
                'Compiled': False,
                'EnvironmentParameters': []
            }
        },
        {
            'Metrics': {
                'CostPerHour': 0.11500000208616257,
                'CostPerInference': 2.92620870823157e-06,
                'MaximumInvocations': 655,
                'ModelLatency': 826019
            },
            'EndpointConfiguration': {
                'EndpointName': 'endpoint-name',
                'VariantName': 'variant-name',
                'InstanceType': 'ml.c5d.large',
                'InitialInstanceCount': 1
            },
            'ModelConfiguration': {
                'Compiled': False,
                'EnvironmentParameters': []
            }
        }
    ]
}
```
The first few lines provide information about the instance recommendation job itself. This includes the job name, role ARN, creation, and deletion time.

The `InferenceRecommendations` dictionary contains a list of Inference Recommender instance recommendations.

The `EndpointConfiguration` nested dictionary contains the instance type (`InstanceType`) recommendation along with the endpoint and variant name (a deployed AWS machine learning model) used during the recommendation job. You can use the endpoint and variant name for monitoring in Amazon CloudWatch Events. See Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663) for more information.

The `Metrics` nested dictionary contains information about the estimated cost per hour (`CostPerHour`) for your real-time endpoint in US dollars, the estimated cost per inference (`CostPerInference`) in US dollars for your real-time endpoint, the expected maximum number of `InvokeEndpoint` requests per minute sent to the endpoint (`MaxInvocations`), and the model latency (`ModelLatency`), which is the interval of time (in milliseconds) that your model took to respond to SageMaker. The model latency includes the local communication times taken to send the request and to fetch the response from the container of a model and the time taken to complete the inference in the container.

For more information about interpreting the results of your recommendation job, see Interpret recommendation results (p. 2732).

Amazon SageMaker Studio

The instance recommendations populate in a new `Inference recommendations` tab within Studio. It can take up to 45 minutes for the results to show up. This tab contains `Results` and `Details` column headings.

The `Details` column provides information about the instance recommendation job, such as the name of the instance recommendation, when the job was created (`Creation time`), and more. It
also provides **Settings** information, such as the maximum number of invocations that occurred per minute and information about the Amazon Resource Names used.

The **Results** column provides a **Deployment goals** and **SageMaker recommendations** window in which you can adjust the order that the results are displayed based on deployment importance. There are three dropdown menus that you can use to provide the level of importance of the **Cost**, **Latency**, and **Throughput** for your use case. For each goal (cost, latency, and throughput), you can set the level of importance: **Lowest Importance**, **Low Importance**, **Moderate importance**, **High importance**, or **Highest importance**.

Based on your selections of importance for each goal, Inference Recommender displays its top recommendation in the **SageMaker recommendation** field on the right of the panel, along with the estimated cost per hour and inference request. It also provides information about the expected model latency, maximum number of invocations, and the number of instances.

In addition to the top recommendation displayed, you can also see the same information displayed for all instances that Inference Recommender tested in the **All runs** section.

### Stop Your Instance Endpoint Recommendation

Stop your Inference Recommender instance recommendation jobs programmatically with the **StopInferenceRecommendationsJob** API or with Studio.

**AWS SDK for Python (Boto3)**

Specify the name of the instance recommendation job for the **JobName** field:

```python
sagemaker_client.stop_inference_recommendations_job(
    JobName='<INSERT>',
)
```

**AWS CLI**

Specify the job name of the instance recommendation job for the **--job-name** flag:

```bash
aws sagemaker stop-inference-recommendations-job --job-name <job-name>
```

**Amazon SageMaker Studio**

Close the tab in which you initiated the instance recommendation to stop your Inference Recommender instance recommendation.

### Get an instance recommendation for an existing endpoint

Inference recommendation jobs run a set of load tests on recommended instance types and existing endpoint. Inference recommendation jobs use performance metrics that are based on load tests using the sample data you provided during model version registration.

You can benchmark and get instance recommendations for an existing SageMaker Inference endpoint to help you improve the performance of your endpoint. The procedure of getting recommendations for an existing SageMaker Inference endpoint is similar to the procedure for getting instance recommendations without an endpoint. There are several feature exclusions to take note of when benchmarking an existing endpoint:

- You can only use one existing endpoint per Inference Recommender job.
- You can only have one variant on your endpoint.
- You can't use an endpoint that enables autoscaling.
This functionality is only supported for Real-Time Inference.
This functionality doesn't support Real-Time Multi-Model Endpoints.

Warning
We strongly recommend that you don't run an Inference Recommender job on a production endpoint that handles live traffic. The synthetic load during benchmarking can affect your production endpoint and cause throttling or provide inaccurate benchmark results. We recommend that you use a non-production or developer endpoint for comparison purposes.

The following sections demonstrate how to use Amazon SageMaker Inference Recommender to create an instance recommendation for an existing endpoint based on your model type using the AWS SDK for Python (Boto3) and the AWS CLI.

Note
Before you create an Inference Recommender recommendation job, make sure you have satisfied the Prerequisites (p. 2713).

Prerequisites
If you don’t already have a SageMaker Inference endpoint, you can either get an instance recommendation without an endpoint, or you can create a Real-Time Inference endpoint by following the instructions in Create your endpoint and deploy your model.

Create an instance recommendation job for an existing endpoint
Create an instance recommendation programmatically using AWS SDK for Python (Boto3), or the AWS CLI. Specify a job name for your instance recommendation, the name of an existing SageMaker Inference endpoint, an AWS IAM role ARN, an input configuration, and your model package ARN from when you registered your model with the model registry.

AWS SDK for Python (Boto3)
Use the CreateInferenceRecommendationsJob API to get an instance endpoint recommendation. Set the JobType field to 'Default' for instance endpoint recommendation jobs. In addition, provide the following:

• Provide a name for your Inference Recommender recommendation job for the JobName field. The Inference Recommender job name must be unique within the AWS Region and within your AWS account.
• The Amazon Resource Name (ARN) of an IAM role that enables Inference Recommender to perform tasks on your behalf. Define this for the RoleArn field.
• The ARN of the versioned model package you created when you registered your model with the model registry. Define this for ModelPackageVersionArn in the InputConfig field.
• Provide the name of an existing SageMaker Inference endpoint that you want to benchmark in Inference Recommender for Endpoints in the InputConfig field.

Import the AWS SDK for Python (Boto3) package and create a SageMaker client object using the client class. If you followed the steps in the Prerequisites section, the model package group ARN was stored in a variable named model_package_arn.

```python
# Create a low-level SageMaker service client.
import boto3
aws_region = '<region>'
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Provide your model package ARN that was created when you registered your # model with Model Registry
test_model_package_arn = '<model-package-arn>'
```

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# Provide a unique job name for SageMaker Inference Recommender job
job_name = '<job-name>'

# Inference Recommender job type. Set to Default to get an initial recommendation
job_type = 'Default'

# Provide an IAM Role that gives SageMaker Inference Recommender permission to
# access AWS services
role_arn = '<arn:aws:iam::<account>:role/*>'

# Provide endpoint name for your endpoint that want to benchmark in Inference Recommender
epsilon_name = '<existing-endpoint-name>'

sagemaker_client.create_inference_recommendations_job(
    JobName = job_name,
    JobType = job_type,
    RoleArn = role_arn,
    InputConfig = {
        'ModelPackageVersionArn': model_package_arn,
        'Endpoints': [{"EndpointName": endpoint_name}]
    }
)

See the Amazon SageMaker API Reference Guide for a full list of optional and required arguments
you can pass to CreateInferenceRecommendationsJob.

AWS CLI

Use the create-inference-recommendations-job API to get an instance endpoint recommendation. Set the job-type field to 'Default' for instance endpoint recommendation jobs. In addition, provide the following:

- Provide a name for your Inference Recommender recommendation job for the job-name field. The Inference Recommender job name must be unique within the AWS Region and within your AWS account.
- The Amazon Resource Name (ARN) of an IAM role that enables Amazon SageMaker Inference Recommender to perform tasks on your behalf. Define this for the role-arn field.
- The ARN of the versioned model package you created when you registered your model with Model Registry. Define this for ModelPackageVersionArn in the input-config field.
- Provide the name of an existing SageMaker Inference endpoint that you want to benchmark in Inference Recommender for Endpoints in the input-config field.

aws sagemaker create-inference-recommendations-job
    --region <region>\n    --job-name <job_name>\n    --job-type Default\n    --role-arn arn:aws:iam::<account:role/*>\n    --input-config "{
        "Endpoints": [{"EndpointName": <endpoint_name>}]}
"

Get your instance recommendation job results

You can collect the results of your instance recommendation job programmatically with the same procedure for standard instance recommendation jobs. For more information, see Get Your Instance Recommendation Job Results (p. 2722).
When you get instance recommendation job results for an existing endpoint, you should receive a JSON response similar to the following:

```
{
  "JobName": "job-name",
  "JobType": "Default",
  "RoleArn": "iam-role-arn",
  "Status": "COMPLETED",
  "CreationTime": 1664922919.2,
  "LastModifiedTime": 1664924208.291,
  "InputConfig": {
    "Endpoints": [
      {
        "EndpointName": "endpoint-name"
      }
    ]
  },
  "InferenceRecommendations": [
    {
      "Metrics": {
        "CostPerHour": 0.7360000014305115,
        "CostPerInference": 7.456940238625975e-06,
        "MaxInvocations": 1645,
        "ModelLatency": 171
      },
      "EndpointConfiguration": {
        "EndpointName": "sm-endpoint-name",
        "VariantName": "variant-name",
        "InstanceType": "ml.g4dn.xlarge",
        "InitialInstanceCount": 1
      },
      "ModelConfiguration": {
        "EnvironmentParameters": [
          {
            "Key": "TS_DEFAULT_WORKERS_PER_MODEL",
            "ValueType": "string",
            "Value": "4"
          }
        ]
      }
    }
  ],
  "EndpointPerformances": [
    {
      "Metrics": {
        "MaxInvocations": 184,
        "ModelLatency": 1312
      },
      "EndpointConfiguration": {
        "EndpointName": "endpoint-name"
      }
    }
  ]
}
```

The first few lines provide information about the instance recommendation job itself. This includes the job name, role ARN, and creation and latest modification times.

The **InferenceRecommendations** dictionary contains a list of Inference Recommender instance recommendations.
The `EndpointConfiguration` nested dictionary contains the instance type (`InstanceType`) recommendation along with the endpoint and variant name (a deployed AWS machine learning model) that was used during the recommendation job.

The `Metrics` nested dictionary contains information about the estimated cost per hour (`CostPerHour`) for your real-time endpoint in US dollars, the estimated cost per inference (`CostPerInference`) in US dollars for your real-time endpoint, the expected maximum number of `InvokeEndpoint` requests per minute sent to the endpoint (`MaxInvocations`), and the model latency (`ModelLatency`), which is the interval of time (in milliseconds) that your model took to respond to SageMaker. The model latency includes the local communication times taken to send the request and to fetch the response from the container of a model and the time taken to complete the inference in the container.

The `EndpointPerformances` nested dictionary contains the name of your existing endpoint on which the recommendation job was run (`EndpointName`) and the performance metrics for your endpoint (`MaxInvocations` and `ModelLatency`).

### Stop your instance endpoint recommendation

You can stop your Inference Recommender instance recommendation jobs programmatically with the same procedure for standard instance recommendation jobs. For more information, see [Stop Your Instance Endpoint Recommendation](#).

### Get compiled recommendations with Neo

In Inference Recommender, you can compile your model with Neo and get endpoint recommendations for your compiled model. SageMaker Neo is a service that can optimize your model for a target hardware platform (that is, a specific instance type or environment). Optimizing a model with Neo might improve the performance of your hosted model.

For Neo-supported frameworks and containers, Inference Recommender automatically suggests Neo-optimized recommendations. To be eligible for Neo compilation, your input must meet the following prerequisites:

- You are using a SageMaker owned [DLC](#) or XGBoost container.
- You are using a framework version supported by Neo. For the framework versions supported by Neo, see Cloud Instances (p. 3079) in the SageMaker Neo documentation.
- Neo requires that you provide a correct input data shape for your model. You can specify this data shape as the `DataInputConfig` in the `InferenceSpecification` when you create a model package. For information about the correct data shapes for each framework, see Prepare Model for Compilation in the SageMaker Neo documentation.

The following example shows how to specify the `DataInputConfig` field in the `InferenceSpecification`, where `data_input_configuration` is a variable that contains the data shape in dictionary format (for example, `{'input':[1,1024,1024,3]}`).

```json
"InferenceSpecification": {
  "Containers": [ {
    "Image": dlc_uri,
    "Framework": framework.upper(),
    "FrameworkVersion": framework_version,
    "NearestModelName": model_name,
    "ModelInput": {"DataInputConfig": data_input_configuration},
  }
  ],
  "SupportedContentTypes": input_mime_types,  # required, must be non-null
  "SupportedResponseMIMETypes": [],
  "SupportedRealtimeInferenceInstanceTypes": supported_realtime_inference_types,  # optional
```
If these conditions are met in your request, then Inference Recommender runs scenarios for both compiled and uncompiled versions of your model, giving you multiple recommendation combinations to choose from. You can compare the configurations for compiled and uncompiled versions of the same instance recommendation and determine which one best suits your use case. The recommendations are ranked by cost per inference.

To get the Neo compilation recommendations, you don't have to do any additional configuration besides making sure that your input meets the above requirements. Inference Recommender automatically runs Neo compilation on your model if your input meets the requirements, and you'll receive a response that includes Neo recommendations.

If you run into errors during your Neo compilation, see Troubleshoot Neo Compilation Errors (p. 3124).

The following table is an example of a response you might get from an Inference Recommender job that includes recommendations for compiled models. If the InferenceSpecificationName field is None, then the recommendation is an uncompiled model. The last row, where the value for the InferenceSpecificationName field is neo-00011122-2333-4445-5566-677788899900, is for a model compiled with Neo. The value in the field is the name of the Neo job used to compile and optimize your model.

<table>
<thead>
<tr>
<th>EndpointName</th>
<th>InstanceType</th>
<th>InitialInstanceCount</th>
<th>EnvironmentParameters</th>
<th>CostPerHour</th>
<th>CostPerInference</th>
<th>MaxInVocations</th>
<th>ModelLatency</th>
<th>InferenceSpecificationName</th>
</tr>
</thead>
<tbody>
<tr>
<td>sm-epc-example-00011122</td>
<td>ml.c5.9xlarge</td>
<td>1</td>
<td>[]</td>
<td>1.836</td>
<td>9.15E-07</td>
<td>33456</td>
<td>7</td>
<td>None</td>
</tr>
<tr>
<td>sm-epc-example-11122233</td>
<td>ml.c5.2xlarge</td>
<td>1</td>
<td>[]</td>
<td>0.408</td>
<td>2.11E-07</td>
<td>32211</td>
<td>21</td>
<td>None</td>
</tr>
<tr>
<td>sm-epc-example-22233344</td>
<td>ml.c5.xlarge</td>
<td>1</td>
<td>[]</td>
<td>0.204</td>
<td>1.86E-07</td>
<td>18276</td>
<td>92</td>
<td>None</td>
</tr>
<tr>
<td>sm-epc-example-33344455</td>
<td>ml.c5.xlarge</td>
<td>1</td>
<td>[]</td>
<td>0.204</td>
<td>1.60E-07</td>
<td>21286</td>
<td>42</td>
<td>neo-00011122-2333-4445-5566-677788899900</td>
</tr>
</tbody>
</table>

Get started

The general steps for creating an Inference Recommender job that includes Neo-optimized recommendations are as follows:

- Prepare your ML model for compilation. For more information, see Prepare Model for Compilation in the Neo documentation.
- Package your model in a model archive (.tar.gz file).
- Create a sample payload archive.
- Register your model in Model Registry.
- Create an Inference Recommender job.
- View the results of the Inference Recommender job and choose a configuration.
- Debug compilation failures, if any. For more information, see Troubleshoot Neo Compilation Errors.

For an example that demonstrates the previous workflow and how to get Neo-optimized recommendations using XGBoost, see the following example notebook. For an example that show how to get Neo-optimized recommendations using TensorFlow, see the following example notebook.
Interpret recommendation results

Each Inference Recommender job result includes InstanceType, InitialInstanceCount, and EnvironmentParameters, which are tuned environment variable parameters for your container to improve its latency and throughput. The results also include performance and cost metrics such as MaxInvocations, ModelLatency, CostPerHour, and CostPerInference.

In the table below we provide a description of these metrics. These metrics can help you narrow down your search for the best endpoint configuration that suits your use case. For example, if your motivation is overall price performance with an emphasis on throughput, then you should focus on CostPerInference.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
<th>Use case</th>
</tr>
</thead>
<tbody>
<tr>
<td>ModelLatency</td>
<td>The interval of time taken by a model to respond as viewed from SageMaker. This interval includes the local communication times taken to send the request and to fetch the response from the container of a model and the time taken to complete the inference in the container. Units: Milliseconds</td>
<td>Latency sensitive workloads such as ad serving and medical diagnosis</td>
</tr>
<tr>
<td>MaximumInvocations</td>
<td>The maximum number of InvokeEndpoint requests sent to a model endpoint in a minute.</td>
<td>Throughput-focused workloads such as video processing or batch inference</td>
</tr>
<tr>
<td>CostPerHour</td>
<td>The estimated cost per hour for your real-time endpoint.</td>
<td>Cost sensitive workloads with no latency deadlines</td>
</tr>
<tr>
<td>CostPerInference</td>
<td>The estimated cost per inference call for your real-time endpoint.</td>
<td>Maximize overall price performance with a focus on throughput</td>
</tr>
</tbody>
</table>

In some cases you might want to explore other SageMaker Endpoint Invocation metrics such as CPUUtilization. Every Inference Recommender job result includes the names of endpoints spun up during the load test. You can use CloudWatch to review the logs for these endpoints even after they've been deleted.

The following image is an example of CloudWatch metrics and charts you can review for a single endpoint from your recommendation result. This recommendation result is from a Default job. The way to interpret the scalar values from the recommendation results is that they are based on the time point when the Invocations graph first begins to level out. For example, the ModelLatency value reported is at the beginning of the plateau around 03:00:31.
For full descriptions of the CloudWatch metrics used in the preceding charts, see SageMaker Endpoint Invocation metrics.

See the Amazon SageMaker Inference Recommender - CloudWatch Metrics Jupyter notebook in the amazon-sagemaker-examples Github repository for an example of how to use the AWS SDK for Python (Boto3) to explore CloudWatch metrics for your endpoints.

Run a custom load test

Amazon SageMaker Inference Recommender load tests conduct extensive benchmarks based on production requirements for latency and throughput, custom traffic patterns, and instances (up to 10) that you select.

The following sections demonstrate how to create, describe, and stop a load test programmatically using AWS SDK for Python (Boto3) and the AWS CLI, and interactively using Amazon SageMaker Studio.

Create a Load Test Job

Create a load test programmatically using AWS SDK for Python (Boto3), with the AWS CLI, or interactively using Studio. As with Inference Recommender instance recommendations, specify a job name for your load test, an AWS IAM role ARN, an input configuration, and your model package ARN when you registered your model with the model registry. Load tests require that you also specify a traffic pattern and stopping conditions.

AWS SDK for Python (Boto3)

Use the CreateInferenceRecommendationsJob API to create an Inference Recommender load test. Specify Advanced for the JobType field and provide:

- A job name for your load test (JobName). The job name must be unique within your AWS Region and within your AWS account.
• The Amazon Resource Name (ARN) of an IAM role that enables Inference Recommender to perform tasks on your behalf. Define this for the RoleArn field.

• An endpoint configuration dictionary (InputConfig) where you specify the following:
  • For TrafficPattern, do the following:
    • For TrafficType, specify PHASES.
    • For Phases, specify the InitialNumberOfUsers (how many concurrent users to start with, with a minimum of 1 and a maximum of 3), SpawnRate (the number of users to be spawned in a minute for a specific phase of load testing, with a minimum of 0 and maximum of 3), and DurationInSeconds (how long the traffic phase should be, with a minimum of 120 and maximum of 3600).

  Note
  A user is defined as a system-generated actor that runs in a loop and invokes requests to an endpoint as part of Inference Recommender. For a typical XGBoost container running on an ml.c5.large instance, endpoints can reach 30,000 invocations per minute (500 tps) with just 15-20 users.

  • For ResourceLimit, specify MaxNumberOfTests (the maximum number of benchmarking load tests for an Inference Recommender job, with a minimum of 1 and a maximum of 10) and MaxParallelOfTests (the maximum number of parallel benchmarking load tests for an Inference Recommender job, with a minimum of 1 and a maximum of 10).

  • For EndpointConfigurations, specify the InstanceType, or the instance type on which you want to run your load tests.

  • A stopping conditions dictionary (StoppingConditions), where if any of the conditions are met, the Inference Recommender job stops. For this example, specify the following fields in the dictionary:
    • For MaxInvocations, specify the maximum number of requests per minute expected for the endpoint, with a minimum of 1 and a maximum of 30,000.
    • For ModelLatencyThresholds, specify Percentile (the model latency percentile threshold) and ValueInMilliseconds (the model latency percentile value in milliseconds).

# Create a low-level SageMaker service client.
import boto3
aws_region=<INSERT>
sagemaker_client=boto3.client('sagemaker', region=aws_region)

# Provide a name to your recommendation based on load testing
load_test_job_name=<INSERT>

# Provide the name of the sagemaker instance type
instance_type=<INSERT>

# Provide the IAM Role that gives SageMaker permission to access AWS services
role_arn='arn:aws:iam::<account>::role/*'

# Provide your model package ARN that was created when you registered your
# model with Model Registry
model_package_arn='arn:aws:sagemaker::<region>::<account>::role/*'

sagemaker_client.create_inference_recommendations_job(
    JobName=load_test_job_name,
    JobType="Advanced",
    RoleArn=role_arn,
    InputConfig={
        'ModelPackageVersionArn': model_package_arn,
        "JobDurationInSeconds": 7200,
        'TrafficPattern': {
            'TrafficType': 'PHASES',
        
```
'Phases': [
  {
    'InitialNumberOfUsers': 1,
    'SpawnRate': 1,
    'DurationInSeconds': 120
  },
  {
    'InitialNumberOfUsers': 1,
    'SpawnRate': 1,
    'DurationInSeconds': 120
  }
],
'ResourceLimit': {
  'MaxNumberOfTests': 10,
  'MaxParallelOfTests': 3
},
"EndpointConfigurations": [{
  'InstanceType': 'ml.c5.xlarge'
},
  {
    'InstanceType': 'ml.m5.xlarge'
  },
  {
    'InstanceType': 'ml.r5.xlarge'
  }
},
'StoppingConditions':{
  'MaxInvocations': 1000,
  'ModelLatencyThresholds':[
    {'Percentile': 'P95',
     'ValueInMilliseconds': 100
  ]
  }
)}

See the [Amazon SageMaker API Reference Guide](https://docs.aws.amazon.com/sagemaker/latest/dg/API_CreateInferenceRecommendationsJob.html) for a full list of optional and required arguments you can pass to `CreateInferenceRecommendationsJob`.

**AWS CLI**

Use the `create-inference-recommendations-job` API to create an Inference Recommender load test. Specify `Advanced` for the `JobType` field and provide:

- A job name for your load test (`job-name`). The job name must be unique within your AWS region and within your AWS account.
- The Amazon Resource Name (ARN) of an IAM role that enables Inference Recommender to perform tasks on your behalf. Define this for the `role-arn` field.
- An endpoint configuration dictionary (`input-config`) where you specify the following:
  - For `TrafficPattern`, do the following:
    - For `TrafficType`, specify `PHASES`.
    - For `Phases`, specify the `InitialNumberOfUsers` (how many concurrent users to start with, with a minimum of 1 and a maximum of 3), `SpawnRate` (the number of users to be spawned in a minute for a specific phase of load testing, with a minimum of 0 and maximum of 3), and `DurationInSeconds` (how long the traffic phase should be, with a minimum of 120 and maximum of 3600).

**Note**

A user is defined as a system-generated actor that runs in a loop and invokes requests to an endpoint as part of Inference Recommender. For a typical XGBoost container running on an `ml.c5.large` instance, endpoints can reach 30,000 invocations per minute (500 tps) with just 15-20 users.
• For **ResourceLimit**, specify **MaxNumberOfTests** (the maximum number of benchmarking load tests for an Inference Recommender job, with a minimum of 1 and a maximum of 10) and **MaxParallelOfTests** (the maximum number of parallel benchmarking load tests for an Inference Recommender job, with a minimum of 1 and a maximum of 10).

• For **EndpointConfigurations**, specify the **InstanceType**, or the instance type on which you want to run your load tests.

• A stopping conditions dictionary (**stopping-conditions**), where if any of the conditions are met, the Inference Recommender job stops. For this example, specify the following fields in the dictionary:

  • For **MaxInvocations**, specify the maximum number of requests per minute expected for the endpoint, with a minimum of 1 and a maximum of 30,000.

  • For **ModelLatencyThresholds**, specify **Percentile** (the model latency percentile threshold) and **ValueInMilliseconds** (the model latency percentile value in milliseconds).

```bash
aws sagemaker create-inference-recommendations-job
--region <region> 
--job-name <job-name>
--job-type ADVANCED
--role-arn arn:aws:iam::<account>:role/*
--input-config "{
  "JobDurationInSeconds": 7200,
  "TrafficPattern": {
    "TrafficType": "PHASES",
    "Phases": [
      { "InitialNumberOfUsers": 1,
        "SpawnRate": 60,
        "DurationInSeconds": 300
      }
    ]
  },
  "ResourceLimit": {
    "MaxNumberOfTests": 10,
    "MaxParallelOfTests": 3
  },
  "EndpointConfigurations": [
    { "InstanceType": "ml.c5.xlarge" },
    { "InstanceType": "ml.m5.xlarge" },
    { "InstanceType": 'ml.r5.xlarge' }
  ]
}" 
--stopping-conditions "{
  "MaxInvocations": 1000,
  "ModelLatencyThresholds": [
    { "Percentile": "P95",
      "ValueInMilliseconds": 100
    }
  ]
}" 
```
Amazon SageMaker Studio

Create a load test with Studio.

1. In the left sidebar of Studio, choose the Components and registries icon.
2. Select Inference Recommender Jobs from the dropdown list. A new tab titled Create inference recommender job opens in the right pane.
3. Select the name of your model group from the dropdown Model group field. The list includes all the model groups registered with the model registry in your account, including models registered outside of Studio.
4. Select a model version from the dropdown Model version field.
5. Choose Continue.
6. Provide a name for the job in the Name field.
7. (Optional) Provide a description of your job in the Description field.
8. Choose an IAM role that grants Inference Recommender permission to access AWS services. You can create a role and attach the AmazonSageMakerFullAccess IAM managed policy to accomplish this, or you can let Studio create a role for you.
9. Choose Stopping Conditions to expand the available input fields. Provide a set of conditions for stopping a deployment recommendation.
   a. Specify the maximum number of requests per minute expected for the endpoint in the Max Invocations Per Minute field.
   b. Specify the model latency threshold in microseconds in the Model Latency Threshold field. The Model Latency Threshold depicts the interval of time taken by a model to respond as viewed from Inference Recommender. The interval includes the local communication time taken to send the request and to fetch the response from the model container and the time taken to complete the inference in the container.
10. Choose Traffic Pattern to expand the available input fields.
    a. Set the initial number of virtual users by specifying an integer in the Initial Number of Users field.
    b. Provide an integer number for the Spawn Rate field. The spawn rate sets the number of users created per second.
    c. Set the duration for the phase in seconds by specifying an integer in the Duration field.
    d. (Optional) Add additional traffic patterns. To do so, choose Add.
11. Choose the Additional setting to reveal the Max test duration field. Specify, in seconds, the maximum time a test can take during a job. New jobs are not scheduled after the defined duration. This helps ensure jobs that are in progress are not stopped and that you only view completed jobs.
12. Choose Continue.
13. Choose Selected Instances.
14. In the Instances for benchmarking field, choose Add instances to test. Select up to 10 instances for Inference Recommender to use for load testing.
15. Choose Additional settings.
    a. Provide an integer that sets an upper limit on the number of tests a job can make for the Max number of tests field. Note that each endpoint configuration results in a new load test.
    b. Provide an integer for the Max parallel test field. This setting defines an upper limit on the number of load tests that can run in parallel.
16. Choose Submit.

The load test can take up to 2 hours.
**Warning**
Do not close this tab. If you close this tab, you cancel the Inference Recommender load test job.

### Get Your Load Test Results

You can collect metrics across all load tests once the load tests are done programatically with AWS SDK for Python (Boto3), the AWS CLI, or Studio.

**AWS SDK for Python (Boto3)**

Collect metrics with the `DescribeInferenceRecommendationsJob` API. Specify the job name of the load test for the `JobName` field:

```python
load_test_response = sagemaker_client.describe_inference_recommendations_job(
    JobName=load_test_job_name)
```

Print the response object.

```python
load_test_response['Status']
```

This returns a JSON response similar to the following:

```json
{
    'JobName': 'job-name',
    'JobDescription': 'job-description',
    'JobType': 'Advanced',
    'Status': 'COMPLETED',
    'CreationTime': datetime.datetime(2021, 10, 26, 19, 38, 30, 957000, tzinfo=tzlocal()),
    'LastModifiedTime': datetime.datetime(2021, 10, 26, 19, 46, 31, 399000, tzinfo=tzlocal()),
    'InputConfig': {
        'JobDurationInSeconds': 7200,
        'TrafficPattern': {
            'TrafficType': 'PHASES'
        },
        'ResourceLimit': {
            'MaxNumberOfTests': 100,
            'MaxParallelOfTests': 100
        },
        'EndpointConfigurations': [
            {
                'InstanceType': 'ml.c5d.xlarge'
            }
        ],
        'StoppingConditions': {
            'MaxInvocations': 1000,
            'ModelLatencyThresholds': [
                {
                    'Percentile': 'P95',
                    'ValueInMilliseconds': 100
                }
            ],
            'InferenceRecommendations': [
                {
                    'Metrics': {
                        'CostPerHour': 0.6899999976158142,
                        'CostPerInference': 1.0332434612791985e-05,
                        'MaximumInvocations': 1113,
```

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The first few lines provide information about the load test job itself. This includes the job name, role ARN, creation, and deletion time.

The InferenceRecommendations dictionary contains a list of Inference Recommender instance recommendations.

The EndpointConfiguration nested dictionary contains the instance type (InstanceType) recommendation along with the endpoint and variant name (a deployed AWS machine learning model) used during the recommendation job. You can use the endpoint and variant name for monitoring in Amazon CloudWatch Events. See Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663) for more information.

The EndpointConfiguration nested dictionary also contains the instance count (InitialInstanceCount) recommendation. This is the number of instances that you should provision in the endpoint to meet the MaxInvocations specified in the StoppingConditions. For example if the InstanceType is ml.m5.large and the InitialInstanceCount is 2, then you should provision 2 ml.m5.large instances for your endpoint so that it can handle the TPS specified in the MaxInvocations stopping condition.

The Metrics nested dictionary contains information about the estimated cost per hour (CostPerHour) for your real-time endpoint in US dollars, the estimated cost per inference (CostPerInference) for your real-time endpoint, the maximum number of InvokeEndpoint requests sent to the endpoint, and the model latency (ModelLatency), which is the interval of time (in microseconds) that your model took to respond to SageMaker. The model latency includes the local communication times taken to send the request and to fetch the response from the model container and the time taken to complete the inference in the container.

AWS CLI

Collect metrics with the describe-inference-recommendations-job API. Specify the job name of the load test for the job-name flag:

```
aws sagemaker describe-inference-recommendations-job --job-name <job-name>
```

This returns a response similar to the following:

```json
{
  ...
}
```
The first few lines provide information about the load test job itself. This includes the job name, role ARN, creation, and deletion time.
The `InferenceRecommendations` dictionary contains a list of Inference Recommender instance recommendations.

The `EndpointConfiguration` nested dictionary contains the instance type (`InstanceType`) recommendation along with the endpoint and variant name (a deployed AWS machine learning model) used during the recommendation job. You can use the endpoint and variant name for monitoring in Amazon CloudWatch Events. See Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663) for more information.

The `Metrics` nested dictionary contains information about the estimated cost per hour (`CostPerHour`) for your real-time endpoint in US dollars, the estimated cost per inference (`CostPerInference`) for your real-time endpoint, the maximum number of `InvokeEndpoint` requests sent to the endpoint, and the model latency (`ModelLatency`), which is the interval of time (in microseconds) that your model took to respond to SageMaker. The model latency includes the local communication times taken to send the request and to fetch the response from the model container and the time taken to complete the inference in the container.

Amazon SageMaker Studio

The recommendations populate in a new tab called **Inference recommendations** within Studio. It can take up to 2 hours for the results to show up. This tab contains **Results** and **Details** columns.

The Details column provides information about the load test job, such as the name given to the load test job, when the job was created (**Creation time**), and more. It also contains **Settings** information, such as the maximum number of invocation that occurred per minute and information about the Amazon Resource Names used.

The Results column provides **Deployment goals** and **SageMaker recommendations** windows in which you can adjust the order in which results are displayed based on deployment importance. There are three dropdown menus in which you can provide the level of importance of the **Cost**, **Latency**, and **Throughput** for your use case. For each goal (cost, latency, and throughput), you can set the level of importance: **Lowest Importance**, **Low Importance**, **Moderate importance**, **High importance**, or **Highest importance**.

Based on your selections of importance for each goal, Inference Recommender displays its top recommendation in the **SageMaker recommendation** field on the right of the panel, along with the estimated cost per hour and inference request. It also provides Information about the expected model latency, maximum number of invocations, and the number of instances.

In addition to the top recommendation displayed, you can also see the same information displayed for all instances that Inference Recommender tested in the **All runs** section.

**Stop Your Load Test**

Stop your load test jobs programmatically with the StopInferenceRecommendationsJob API or with Studio.

AWS SDK for Python (Boto3)

Specify the job name of the load test for the `JobName` field:

```python
sagemaker_client.stop_inference_recommendations_job(
    JobName='<INSERT>'
)
```

AWS CLI

Specify the job name of the load test for the `job-name` flag:
aws sagemaker stop-inference-recommendations-job --job-name <job-name>

Amazon SageMaker Studio

Close the tab where you initiated your custom load job to stop your Inference Recommender load test.

Troubleshoot Inference Recommender errors

This section contains information about how to understand and prevent common errors, the error messages they generate, and guidance on how to resolve these errors.

How to troubleshoot

You can attempt to resolve your error by going through the following steps:

- Check if you've covered all the prerequisites to use Inference Recommender. See the Inference Recommender Prerequisites.
- Check that you are able to deploy your model from Model Registry to an endpoint and that it can process your payloads without errors. See Deploy a Model from the Registry.
- When you kick off an Inference Recommender job, you should see endpoints being created in the console and you can review the CloudWatch logs.

Common errors

Review the following table for common Inference Recommender errors and their solutions.

<table>
<thead>
<tr>
<th>Error</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specify Domain in the Model Package version 1. Domain is a mandatory parameter for the job.</td>
<td>Make sure you provide the ML Domain or OTHER if unknown.</td>
</tr>
<tr>
<td>Provided role ARN cannot be assumed and an AWSSecurityTokenServiceException error occurred.</td>
<td>Make sure the execution role provided has the necessary permissions specified in the prerequisites.</td>
</tr>
<tr>
<td>Specify Framework in the Model Package version 1. Framework is a mandatory parameter for the job.</td>
<td>Make sure you provide the ML Framework or OTHER if unknown.</td>
</tr>
<tr>
<td>Users at the end of prev phase is 0 while initial users of current phase is 1.</td>
<td>Users here refers to virtual users or threads used to send requests. Each phase starts with A users and ends with B users such that B &gt; A. Between sequential phases, x_1 and x_2, we require that abs(x_2.A - x_1.B) &lt;= 3 and &gt;= 0.</td>
</tr>
<tr>
<td>Total Traffic duration (across) should not be more than Job duration.</td>
<td>The total duration of all your Phases cannot exceed the Job duration.</td>
</tr>
<tr>
<td>Burstable instance type ml.t2.medium is not allowed.</td>
<td>Inference Recommender doesn't support load testing on t2 instance family because burstable instances do not provide consistent performance.</td>
</tr>
<tr>
<td>ResourceLimitExceeded when calling CreateEndpoint operation</td>
<td>You have exceeded a SageMaker resource limit. For example, Inference Recommender might be</td>
</tr>
<tr>
<td>Error</td>
<td>Solution</td>
</tr>
<tr>
<td>--------------------------------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Error</td>
<td>unable to provision endpoints for benchmarking if the account has reached the endpoint quota. For more information about SageMaker limits and quotas, see Amazon SageMaker endpoints and quotas.</td>
</tr>
<tr>
<td>ModelError when calling InvokeEndpoint</td>
<td>A model error can happen for the following reasons:</td>
</tr>
<tr>
<td>operation</td>
<td>• The invocation timed out while waiting for a response from the model container.</td>
</tr>
<tr>
<td></td>
<td>• The model couldn't process the input payload.</td>
</tr>
<tr>
<td>PayloadError when calling InvokeEndpoint</td>
<td>A payload error can happen for the following reasons:</td>
</tr>
<tr>
<td>operation</td>
<td>• The payload source isn't in the Amazon S3 bucket.</td>
</tr>
<tr>
<td></td>
<td>• The payload is in a non-file object format.</td>
</tr>
<tr>
<td></td>
<td>• The payload is in an invalid file type. For example, a model expects an image type payload but is passed a text file.</td>
</tr>
<tr>
<td></td>
<td>• The payload is empty.</td>
</tr>
</tbody>
</table>

**Check CloudWatch**

When you kick off an Inference Recommender job, you should see endpoints being created in the console. Select one of the endpoints and view the CloudWatch logs to monitor for any 4xx/5xx errors. If you have a successful Inference Recommender job, you will be able to see the endpoint names as part of the results. Even if your Inference Recommender job is unsuccessful, you can still check the CloudWatch logs for the deleted endpoints by following the steps below:

1. Open the Amazon CloudWatch console at [https://console.aws.amazon.com/cloudwatch/](https://console.aws.amazon.com/cloudwatch/).
2. Select the Region in which you created the Inference Recommender job from the Region dropdown list in the top right.
3. In the navigation pane of CloudWatch, choose Logs, and then select Log groups.
4. Search for the log group called `/aws/sagemaker/Endpoints/sm-epc-*`. Select the log group based on your most recent Inference Recommender job.

**Check benchmarks**

When you kick off an Inference Recommender job, Inference Recommender creates several benchmarks to evaluate the performance of your model on different instance types. You can use the `ListInferenceRecommendationsJobSteps` API to view the details for all the benchmarks. If you have a failed benchmark, you can see the failure reasons as part of the results.

To use the `ListInferenceRecommendationsJobSteps` API, provide the following values:

- For JobName, provide the name of the Inference Recommender job.
- For StepType, use BENCHMARK to return details about the job's benchmarks.
- For Status, use FAILED to return details about only the failed benchmarks. For a list of the other status types, see the Status field in the `ListInferenceRecommendationsJobSteps` API.
# Create a low-level SageMaker service client.
import boto3
aws_region = '<region>'
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Provide the job name for the SageMaker Inference Recommender job
job_name = '<job-name>'

# Filter for benchmarks
step_type = 'BENCHMARK'

# Filter for benchmarks that have a FAILED status
status = 'FAILED'

response = sagemaker_client.list_inference_recommendations_job_steps(
    JobName = job_name,
    StepType = step_type,
    Status = status
)

You can print the response object to view the results. The preceding code example stored the response in a variable called response:

print(response)

---

Real-time inference

Real-time inference is ideal for inference workloads where you have real-time, interactive, low latency requirements. You can deploy your model to SageMaker hosting services and get an endpoint that can be used for inference. These endpoints are fully managed and support autoscaling (see Automatically Scale Amazon SageMaker Models (p. 2803)).

**Topics**
- Hosting options (p. 2744)
- Automatically Scale Amazon SageMaker Models (p. 2803)
- Host instance storage volumes (p. 2819)
- Safely update models in production (p. 2819)
- Best practices (p. 2826)
- Online Explainability with SageMaker Clarify (p. 2834)
- Invite real-time endpoints (p. 2851)

**Hosting options**

The following topics describe available SageMaker realtime hosting options along with how to set up, invoke, and delete each hosting option.

**Topics**
- Host a single model (p. 2745)
- Host multiple models in one container behind one endpoint (p. 2755)
- Host multiple models which use different containers behind one endpoint (p. 2782)
- Host models along with pre-processing logic as serial inference pipeline behind one endpoint (p. 2789)
Host a single model

Create, update, and delete real-time inference endpoints that host a single model with the AWS SDK for Python (Boto3), the SageMaker Python SDK, the SageMaker console, or the AWS CLI.

Topics

- Create your endpoint and deploy your model (p. 2745)
- Delete Endpoints and Resources (p. 2751)

Create your endpoint and deploy your model

There are several options to deploy a model using SageMaker hosting services. You can programmatically deploy a model using an AWS SDK (for example, the SDK for Python (Boto3)), the SageMaker Python SDK, the AWS CLI, or you can interactively deploy a model with the SageMaker console. The AWS SDK is a low-level API and supports Java, C++, Go, JavaScript, Node.js, PHP, Ruby, and Python whereas the SageMaker Python SDK is a high-level Python API. The following documentation demonstrates how to deploy a model using the AWS SDK for Python (Boto3) and the SageMaker Python SDK.

Deploying a model using SageMaker hosting services is a three-step process if you use AWS SDK for Python (Boto3), the AWS CLI, or the SageMaker console:

2. Create an endpoint configuration for an HTTPS endpoint.
3. Create an HTTPS endpoint.

Deploying a model using the SageMaker Python SDK does not require that you create an endpoint configuration. It is therefore a two-step process:

1. Create a model object from the Model class that can be deployed to an HTTPS endpoint.
2. Create an HTTPS endpoint with the Model object's pre-built deploy() method.

To use the proceeding code snippets, replace the italicized placeholder text in the example code with your own information.

Note

- SageMaker supports running (a) multiple models, (b) multiple variants of a model, or (c) combinations of models and variants on the same endpoint. Model variants can reference the same model inference container (i.e. run the same algorithm), but use different model artifacts (e.g., different model weight values based on other hyper-parameter configurations). In contrast, two different models may use the same algorithm, but focus on different business problems or underlying goals and may operate on different data sets.
- When you create an endpoint, SageMaker attaches an Amazon EBS storage volume to each ML compute instance that hosts the endpoint. The size of the storage volume depends on the instance type. For a list of instance types that SageMaker hosting service supports, see AWS Service Limits. For a list of the sizes of the storage volumes that SageMaker attaches to each instance, see Host instance storage volumes (p. 2819).
- Endpoints are scoped to an individual AWS account, and are not public. The URL does not contain the account ID, but SageMaker determines the account ID from the authentication token that is supplied by the caller.

For an example of how to use Amazon API Gateway and AWS Lambda to set up and deploy a web service that you can call from a client application that is not within the scope of your
Before you begin

Before you create and deploy a SageMaker model, locate and make note of the:

- AWS region where your Amazon S3 bucket is located
- Amazon S3 URI path where the model artifacts are stored
- IAM role for SageMaker
- Docker Amazon ECR URI registry path for the custom image that contains the inference code, or the framework and version of a built-in Docker image that is supported and by AWS.

For a list of AWS Services available in each AWS Region, see Region Maps and Edge Networks. See Creating IAM roles for information on how to create an IAM role.

**Important**

The Amazon S3 bucket where the model artifacts are stored must be in the same region as the model that you are creating.

The following demonstrates how to define the aforementioned parameters programmatically.

**AWS SDK for Python (Boto3)**

Import Boto3. Define your AWS region. Next, initialize a low-level SageMaker service client object using the Client class. This will make it easy to send and receive requests to AWS services. In addition, define the AWS role that gives SageMaker permission to access AWS services on your behalf:

```python
import boto3

# Specify your AWS Region
aws_region='<aws_region>'

# Create a low-level SageMaker service client.
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Role to give SageMaker permission to access AWS services.
sagemaker_role= "arn:aws:iam::<region>::<account>::role/*"
```

The first few lines define:

- `sagemaker_client`: A low-level SageMaker client object that makes it easy to send and receive requests to AWS services.
- `sagemaker_role`: A string variable with the SageMaker IAM role Amazon Resource Name (ARN).
- `aws_region`: A string variable with the name of your AWS region.

Import the `image_uris` module from the SageMaker Python SDK. Use the `retrieve()` function to retrieve the Amazon ECR URI for the Docker image matching the given arguments. Provide both the name of the framework or algorithm (framework field) along with the version of the framework or algorithm (version field). For a list of built-in Docker images provided by AWS, see Available Deep Learning Containers Images. For more information on how to bring your own image, see Use Your Own Inference Code (p. 3191).

```python
from sagemaker import image_uris
```
# Name of the framework or algorithm
framework='<framework>'
# Example

# Version of the framework or algorithm
version = '<version-number>'
# Example

# Specify an AWS container image.
container = image_uris.retrieve(region=aws_region,
                                 framework=framework,
                                 version=version)

Next, provide the Amazon S3 URI of the pre-trained model. This model will be used to create a
SageMaker Python SDK Model object in the next step. In this example, the full Amazon S3
URI is stored in a string variable model_url:

# Create a variable w/ the model S3 URI
# First, provide the name of your S3 bucket
s3_bucket = '<your-bucket-name>'

# Specify what directory within your S3 bucket your model is stored in
bucket_prefix = '<directory-name>'

# Replace with the name of your model artifact
model_filename = '<model-name>.tar.gz'

# Relative S3 path
model_s3_key = f'{bucket_prefix}/{model_filename}

# Combine bucket name, model file name, and relative S3 path to create S3 model URI
model_url = f's3://{s3_bucket}/{model_s3_key}'

SageMaker Python SDK

Define your AWS region. In addition, define the AWS role that gives SageMaker permission to access
AWS services on your behalf:

# Specify your AWS Region
aws_region='<aws_region>'

# Role to give SageMaker permission to access AWS services.
sagemaker_role= "arn:aws:iam::<region>::account::role/*"

The first few lines define:

- sagemaker_role: A string variable with the SageMaker IAM role Amazon Resource Name (ARN).
- aws_region: A string variable with the name of your AWS region.

Import the image_uris module from the SageMaker Python SDK. Use the retrieve() function to
retrieve the Amazon ECR URI for the Docker image matching the given arguments. Provide both the
name of the framework or algorithm (framework field) along with the version of the framework or
algorithm (version field). For a list of built-in Docker images provided by AWS, see Available Deep
Learning Containers Images. For more information on how to bring your own image, see Use Your
Own Inference Code (p. 3191).

from sagemaker import image_uris
# Name of the framework or algorithm
framework='<framework>'
#framework='xgboost' # Example

# Version of the framework or algorithm
version = '<version-number>'
#version = '0.9.0-1' # Example

# Specify an AWS container image.
container = image_uris.retrieve(region=aws_region,
                                  framework=framework,
                                  version=version)

Next, provide the Amazon S3 URI of the pre-trained model. This model will be used to create a SageMaker Python SDK Model.model object in the next step. In this example, the full Amazon S3 URI is stored in a string variable model_url:

```python
# Create a variable w/ the model S3 URI
# First, provide the name of your S3 bucket
s3_bucket = '<your-bucket-name>'

# Specify what directory within your S3 bucket your model is stored in
bucket_prefix = '<directory-name>'

# Replace with the name of your model artifact
model_filename = '<model-name>.tar.gz'

# Relative S3 path
model_s3_key = f'{bucket_prefix}/'+model_filename

# Combine bucket name, model file name, and relate S3 path to create S3 model URI
model_url = f's3://{s3_bucket}/{model_s3_key}'
```

Create a Model

By creating a model, you tell SageMaker where it can find the model components.

AWS SDK for Python (Boto3)

Create a model in SageMaker with CreateModel. Specify the following:

- **ModelName**: A name for your model (in this example it is stored as a string variable called model_name).
- **ExecutionRoleArn**: The Amazon Resource Name (ARN) of the IAM role that Amazon SageMaker can assume to access model artifacts and Docker images for deployment on ML compute instances or for batch transform jobs.
- **PrimaryContainer**: The location of the primary Docker image containing inference code, associated artifacts, and custom environment maps that the inference code uses when the model is deployed for predictions.

For the primary container, specify the Docker image that contains inference code, artifacts (from prior training), and a custom environment map that the inference code uses when you deploy the model for predictions.

```python
model_name = '<The_name_of_the_model>'
```
# Create model
create_model_response = sagemaker_client.create_model(
    ModelName = model_name,
    ExecutionRoleArn = sagemaker_role,
    PrimaryContainer = {
        'Image': container,
        'ModelDataUrl': model_url,
    })


SageMaker Python SDK

Create a model object from the SageMaker Python SDK Model Class. You will use this object to deploy your model to an endpoint in a later step.

```python
from sagemaker.model import Model

model = Model(image_uri=container,
               model_data=model_url,
               role=sagemaker_role)
```

Create an Endpoint Configuration

Create an endpoint configuration for an HTTPS endpoint. Specify the name of one or more models in production (variants) and the ML compute instances that you want SageMaker to launch to host each production variant.

**Note**
Skip this section if you are exclusively using the SageMaker Python SDK.

When hosting models in production, you can configure the endpoint to elastically scale the deployed ML compute instances. For each production variant, you specify the number of ML compute instances that you want to deploy. When you specify two or more instances, SageMaker launches them in multiple Availability Zones. This ensures continuous availability. SageMaker manages deploying the instances.

AWS SDK for Python (Boto3)

Create an endpoint configuration with CreateEndpointConfig. Amazon SageMaker hosting services uses this configuration to deploy models. In the configuration, you identify one or more models, created using with CreateModel, to deploy the resources that you want Amazon SageMaker to provision.

The following example shows how to create an endpoint configuration using AWS SDK for Python (Boto3):

```python
import datetime
from time import gmtime, strftime

# Create an endpoint config name. Here we create one based on the date # so it we can search endpoints based on creation time.
endpoint_config_name = '<endpoint-config-name>'

# The name of the model that you want to host. This is the name that you specified when creating the model.
model_name = '<The_name_of_your_model>'
```
instance_type = '<instance-type>'
# instance_type='ml.m5.xlarge' # Example

endpoint_config_response = sagemaker_client.create_endpoint_config(
    EndpointConfigName=endpoint_config_name, # You will specify this name in a
    CreateEndpoint request.
    # List of ProductionVariant objects, one for each model that you want to host at
    # this endpoint.
    ProductionVariants=[
        {
            "VariantName": "variant1", # The name of the production variant.
            "ModelName": model_name,
            "InstanceType": instance_type, # Specify the compute instance type.
            "InitialInstanceCount": 1 # Number of instances to launch initially.
        }
    ]
)

print(f"Created EndpointConfig: {endpoint_config_response['EndpointConfigArn']}")

In the aforementioned example, you specify the following keys for the ProductionVariants field:

- **VariantName**: The name of the production variant.
- **ModelName**: The name of the model that you want to host. This is the name that you specified when creating the model.
- **InstanceType**: The compute instance type. See the `InstanceType` field in [https://docs.aws.amazon.com/sagemaker/latest/APIReference/API_ProductionVariant.html](https://docs.aws.amazon.com/sagemaker/latest/APIReference/API_ProductionVariant.html) and SageMaker Pricing for a list of supported compute instance types and pricing for each instance type.

You do not need to define an endpoint configuration for real-time endpoints if you use the SageMaker Python SDK Model Class.

**Deploy your model**

Deploy your model and create an HTTPS endpoint.

**AWS SDK for Python (Boto3)**

Provide the endpoint configuration to SageMaker. The service launches the ML compute instances and deploys the model or models as specified in the configuration.

Once you have your model and endpoint configuration, use the CreateEndpoint API to create your endpoint. The endpoint name must be unique within an AWS Region in your AWS account.

The following creates an endpoint using the endpoint configuration specified in the request. Amazon SageMaker uses the endpoint to provision resources and deploy models.

```python
# The name of the endpoint. The name must be unique within an AWS Region in your AWS account.
endpoint_name = '<endpoint-name>'

# The name of the endpoint configuration associated with this endpoint.
endpoint_config_name='<endpoint-config-name>'

create_endpoint_response = sagemaker_client.create_endpoint(
    EndpointName=endpoint_name,
```
Hosting options

For more information, see the CreateEndpoint API.

**SageMaker Python SDK**

Define a name for your endpoint. This step is optional. If you do not provide one, SageMaker will create a unique name for you:

```python
from datetime import datetime

endpoint_name = f"DEMO-{datetime.utcnow():%Y-%m-%d-%H%M}" 
print("EndpointName =", endpoint_name)
```

Deploy your model to a real-time, HTTPS endpoint with the Model object’s built-in `deploy()` method. Provide the name of the Amazon EC2 instance type to deploy this model to in the `instance_type` field along with the initial number of instances to run the endpoint on for the `initial_instance_count` field:

```python
initial_instance_count=<integer> 
# initial_instance_count=1 # Example

instance_type='<instance-type>' 
# instance_type='ml.m4.xlarge' # Example

model.deploy( 
    initial_instance_count=initial_instance_count, 
    instance_type=instance_type, 
    endpoint_name=endpoint_name 
)
```

**Delete Endpoints and Resources**

Delete endpoints to stop incurring charges.

**Delete Endpoint**

Delete your endpoint programmatically using AWS SDK for Python (Boto3), with the AWS CLI, or interactively using the SageMaker console.

SageMaker frees up all of the resources that were deployed when the endpoint was created. Deleting an endpoint will not delete the endpoint configuration or the SageMaker model. See Delete Endpoint Configuration (p. 2752) and Delete Model (p. 2753) for information on how to delete your endpoint configuration and SageMaker model.

**AWS SDK for Python (Boto3)**

Use the DeleteEndpoint API to delete your endpoint. Specify the name of your endpoint for the EndpointName field.

```python
import boto3

# Specify your AWS Region
aws_region='<aws_region>'

# Specify the name of your endpoint
endpoint_name='<endpoint_name>'

# Create a low-level SageMaker service client.
```
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Delete endpoint
sagemaker_client.delete_endpoint(EndpointName=endpoint_name)

AWS CLI

Use the `delete-endpoint` command to delete your endpoint. Specify the name of your endpoint for the `endpoint-name` flag.

```
aws sagemaker delete-endpoint --endpoint-name <endpoint-name>
```

SageMaker Console

Delete your endpoint interactively with the SageMaker console.

2. Choose Endpoints from the drop down menu. A list of endpoints created in you AWS account will appear by name, Amazon Resource Name (ARN), creation time, status, and a time stamp of when the endpoint was last updated.
3. Select the endpoint you want to delete.
4. Select the Actions dropdown button in the top right corner.
5. Choose Delete.

Delete Endpoint Configuration

Delete your endpoint configuration programmatically using AWS SDK for Python (Boto3), with the AWS CLI, or interactively using the SageMaker console. Deleting an endpoint configuration does not delete endpoints created using this configuration. See Delete Endpoint (p. 2751) for information on how to delete your endpoint.

Do not delete an endpoint configuration in use by an endpoint that is live or while the endpoint is being updated or created. You might lose visibility into the instance type the endpoint is using if you delete the endpoint configuration of an endpoint that is active or being created or updated.

AWS SDK for Python (Boto3)

Use the `DeleteEndpointConfig` API to delete your endpoint. Specify the name of your endpoint configuration for the `EndpointConfigName` field.

```
import boto3

# Specify your AWS Region
aws_region='<aws_region>'

# Specify the name of your endpoint configuration
endpoint_config_name='<endpoint_name>'

# Create a low-level SageMaker service client.
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Delete endpoint configuration
sagemaker_client.delete_endpoint_config(EndpointConfigName=endpoint_config_name)
```

You can optionally use the `DescribeEndpointConfig` API to return information about the name of the your deployed models (production variants) such as the name of your model and the name of
the endpoint configuration associated with that deployed model. Provide the name of your endpoint for the EndpointConfigName field.

```python
# Specify the name of your endpoint
endpoint_name='<endpoint_name>'

# Create a low-level SageMaker service client.
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Store DescribeEndpointConfig response into a variable that we can index in the next step.
response = sagemaker_client.describe_endpoint_config(EndpointConfigName=endpoint_name)

# Delete endpoint
endpoint_config_name = response['ProductionVariants'][0]['EndpointConfigName']

# Delete endpoint configuration
sagemaker_client.delete_endpoint_config(EndpointConfigName=endpoint_config_name)
```

For more information about other response elements returned by DescribeEndpointConfig, see DescribeEndpointConfig in the SageMaker API Reference guide.

AWS CLI

Use the delete-endpoint-config command to delete your endpoint configuration. Specify the name of your endpoint configuration for the endpoint-config-name flag.

```bash
aws sagemaker delete-endpoint-config --endpoint-config-name <endpoint-config-name>
```

You can optionally use the describe-endpoint-config command to return information about the name of the your deployed models (production variants) such as the name of your model and the name of the endpoint configuration associated with that deployed model. Provide the name of your endpoint for the endpoint-config-name flag.

```bash
aws sagemaker describe-endpoint-config --endpoint-config-name <endpoint-config-name>
```

This will return a JSON response. You can copy and paste, use a JSON parser, or use a tool built for JSON parsing to obtain the endpoint configuration name associated with that endpoint.

SageMaker Console

Delete your endpoint configuration interactively with the SageMaker console.

1. In the SageMaker console at https://console.aws.amazon.com/sagemaker/ navigation menu, choose **Inference**.
2. Choose **Endpoint configurations** from the dropdown menu. A list of endpoint configurations created in you AWS account will appear by name, Amazon Resource Name (ARN), and creation time.
3. Select the endpoint configuration you want to delete.
4. Select the **Actions** dropdown button in the top right corner.
5. Choose **Delete**.

Delete Model

Delete your SageMaker model programmatically using AWS SDK for Python (Boto3), with the AWS CLI, or interactively using the SageMaker console. Deleting a SageMaker model only deletes the model entry
that was created in SageMaker. Deleting a model does not delete model artifacts, inference code, or the IAM role that you specified when creating the model.

AWS SDK for Python (Boto3)

Use the `DeleteModel` API to delete your SageMaker model. Specify the name of your model for the `ModelName` field.

```python
import boto3

# Specify your AWS Region
aws_region = '<aws_region>'

# Specify the name of your endpoint configuration
model_name = '<model_name>'

# Create a low-level SageMaker service client.
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Delete model
sagemaker_client.delete_model(ModelName=model_name)
```

You can optionally use the `DescribeEndpointConfig` API to return information about the name of your deployed models (production variants) such as the name of your model and the name of the endpoint configuration associated with that deployed model. Provide the name of your endpoint for the `EndpointConfigName` field.

```python
# Specify the name of your endpoint
endpoint_name = '<endpoint_name>'

# Create a low-level SageMaker service client.
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Store DescribeEndpointConfig response into a variable that we can index in the next step.
response = sagemaker_client.describe_endpoint_config(EndpointConfigName=endpoint_name)

# Delete endpoint
model_name = response['ProductionVariants'][0]['ModelName']
sagemaker_client.delete_model(ModelName=model_name)
```

For more information about other response elements returned by `DescribeEndpointConfig`, see `DescribeEndpointConfig` in the SageMaker API Reference guide.

AWS CLI

Use the `delete-model` command to delete your SageMaker model. Specify the name of your model for the `model-name` flag.

```bash
aws sagemaker delete-model \
  --model-name <model-name>
```

You can optionally use the `describe-endpoint-config` command to return information about the name of your deployed models (production variants) such as the name of your model and the name of the endpoint configuration associated with that deployed model. Provide the name of your endpoint for the `endpoint-config-name` flag.

```bash
aws sagemaker describe-endpoint-config --endpoint-config-name <endpoint-config-name>
```
This will return a JSON response. You can copy and paste, use a JSON parser, or use a tool built for JSON parsing to obtain the name of the model associated with that endpoint.

SageMaker Console

Delete your SageMaker model interactively with the SageMaker console.

1. In the SageMaker console at https://console.aws.amazon.com/sagemaker/ navigation menu, choose **Inference**.
2. Choose **Models** from the dropdown menu. A list of models created in you AWS account will appear by name, Amazon Resource Name (ARN), and creation time.
3. Select the model you want to delete.
4. Select the **Actions** dropdown button in the top right corner.
5. Choose **Delete**.

**Host multiple models in one container behind one endpoint**

Multi-model endpoints provide a scalable and cost-effective solution to deploying large numbers of models. They use the same fleet of resources and a shared serving container to host all of your models. This reduces hosting costs by improving endpoint utilization compared with using single-model endpoints. It also reduces deployment overhead because Amazon SageMaker manages loading models in memory and scaling them based on the traffic patterns to your endpoint.

The following diagram shows how multi-model endpoints work compared to single-model endpoints.

Multi-model endpoints are ideal for hosting a large number of models that use the same ML framework on a shared serving container. If you have a mix of frequently and infrequently accessed models, a multi-model endpoint can efficiently serve this traffic with fewer resources and higher cost savings. Your application should be tolerant of occasional cold start-related latency penalties that occur when invoking infrequently used models.

Multi-model endpoints support hosting both CPU and GPU backed models. By using GPU backed models, you can lower your model deployment costs through increased usage of the endpoint and its underlying accelerated compute instances.
Multi-model endpoints also enable time-sharing of memory resources across your models. This works best when the models are fairly similar in size and invocation latency. When this is the case, multi-model endpoints can effectively use instances across all models. If you have models that have significantly higher transactions per second (TPS) or latency requirements, we recommend hosting them on dedicated endpoints.

You can use multi-model endpoints with the following features:

- AWS PrivateLink and VPCs
- Auto scaling (p. 2780)
- Serial inference pipelines (but only one multi-model enabled container can be included in an inference pipeline)
- A/B testing

You can't use multi-model-enabled containers with Amazon Elastic Inference.

You can use the AWS SDK for Python (Boto) or the SageMaker console to create a multi-model endpoint. For CPU backed multi-model endpoints, you can create your endpoint with custom-built containers by integrating the Multi Model Server library.

**Topics**

- Supported algorithms, frameworks, and instances (p. 2756)
- Sample notebooks for multi-model endpoints (p. 2757)
- How multi-model endpoints work (p. 2758)
- Setting SageMaker multi-model endpoint model caching behavior (p. 2759)
- Instance recommendations for multi-model endpoint deployments (p. 2759)
- Create a Multi-Model Endpoint (p. 2760)
- Invoke a Multi-Model Endpoint (p. 2767)
- Add or Remove Models (p. 2768)
- Build Your Own Container for SageMaker Multi-Model Endpoints (p. 2769)
- Multi-Model Endpoint Security (p. 2774)
- CloudWatch Metrics for Multi-Model Endpoint Deployments (p. 2775)
- Set Auto Scaling Policies for Multi-Model Endpoint Deployments (p. 2780)

**Supported algorithms, frameworks, and instances**

For information about the algorithms, frameworks, and instance types that you can use with multi-model endpoints, see the following sections.

**Supported algorithms, frameworks, and instances for multi-model endpoints using CPU backed instances**

The inference containers for the following algorithms and frameworks support multi-model endpoints:

- XGBoost Algorithm (p. 2038)
- K-Nearest Neighbors (k-NN) Algorithm (p. 1996)
- Linear Learner Algorithm (p. 2014)
- Random Cut Forest (RCF) Algorithm (p. 2163)
- Use TensorFlow with Amazon SageMaker (p. 30)
- Use Scikit-learn with Amazon SageMaker (p. 29)
Hosting options

- Use Apache MXNet with Amazon SageMaker (p. 14)
- Use PyTorch with Amazon SageMaker (p. 26)

To use any other framework or algorithm, use the SageMaker inference toolkit to build a container that supports multi-model endpoints. For information, see Build Your Own Container for SageMaker Multi-Model Endpoints (p. 2769).

Multi-model endpoints support all of the CPU instance types.

**Supported algorithms, frameworks, and instances for multi-model endpoints using GPU backed instances**

Hosting multiple GPU backed models on multi-model endpoints is supported through the SageMaker Triton Inference server. This supports all major inference frameworks such as NVIDIA® TensorRT™, PyTorch, MXNet, Python, ONNX, XGBoost, scikit-learn, Random Forest, OpenVINO, custom C++, and more.

To use any other framework or algorithm, you can use Triton backend for Python or C++ to write your model logic and serve any custom model. After you have the server ready, you can start deploying 100s of Deep Learning models behind one endpoint.

Multi-model endpoints support the following GPU instance types:

<table>
<thead>
<tr>
<th>Instance family</th>
<th>Instance type</th>
<th>vCPUs</th>
<th>GiB of memory per vCPU</th>
<th>GPUs</th>
<th>GPU memory</th>
</tr>
</thead>
<tbody>
<tr>
<td>p2</td>
<td>ml.p2.xlarge</td>
<td>4</td>
<td>15.25</td>
<td>1</td>
<td>12</td>
</tr>
<tr>
<td>p3</td>
<td>ml.p3.2xlarge</td>
<td>8</td>
<td>7.62</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>g5</td>
<td>ml.g5.xlarge</td>
<td>4</td>
<td>4</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>g5</td>
<td>ml.g5.2xlarge</td>
<td>8</td>
<td>4</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>g5</td>
<td>ml.g5.4xlarge</td>
<td>16</td>
<td>4</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>g5</td>
<td>ml.g5.8xlarge</td>
<td>32</td>
<td>4</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>g5</td>
<td>ml.g5.16xlarge</td>
<td>64</td>
<td>4</td>
<td>1</td>
<td>24</td>
</tr>
<tr>
<td>g4dn</td>
<td>ml.g4dn.xlarge</td>
<td>4</td>
<td>4</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>g4dn</td>
<td>ml.g4dn.2xlarge</td>
<td>8</td>
<td>4</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>g4dn</td>
<td>ml.g4dn.4xlarge</td>
<td>16</td>
<td>4</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>g4dn</td>
<td>ml.g4dn.8xlarge</td>
<td>32</td>
<td>4</td>
<td>1</td>
<td>16</td>
</tr>
<tr>
<td>g4dn</td>
<td>ml.g4dn.16xlarge64</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>16</td>
</tr>
</tbody>
</table>

**Sample notebooks for multi-model endpoints**

To learn more about how to use multi-model endpoints, you can try the following sample notebooks:

- Examples for multi-model endpoints using CPU backed instances:
  - Multi-Model Endpoint XGBoost Sample Notebook – This notebook shows how to deploy multiple XGBoost models to an endpoint.
Hosting options

- **Multi-Model Endpoints BYOC Sample Notebook** – This notebook shows how to set up and deploy a customer container that supports multi-model endpoints in SageMaker.

- Example for multi-model endpoints using GPU backed instances:
  - **Run multiple deep learning models on GPUs with Amazon SageMaker Multi-model endpoints (MME)** – This notebook shows how to use an NVIDIA Triton Inference container to deploy ResNet-50 models to a multi-model endpoint.

For instructions on how to create and access Jupyter notebook instances that you can use to run the previous examples in SageMaker, see *Use Amazon SageMaker Notebook Instances* (p. 291). After you've created a notebook instance and opened it, choose the **SageMaker Examples** tab to see a list of all the SageMaker samples. The multi-model endpoint notebooks are located in the **ADVANCED FUNCTIONALITY** section. To open a notebook, choose its **Use** tab and choose **Create copy**.

For more information about use cases for multi-model endpoints, see the following blogs and resources:

- **Video**: Hosting thousands of models on SageMaker
- **Video**: SageMaker ML for SaaS
- **Blog**: How to scale machine learning inference for multi-tenant SaaS use cases
- **Case study**: Veeva Systems

**How multi-model endpoints work**

SageMaker manages the lifecycle of models hosted on multi-model endpoints in the container's memory. Instead of downloading all of the models from an Amazon S3 bucket to the container when you create the endpoint, SageMaker dynamically loads and caches them when you invoke them. When SageMaker receives an invocation request for a particular model, it does the following:

1. Routes the request to an instance behind the endpoint.
2. Downloads the model from the S3 bucket to that instance's storage volume.
3. Loads the model to the container's memory (CPU or GPU, depending on whether you have CPU or GPU backed instances) on that accelerated compute instance. If the model is already loaded in the container's memory, invocation is faster because SageMaker doesn't need to download and load it.

SageMaker continues to route requests for a model to the instance where the model is already loaded. However, if the model receives many invocation requests, and there are additional instances for the multi-model endpoint, SageMaker routes some requests to another instance to accommodate the traffic. If the model isn't already loaded on the second instance, the model is downloaded to that instance's storage volume and loaded into the container's memory.

When an instance's memory utilization is high and SageMaker needs to load another model into memory, it unloads unused models from that instance's container to ensure that there is enough memory to load the model. Models that are unloaded remain on the instance's storage volume and can be loaded into the container's memory later without being downloaded again from the S3 bucket. If the instance's storage volume reaches its capacity, SageMaker deletes any unused models from the storage volume.

To delete a model, stop sending requests and delete it from the S3 bucket. SageMaker provides multi-model endpoint capability in a serving container. Adding models to, and deleting them from, a multi-model endpoint doesn't require updating the endpoint itself. To add a model, you upload it to the S3 bucket and invoke it. You don't need code changes to use it.

**Note**

When you update a multi-model endpoint, initial invocation requests on the endpoint might experience higher latencies as Smart Routing in multi-model endpoints adapt to your traffic pattern. However, once it learns your traffic pattern, you can experience low latencies for most
frequently used models. Less frequently used models may incur some cold start latencies since
the models are dynamically loaded to an instance.

**Setting SageMaker multi-model endpoint model caching behavior**

By default, multi-model endpoints cache frequently used models in memory (CPU or GPU, depending
on whether you have CPU or GPU backed instances) and on disk to provide low latency inference. The
cached models are unloaded and/or deleted from disk only when a container runs out of memory or disk
space to accommodate a newly targeted model.

You can change the caching behavior of a multi-model endpoint and explicitly enable or disable model
caching by setting the parameter `ModelCacheSetting` when you call `create_model`.

We recommend setting the value of the `ModelCacheSetting` parameter to `Disabled` for use cases
that do not benefit from model caching. For example, when a large number of models need to be served
from the endpoint but each model is invoked only once (or very infrequently). For such use cases, setting
the value of the `ModelCacheSetting` parameter to `Disabled` allows higher transactions per second
(TPS) for `invoke_endpoint` requests compared to the default caching mode. Higher TPS in these use
cases is because SageMaker does the following after the `invoke_endpoint` request:

- Asynchronously unloads the model from memory and deletes it from disk immediately after it is
  invoked.
- Provides higher concurrency for downloading and loading models in the inference container. For
  both CPU and GPU backed endpoints, the concurrency is a factor of the number of the vCPUs of the
  container instance.

For guidelines on choosing a SageMaker ML instance type for a multi-model endpoint, see `Instance
recommendations for multi-model endpoint deployments (p. 2759)`.

**Instance recommendations for multi-model endpoint deployments**

There are several items to consider when selecting a SageMaker ML instance type for a multi-model
endpoint:

- Provision sufficient [Amazon Elastic Block Store (Amazon EBS)](https://aws.amazon.com/ebs) capacity for all of the models that need
to be served.
- Balance performance (minimize cold starts) and cost (don't over-provision instance capacity). For
  information about the size of the storage volume that SageMaker attaches for each instance type for
  an endpoint and for a multi-model endpoint, see `Host instance storage volumes (p. 2819)`.
- For a container configured to run in `MultiModel` mode, the storage volume provisioned for its
  instances are larger than the default `SingleModel` mode. This allows more models to be cached on
  the instance storage volume than in `SingleModel` mode.

When choosing a SageMaker ML instance type, consider the following:

- Multi-model endpoints are currently supported for all CPU instances types and on single-GPU instance
types.
- For the traffic distribution (access patterns) to the models that you want to host behind the multi-
  model endpoint, along with the model size (how many models could be loaded in memory on the
  instance), keep the following information in mind:
  - Think of the amount of memory on an instance as the cache space for models to be loaded, and
    think of the number of vCPUs as the concurrency limit to perform inference on the loaded models
    (assuming that invoking a model is bound to CPU).
  - For CPU backed instances, the number of vCPUs impacts your maximum concurrency invocations per
    instance (assuming that invoking a model is bound to CPU). A higher amount of vCPUs enables you
to invoke more unique models concurrently.
Hosting options

- For GPU backed instances, a higher amount of instance and GPU memory enables you to have more models loaded and ready to serve inference requests.
- For both CPU and GPU backed instances, have some "slack" memory available so that unused models can be unloaded, and especially for multi-model endpoints with multiple instances. If an instance or an Availability Zone fails, the models on those instances will be rerouted to other instances behind the endpoint.
- Determine your tolerance to loading/downloading times:
  - d instance type families (for example, m5d, c5d, or r5d) and g5s come with an NVMe (non-volatile memory express) SSD, which offers high I/O performance and might reduce the time it takes to download models to the storage volume and for the container to load the model from the storage volume.
  - Because d and g5 instance types come with an NVMe SSD storage, SageMaker does not attach an Amazon EBS storage volume to these ML compute instances that hosts the multi-model endpoint. Auto scaling works best when the models are similarly sized and homogenous, that is when they have similar inference latency and resource requirements.

You can also use the following guidance to help you optimize model loading on your multi-model endpoints:

**Choosing an instance type that can't hold all of the targeted models in memory**

In some cases, you might opt to reduce costs by choosing an instance type that can't hold all of the targeted models in memory at once. SageMaker dynamically unloads models when it runs out of memory to make room for a newly targeted model. For infrequently requested models, you sacrifice dynamic load latency. In cases with more stringent latency needs, you might opt for larger instance types or more instances. Investing time up front for performance testing and analysis helps you to have successful production deployments.

**Evaluating your model cache hits**

Amazon CloudWatch metrics can help you evaluate your models. For more information about metrics you can use with multi-model endpoints, see [CloudWatch Metrics for Multi-Model Endpoint Deployments](p. 2775).

You can use the Average statistic of the ModelCacheHit metric to monitor the ratio of requests where the model is already loaded. You can use the SampleCount statistic for the ModelUnloadingTime metric to monitor the number of unload requests sent to the container during a time period. If models are unloaded too frequently (an indicator of *thrashing*, where models are being unloaded and loaded again because there is insufficient cache space for the working set of models), consider using a larger instance type with more memory or increasing the number of instances behind the multi-model endpoint. For multi-model endpoints with multiple instances, be aware that a model might be loaded on more than 1 instance.

**Create a Multi-Model Endpoint**

You can use the SageMaker console or the AWS SDK for Python (Boto) to create a multi-model endpoint. To create either a CPU or GPU backed endpoint through the console, see the console procedure in the following sections. If you want to create a multi-model endpoint with the AWS SDK for Python (Boto), use either the CPU or GPU procedure in the following sections. The CPU and GPU workflows are similar but have several differences, such as the container requirements.

**Topics**

- [Create a multi-model endpoint (console)](p. 2761)
- [Create a multi-model endpoint using CPUs with the AWS SDK for Python (Boto3)](p. 2763)
- [Create a multi-model endpoint using GPUs with the AWS SDK for Python (Boto3)](p. 2765)
Create a multi-model endpoint (console)

You can create both CPU and GPU backed multi-model endpoints through the console. Use the following procedure to create a multi-model endpoint through the SageMaker console.

To create a multi-model endpoint (console)

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Choose Model, and then from the Inference group, choose Create model.
3. For Model name, enter a name.
4. For IAM role, choose or create an IAM role that has the AmazonSageMakerFullAccess IAM policy attached.
5. In the Container definition section, for Provide model artifacts and inference image options, choose Use multiple models.
Create model

To deploy a model to Amazon SageMaker, first create the model by providing the location of the inference code. See Deploying a Model on Amazon SageMaker Hosting Services [Learn]

Model settings

Model name

mml-test-model

Maximum of 63 alphanumeric characters. Can include hyphens (-), but not spaces. Must be unique within your account in an AWS Region.

IAM role

Amazon SageMaker requires permissions to call other services on your behalf. Choose a role or let us create a role that has the AmazonSageMakerFullAccess IAM policy attached.

AmazonSageMaker-ExecutionRole-XXXXXXXXXXXXXXXX

Container definition 1

▶ Container input options

Provide model artifacts and inference image location

▶ Provide model artifacts and inference image options

- Use a single model
  Use this to host a single model in this container.

- Use multiple models
  Use this to host multiple models in this container.

Location of inference code image

Type the registry path where the inference code image is stored in Amazon ECR.

123456789012.dkr.ecr.us-east-1.amazonaws.com/myimage:mytag

Location of model artifacts

Type the URL where model artifacts are stored in S3.

s3://my-bucket/path/to/artifacts/
6. For the Inference container image, enter the Amazon ECR path for your desired container image.

   For GPU models, you must use a container backed by the NVIDIA Triton Inference Server. For a list of container images that work with GPU backed endpoints, see the NVIDIA Triton Inference Containers (SM support only). For more information about the NVIDIA Triton Inference Server, see Use Triton Inference Server with SageMaker.

7. Choose Create model.

8. Deploy your multi-model endpoint as you would a single model endpoint. For instructions, see Deploy the Model to SageMaker Hosting Services (p. 85).

Create a multi-model endpoint using CPUs with the AWS SDK for Python (Boto3)

Use the following section to create a multi-model endpoint backed by CPU instances. You create a multi-model endpoint using the Amazon SageMaker create_model, create_endpoint_config, and create_endpoint APIs just as you would create a single model endpoint, but with two changes. When defining the model container, you need to pass a new Mode parameter value, MultiModel. You also need to pass the ModelDataUrl field that specifies the prefix in Amazon S3 where the model artifacts are located, instead of the path to a single model artifact, as you would when deploying a single model.

For a sample notebook that uses SageMaker to deploy multiple XGBoost models to an endpoint, see Multi-Model Endpoint XGBoost Sample Notebook.

The following procedure outlines the key steps used in that sample to create a CPU backed multi-model endpoint.

To deploy the model (AWS SDK for Python (Boto 3))

1. Get a container with an image that supports deploying multi-model endpoints. For a list of built-in algorithms and framework containers that support multi-model endpoints, see Supported algorithms, frameworks, and instances (p. 2756). For this example, we use the K-Nearest Neighbors (k-NN) Algorithm (p. 1996) built-in algorithm. We call the SageMaker Python SDK utility function image_uris.retrieve() to get the address for the K-Nearest Neighbors built-in algorithm image.

   ```python
   import sagemaker
   region = sagemaker_session.boto_region_name
   image = sagemaker.image_uris.retrieve("knn", region=region)
   container = {
       'Image':        image,
       'ModelDataUrl': 's3://<BUCKET_NAME>/<PATH_TO_ARTIFACTS>',
       'Mode':         'MultiModel'
   }
   ```

2. Get an AWS SDK for Python (Boto3) SageMaker client and create the model that uses this container.

   ```python
   import boto3
   sagemaker_client = boto3.client('sagemaker')
   response = sagemaker_client.create_model(
       ModelName        = '<MODEL_NAME>',
       ExecutionRoleArn = role,
       Containers       = [container])
   ```

3. (Optional) If you are using a serial inference pipeline, get the additional container(s) to include in the pipeline, and include it in the Containers argument of CreateModel:

   ```python
   preprocessor_container = {
       'Image':
       '<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/<PREPROCESSOR_IMAGE>:<TAG>'
   }
   ```
Hosting options

multi_model_container = {
    'Image': '<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/<IMAGE>:<TAG>',
    'ModelDataUrl': 's3://<BUCKET_NAME>/<PATH_TO_ARTIFACTS>',
    'Mode': 'MultiModel'
}

response = sagemaker_client.create_model(
    ModelName = '<MODEL_NAME>',
    ExecutionRoleArn = role,
    Containers = [preprocessor_container, multi_model_container]
)

Note
You can use only one multi-model-enabled endpoint in a serial inference pipeline.

4. (Optional) If your use case does not benefit from model caching, set the value of the `ModelCacheSetting` field of the `MultiModelConfig` parameter to `Disabled`, and include it in the `Container` argument of the call to `create_model`. The value of the `ModelCacheSetting` field is `Enabled` by default.

container = {
    'Image': image,
    'ModelDataUrl': 's3://<BUCKET_NAME>/<PATH_TO_ARTIFACTS>',
    'Mode': 'MultiModel'
    'MultiModelConfig': {
        // Default value is 'Enabled'
        'ModelCacheSetting': 'Disabled'
    }
}

response = sagemaker_client.create_model(
    ModelName = '<MODEL_NAME>',
    ExecutionRoleArn = role,
    Containers = [container]
)

5. Configure the multi-model endpoint for the model. We recommend configuring your endpoints with at least two instances. This allows SageMaker to provide a highly available set of predictions across multiple Availability Zones for the models.

response = sagemaker_client.create_endpoint_config(
    EndpointConfigName = '<ENDPOINT_CONFIG_NAME>',
    ProductionVariants = [
        {
            'InstanceType': 'ml.m4.xlarge',
            'InitialInstanceCount': 2,
            'InitialVariantWeight': 1,
            'ModelName': '<MODEL_NAME>',
            'VariantName': 'AllTraffic'
        }
    ]
)

Note
You can use only one multi-model-enabled endpoint in a serial inference pipeline.

6. Create the multi-model endpoint using the `EndpointName` and `EndpointConfigName` parameters.

response = sagemaker_client.create_endpoint(

Create a multi-model endpoint using GPUs with the AWS SDK for Python (Boto3)

Use the following section to create a GPU backed multi-model endpoint. You create a multi-model endpoint using the Amazon SageMaker `create_model`, `create_endpoint_config`, and `create_endpoint` APIs similarly to creating single model endpoints, but there are several changes. When defining the model container, you need to pass a new `Mode` parameter value, `MultiModel`. You also need to pass the `ModelDataUrl` field that specifies the prefix in Amazon S3 where the model artifacts are located, instead of the path to a single model artifact, as you would when deploying a single model. For GPU backed multi-model endpoints, you also must use a container with the NVIDIA Triton Inference Server that is optimized for running on GPU instances. For a list of container images that work with GPU backed endpoints, see the NVIDIA Triton Inference Containers (SM support only).

For an example notebook that demonstrates how to create a multi-model endpoint backed by GPUs, see Run multiple deep learning models on GPUs with Amazon SageMaker Multi-model endpoints (MME).

The following procedure outlines the key steps to create a GPU backed multi-model endpoint.

**To deploy the model (AWS SDK for Python (Boto 3))**

1. Define the container image. To create a multi-model endpoint with GPU support for ResNet models, define the container to use the NVIDIA Triton Server image. This container supports multi-model endpoints and is optimized for running on GPU instances. We call the SageMaker Python SDK utility function `image_uris.retrieve()` to get the address for the image. For example:

   ```python
   import sagemaker
   region = sagemaker_session.boto_region_name
   image = "<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/sagemaker-tritonserver:<TAG>".format(
       account_id=account_id_map[region], region=region)
   container = {
       'Image': image,
       'ModelDataUrl': 's3:<BUCKET_NAME>/<PATH_TO_ARTIFACTS>',
       'Mode': 'MultiModel',
       'Environment': {"SAGEMAKER_TRITON_DEFAULT_MODEL_NAME": "resnet"},
   }
   ```

2. Get an AWS SDK for Python (Boto3) SageMaker client and create the model that uses this container.

   ```python
   import boto3
   sagemaker_client = boto3.client('sagemaker')
   response = sagemaker_client.create_model(
       ModelName = '<MODEL_NAME>',
       ExecutionRoleArn = role,
       Containers = [container])
   ```

3. (Optional) If you are using a serial inference pipeline, get the additional container(s) to include in the pipeline, and include it in the `Containers` argument of `CreateModel`:
Hosting options

preprocessor_container = {
    'Image':
        '<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/<PREPROCESSOR_IMAGE>:<TAG>'
}

dosr_multi_model_container = {
    'Image':
        '<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/<IMAGE>:<TAG>',
        'ModelDataUrl': 's3://<BUCKET_NAME>/<PATH_TO_ARTIFACTS>',
        'Mode':        'MultiModel'
}

response = sagemaker_client.create_model(
    ModelName        = '<MODEL_NAME>',
    ExecutionRoleArn = role,
    Containers       = [preprocessor_container, multi_model_container]
)

Note
You can use only one multi-model-enabled endpoint in a serial inference pipeline.

4. (Optional) If your use case does not benefit from model caching, set the value of the ModelCacheSetting field of the MultiModelConfig parameter to Disabled, and include it in the Container argument of the call to create_model. The value of the ModelCacheSetting field is Enabled by default.

container = {
    'Image': image,
    'ModelDataUrl': 's3://<BUCKET_NAME>/<PATH_TO_ARTIFACTS>',
    'Mode': 'MultiModel'
    'MultiModelConfig': {
        // Default value is 'Enabled'
        'ModelCacheSetting': 'Disabled'
    }
}

response = sagemaker_client.create_model(
    ModelName        = '<MODEL_NAME>',
    ExecutionRoleArn = role,
    Containers       = [container]
)

5. Configure the multi-model endpoint with GPU backed instances for the model. We recommend configuring your endpoints with more than one instance to allow for high availability and higher cache hits.

response = sagemaker_client.create_endpoint_config(      
    EndpointConfigName = '<ENDPOINT_CONFIG_NAME>',
    ProductionVariants=[
        {      
            'InstanceType':        'ml.g4dn.4xlarge',
            'InitialInstanceCount': 2,
            'InitialVariantWeight': 1,
            'ModelName':        '<MODEL_NAME>',
            'VariantName':        'AllTraffic'
        }
    ]
)

6. Create the multi-model endpoint using the EndpointName and EndpointConfigName parameters.
Invoke a Multi-Model Endpoint

To invoke a multi-model endpoint, use the `invoke_endpoint` from the SageMaker Runtime just as you would invoke a single model endpoint, with one change. Pass a new `TargetModel` parameter that specifies which of the models at the endpoint to target. The SageMaker Runtime `InvokeEndpoint` request supports `X-Amzn-SageMaker-Target-Model` as a new header that takes the relative path of the model specified for invocation. The SageMaker system constructs the absolute path of the model by combining the prefix that is provided as part of the `CreateModel` API call with the relative path of the model.

The following procedures are the same for both CPU and GPU-backed multi-model endpoints.

**AWS SDK for Python (Boto 3)**

The following example prediction request uses the AWS SDK for Python (Boto 3) in the sample notebook.

```python
response = runtime_sagemaker_client.invoke_endpoint(
    EndpointName = "<ENDPOINT_NAME>",
    ContentType = "text/csv",
    TargetModel = "<MODEL_FILENAME>.tar.gz",
    Body = body)
```

**AWS CLI**

The following example shows how to make a CSV request with two rows using the AWS Command Line Interface (AWS CLI):

```bash
aws sagemaker-runtime invoke-endpoint \
    --endpoint-name "<ENDPOINT_NAME>" \
    --body "1.0,2.0,5.0\n2.0,3.0,4.0" \
    --content-type "text/csv" \ 
    --target-model "<MODEL_NAME>.tar.gz" \
    output_file.txt
```

An `output_file.txt` with information about your inference requests is made if the inference was successful. For more examples on how to make predictions with the AWS CLI, see Making predictions with the AWS CLI in the SageMaker Python SDK documentation.

The multi-model endpoint dynamically loads target models as needed. You can observe this when running the MME Sample Notebook as it iterates through random invocations against multiple target models hosted behind a single endpoint. The first request against a given model takes longer because the model has to be downloaded from Amazon Simple Storage Service (Amazon S3) and loaded into memory. This is called a cold start, and it is expected on multi-model endpoints to optimize for better price performance for customers. Subsequent calls finish faster because there's no additional overhead after the model has loaded.

**Note**

For GPU backed instances, the HTTP response code with 507 from the GPU container indicates a lack of memory or other resources. This causes unused models to be unloaded from the container in order to load more frequently used models.
### Retry Requests on ModelNotReadyException Errors

The first time you call `invoke_endpoint` for a model, the model is downloaded from Amazon Simple Storage Service and loaded into the inference container. This makes the first call take longer to return. Subsequent calls to the same model finish faster, because the model is already loaded.

SageMaker returns a response for a call to `invoke_endpoint` within 60 seconds. Some models are too large to download within 60 seconds. If the model does not finish loading before the 60 second timeout limit, the request to `invoke_endpoint` returns with the error code `ModelNotReadyException`, and the model continues to download and load into the inference container for up to 360 seconds. If you get a `ModelNotReadyException` error code for an `invoke_endpoint` request, retry the request. By default, the AWS SDKs for Python (Boto 3) (using `Legacy retry mode`) and Java retry `invoke_endpoint` requests that result in `ModelNotReadyException` errors. You can configure the retry strategy to continue retrying the request for up to 360 seconds. If you expect your model to take longer than 60 seconds to download and load into the container, set the SDK socket timeout to 70 seconds. For more information about configuring the retry strategy for the AWS SDK for Python (Boto3), see Configuring a retry mode. The following code shows an example that configures the retry strategy to retry calls to `invoke_endpoint` for up to 180 seconds.

```python
import boto3
from botocore.config import Config

# This example retry strategy sets the retry attempts to 2.
# With this setting, the request can attempt to download and/or load the model
# for up to 180 seconds: 1 orginal request (60 seconds) + 2 retries (120 seconds)
config = Config(
    read_timeout=70,
    retries={
        'max_attempts': 2  # This value can be adjusted to 5 to go up to the 360s max timeout
    }
)
runtime_sagemaker_client = boto3.client('sagemaker-runtime', config=config)
```

### Add or Remove Models

You can deploy additional models to a multi-model endpoint and invoke them through that endpoint immediately. When adding a new model, you don’t need to update or bring down the endpoint, so you avoid the cost of creating and running a separate endpoint for each new model. The process for adding and removing models is the same for CPU and GPU-backed multi-model endpoints.

SageMaker unloads unused models from the container when the instance is reaching memory capacity and more models need to be downloaded into the container. SageMaker also deletes unused model artifacts from the instance storage volume when the volume is reaching capacity and new models need to be downloaded. The first invocation to a newly added model takes longer because the endpoint takes time to download the model from S3 to the container’s memory in instance hosting the endpoint.

With the endpoint already running, copy a new set of model artifacts to the Amazon S3 location there you store your models.

```bash
# Add an AdditionalModel to the endpoint and exercise it
aws s3 cp AdditionalModel.tar.gz s3://my-bucket/path/to/artifacts/
```

**Important**

To update a model, proceed as you would when adding a new model. Use a new and unique name. Don’t overwrite model artifacts in Amazon S3 because the old version of the model might still be loaded in the containers or on the storage volume of the instances on the endpoint. Invocations to the new model could then invoke the old version of the model.
Client applications can request predictions from the additional target model as soon as it is stored in S3.

```python
response = runtime_sagemaker_client.invoke_endpoint(
    EndpointName='<ENDPOINT_NAME>',
    ContentType='text/csv',
    TargetModel='AdditionalModel.tar.gz',
    Body=body)
```

To delete a model from a multi-model endpoint, stop invoking the model from the clients and remove it from the S3 location where model artifacts are stored.

**Build Your Own Container for SageMaker Multi-Model Endpoints**

Refer to the following sections for bringing your own container and dependencies to multi-model endpoints.

**Topics**

- Bring your own dependencies for multi-model endpoints on CPU backed instances (p. 2769)
- Bring your own dependencies for multi-model endpoints on GPU backed instances (p. 2770)
- Use the SageMaker Inference Toolkit (p. 2770)
- Custom Containers Contract for Multi-Model Endpoints (p. 2772)

**Bring your own dependencies for multi-model endpoints on CPU backed instances**

If none of the pre-built container images serve your needs, you can build your own container for use with CPU backed multi-model endpoints.

Custom Amazon Elastic Container Registry (Amazon ECR) images deployed in Amazon SageMaker are expected to adhere to the basic contract described in [Use Your Own Inference Code with Hosting Services (p. 3191)] that govern how SageMaker interacts with a Docker container that runs your own inference code. For a container to be capable of loading and serving multiple models concurrently, there are additional APIs and behaviors that must be followed. This additional contract includes new APIs to load, list, get, and unload models, and a different API to invoke models. There are also different behaviors for error scenarios that the APIs need to abide by. To indicate that the container complies with the additional requirements, you can add the following command to your Docker file:

```
LABEL com.amazonaws.sagemaker.capabilities.multi-models=true
```

SageMaker also injects an environment variable into the container

```
SAGEMAKER_MULTI_MODEL=true
```

If you are creating a multi-model endpoint for a serial inference pipeline, your Docker file must have the required labels for both multi-models and serial inference pipelines. For more information about serial information pipelines, see [Run Real-time Predictions with an Inference Pipeline (p. 2793)].

To help you implement these requirements for a custom container, two libraries are available:

- **Multi Model Server** is an open source framework for serving machine learning models that can be installed in containers to provide the front end that fulfills the requirements for the new multi-model endpoint container APIs. It provides the HTTP front end and model management capabilities required by multi-model endpoints to host multiple models within a single container, load models into and unload models out of the container dynamically, and performs inference on a specified loaded model. It also provides a pluggable backend that supports a pluggable custom backend handler where you can implement your own algorithm.
SageMaker Inference Toolkit is a library that bootstraps Multi Model Server with a configuration and settings that make it compatible with SageMaker multi-model endpoints. It also allows you to tweak important performance parameters, such as the number of workers per model, depending on the needs of your scenario.

Bring your own dependencies for multi-model endpoints on GPU backed instances

The bring your own container (BYOC) capability on multi-model endpoints with GPU backed instances is not currently supported by the Multi Model Server and SageMaker Inference Toolkit libraries.

For creating multi-model endpoints with GPU backed instances, you can use the SageMaker supported NVIDIA Triton Inference Server, with the NVIDIA Triton Inference Containers. To bring your own dependencies, you can build your own container with the SageMaker supported NVIDIA Triton Inference Server as the base image to your Docker file:

```
FROM 301217895009.dkr.ecr.us-west-2.amazonaws.com/sagemaker-tritonserver:22.07-py3
```

**Important**

Containers with the Triton Inference Server are the only supported containers you can use for GPU backed multi-model endpoints.

Use the SageMaker Inference Toolkit

**Note**

The SageMaker Inference Toolkit is only supported for CPU backed multi-model endpoints. The SageMaker Inference Toolkit is not currently supported for GPU backed multi-model endpoints.

Pre-built containers that support multi-model endpoints are listed in Supported algorithms, frameworks, and instances (p. 2756). If you want to use any other framework or algorithm, you need to build a container. The easiest way to do this is to use the SageMaker Inference Toolkit to extend an existing pre-built container. The SageMaker inference toolkit is an implementation for the multi-model server (MMS) that creates endpoints that can be deployed in SageMaker. For a sample notebook that shows how to set up and deploy a custom container that supports multi-model endpoints in SageMaker, see the Multi-Model Endpoint BYOC Sample Notebook.

**Note**

The SageMaker inference toolkit supports only Python model handlers. If you want to implement your handler in any other language, you must build your own container that implements the additional multi-model endpoint APIs. For information, see Custom Containers Contract for Multi-Model Endpoints (p. 2772).

To extend a container by using the SageMaker inference toolkit

1. Create a model handler. MMS expects a model handler, which is a Python file that implements functions to pre-process, get predictions from the model, and process the output in a model handler. For an example of a model handler, see `model_handler.py` from the sample notebook.

2. Import the inference toolkit and use its `model_server.start_model_server` function to start MMS. The following example is from the `dockerd-entrypoint.py` file from the sample notebook. Notice that the call to `model_server.start_model_server` passes the model handler described in the previous step:

   ```python
   import subprocess
   import sys
   import shlex
   import os
   from retrying import retry
   from subprocess import CalledProcessError
   ```
from sagemaker_inference import model_server

def _retry_if_error(exception):
    return isinstance(exception, CalledProcessError or OSError)

@retry(stop_max_delay=1000 * 50,
       retry_on_exception=_retry_if_error)
def _start_mms():
    # by default the number of workers per model is 1, but we can configure it through
    # environment variable below if desired.
    # os.environ['SAGEMAKER_MODEL_SERVER_WORKERS'] = '2'
    model_server.start_model_server(handler_service='/home/model-server/model_handler.py:handle')

def main():
    if sys.argv[1] == 'serve':
        _start_mms()
    else:
        subprocess.check_call(shlex.split(' '.join(sys.argv[1:])))

        # prevent docker exit
        subprocess.call(['tail', '-f', '/dev/null'])

main()

3. In your Dockerfile, copy the model handler from the first step and specify the Python file from the previous step as the entrypoint in your Dockerfile. The following lines are from the Dockerfile used in the sample notebook:

```bash
# Copy the default custom service file to handle incoming data and inference requests
COPY model_handler.py /home/model-server/model_handler.py

# Define an entrypoint script for the docker image
ENTRYPOINT ["python", "/usr/local/bin/dockerd-entrypoint.py"]
```

4. Build and register your container. The following shell script from the sample notebook builds the container and uploads it to an Amazon Elastic Container Registry repository in your AWS account:

```bash
%%sh

    # The name of our algorithm
    algorithm_name=demo-sagemaker-multimodel

    cd container

    account=$(aws sts get-caller-identity --query Account --output text)

    # Get the region defined in the current configuration (default to us-west-2 if none defined)
    region=$(aws configure get region)

    region=${region:-us-west-2}

    fullname="${account}.dkr.ecr.${region}.amazonaws.com/${algorithm_name}:latest"

    # If the repository doesn't exist in ECR, create it.
    aws ecr describe-repositories --repository-names "${algorithm_name}" > /dev/null 2>&1

    if [ $? -ne 0 ]
    then
        aws ecr create-repository --repository-name "${algorithm_name}" > /dev/null
    fi

    # Get the login command from ECR and execute it directly
```
$(aws ecr get-login --region ${region} --no-include-email)

# Build the docker image locally with the image name and then push it to ECR
# with the full name.
docker build -q -t ${algorithm_name} .
docker tag ${algorithm_name} ${fullname}
docker push ${fullname}

You can now use this container to deploy multi-model endpoints in SageMaker.

Topics

• Custom Containers Contract for Multi-Model Endpoints (p. 2772)

Custom Containers Contract for Multi-Model Endpoints

To handle multiple models, your container must support a set of APIs that enable Amazon SageMaker to communicate with the container for loading, listing, getting, and unloading models as required. The model_name is used in the new set of APIs as the key input parameter. The customer container is expected to keep track of the loaded models using model_name as the mapping key. Also, the model_name is an opaque identifier and is not necessarily the value of the TargetModel parameter passed into the InvokeEndpoint API. The original TargetModel value in the InvokeEndpoint request is passed to container in the APIs as a X-Amzn-SageMaker-Target-Model header that can be used for logging purposes.

Note

Multi-model endpoints for GPU backed instances are currently supported only with SageMaker's NVIDIA Triton Inference Server container. This container already implements the contract defined below. Customers can directly use this container with their multi-model GPU endpoints, without any additional work.

You can configure the following APIs on your containers for CPU backed multi-model endpoints.

Topics

• Load Model API (p. 2772)
• List Model API (p. 2773)
• Get Model API (p. 2773)
• Unload Model API (p. 2774)
• Invoke Model API (p. 2774)

Load Model API

Instructs the container to load a particular model present in the url field of the body into the memory of the customer container and to keep track of it with the assigned model_name. After a model is loaded, the container should be ready to serve inference requests using this model_name.

POST /models HTTP/1.1
Content-Type: application/json
Accept: application/json

{  
  "model_name" : "{model_name}",  
  "url" : "/opt/ml/models/{model_name}/model",
}
Note

If `model_name` is already loaded, this API should return 409. Any time a model cannot be loaded due to lack of memory or to any other resource, this API should return a 507 HTTP status code to SageMaker, which then initiates unloading unused models to reclaim.

List Model API

Returns the list of models loaded into the memory of the customer container.

```
GET /models HTTP/1.1
Accept: application/json

Response =
{
    "models": [
        {
            "modelName" : "{model_name}",
            "modelUrl" : "/opt/ml/models/{model_name}/model",
        },
        {
            "modelName" : "{model_name}",
            "modelUrl" : "/opt/ml/models/{model_name}/model",
        },
        ....
    ]
}
```

This API also supports pagination.

```
GET /models HTTP/1.1
Accept: application/json

Response =
{
    "models": [
        {
            "modelName" : "{model_name}",
            "modelUrl" : "/opt/ml/models/{model_name}/model",
        },
        {
            "modelName" : "{model_name}",
            "modelUrl" : "/opt/ml/models/{model_name}/model",
        },
        ....
    ]
}
```

SageMaker can initially call the List Models API without providing a value for `next_page_token`. If a `nextPageToken` field is returned as part of the response, it will be provided as the value for `next_page_token` in a subsequent List Models call. If a `nextPageToken` is not returned, it means that there are no more models to return.

Get Model API

This is a simple read API on the `model_name` entity.

```
GET /models/{model_name} HTTP/1.1
Accept: application/json

{
    "modelName" : "{model_name}",
}
```
Hosting options

"modelUrl" : "/opt/ml/models/{model_name}/model",
}

**Note**
If model_name is not loaded, this API should return 404.

**Unload Model API**

Instructs the SageMaker platform to instruct the customer container to unload a model from memory. This initiates the eviction of a candidate model as determined by the platform when starting the process of loading a new model. The resources provisioned to model_name should be reclaimed by the container when this API returns a response.

DELETE /models/{model_name}

**Note**
If model_name is not loaded, this API should return 404.

**Invoke Model API**

Makes a prediction request from the particular model_name supplied. The SageMaker Runtime InvokeEndpoint request supports X-Amzn-SageMaker-Target-Model as a new header that takes the relative path of the model specified for invocation. The SageMaker system constructs the absolute path of the model by combining the prefix that is provided as part of the CreateModel API call with the relative path of the model.

POST /models/{model_name}/invoke HTTP/1.1
Content-Type: ContentType
Accept: Accept
X-Amzn-SageMaker-Custom-Attributes: CustomAttributes
X-Amzn-SageMaker-Target-Model: [relativePath]/{artifactName}.tar.gz

**Note**
If model_name is not loaded, this API should return 404.

Additionally, on GPU instances, if InvokeEndpoint fails due to a lack of memory or other resources, this API should return a 507 HTTP status code to SageMaker, which then initiates unloading unused models to reclaim.

**Multi-Model Endpoint Security**

Models and data in a multi-model endpoint are co-located on instance storage volume and in container memory. All instances for Amazon SageMaker endpoints run on a single tenant container that you own. Only your models can run on your multi-model endpoint. It’s your responsibility to manage the mapping of requests to models and to provide access for users to the correct target models. SageMaker uses IAM roles to provide IAM identity-based policies that you use to specify allowed or denied actions and resources and the conditions under which actions are allowed or denied.

By default, an IAM principal with InvokeEndpoint permissions on a multi-model endpoint can invoke any model at the address of the S3 prefix defined in the CreateModel operation, provided that the IAM Execution Role defined in operation has permissions to download the model. If you need to restrict InvokeEndpoint access to a limited set of models in S3, you can do one of the following:

- Restrict InvokeEndpoint calls to specific models hosted at the endpoint by using the sagemaker:TargetModel IAM condition key. For example, the following policy allows InvokeEndpoint requests only when the value of the TargetModel field matches one of the specified regular expressions:

````
```
Hosting options

```json
"Version": "2012-10-17",
"Statement": [
  {
    "Action": [
      "sagemaker:InvokeEndpoint"
    ],
    "Effect": "Allow",
    "Condition": {
      "StringLike": {
        "sagemaker:TargetModel": ["company_a/*", "common/*"]
      }
    }
  }
]
```


- Create multi-model endpoints with more restrictive S3 prefixes.

For more information about how SageMaker uses roles to manage access to endpoints and perform operations on your behalf, see [SageMaker Roles](https://docs.aws.amazon.com/sagemaker/latest/dg/sagemaker-roles.html) (p. 3536). Your customers might also have certain data isolation requirements dictated by their own compliance requirements that can be satisfied using IAM identities.

### CloudWatch Metrics for Multi-Model Endpoint Deployments

Amazon SageMaker provides metrics for endpoints so you can monitor the cache hit rate, the number of models loaded and the model wait times for loading, downloading, and uploading at a multi-model endpoint. Some of the metrics are different for CPU and GPU backed multi-model endpoints, so the following sections describe the Amazon CloudWatch metrics that you can use for each type of multi-model endpoint.

For more information about the metrics, see [Multi-Model Endpoint Model Loading Metrics](https://docs.aws.amazon.com/sagemaker/latest/dg/multi-model-metrics.html) and [Multi-Model Endpoint Model Instance Metrics](https://docs.aws.amazon.com/sagemaker/latest/dg/multi-model-instance-metrics.html) in Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663). Per-model metrics aren't supported.

#### CloudWatch metrics for CPU backed multi-model endpoints

You can monitor the following metrics on CPU backed multi-model endpoints.

The `AWS/SageMaker` namespace includes the following model loading metrics from calls to `InvokeEndpoint`.

Metrics are available at a 1-minute frequency.


##### Multi-Model Endpoint Model Loading Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ModelLoadingWaitTime</td>
<td>The interval of time that an invocation request has waited for the target</td>
</tr>
<tr>
<td></td>
<td>model to be downloaded, or loaded, or both in order to perform inference.</td>
</tr>
<tr>
<td>Metric</td>
<td>Description</td>
</tr>
<tr>
<td>------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>ModelUnloadingTime</td>
<td>The interval of time that it took to unload the model through the container's UnloadModel API call.</td>
</tr>
<tr>
<td>ModelDownloadingTime</td>
<td>The interval of time that it took to download the model from Amazon Simple Storage Service (Amazon S3).</td>
</tr>
<tr>
<td>ModelLoadingTime</td>
<td>The interval of time that it took to load the model through the container's LoadModel API call.</td>
</tr>
<tr>
<td>ModelCacheHit</td>
<td>The number of InvokeEndpoint requests sent to the multi-model endpoint for which the model was already loaded. The Average statistic shows the ratio of requests for which the model was already loaded.</td>
</tr>
</tbody>
</table>

Dimensions for Multi-Model Endpoint Model Loading Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EndpointName, VariantName</td>
<td>Filters endpoint invocation metrics for a ProductionVariant of the specified endpoint and variant.</td>
</tr>
</tbody>
</table>

The /aws/sagemaker/Endpoints namespaces include the following instance metrics from calls to InvokeEndpoint.

Metrics are available at a 1-minute frequency.

For information about how long CloudWatch metrics are retained for, see GetMetricStatistics in the Amazon CloudWatch API Reference.

Multi-Model Endpoint Model Instance Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>LoadedModelCount</td>
<td>The number of models loaded in the containers of the multi-model endpoint. This metric is emitted per instance.</td>
</tr>
</tbody>
</table>
### Hosting options

#### Metric

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>The Average statistic with a period of 1 minute tells you the average number of models loaded per instance. The Sum statistic tells you the total number of models loaded across all instances in the endpoint. The models that this metric tracks are not necessarily unique because a model might be loaded in multiple containers at the endpoint. Units: None Valid statistics: Average, Sum, Min, Max, Sample Count</td>
<td></td>
</tr>
<tr>
<td>CPUUtilization</td>
<td>The sum of each individual CPU core's utilization. The CPU utilization of each core range is 0–100. For example, if there are four CPUs, the CPUUtilization range is 0%–400%. For endpoint variants, the value is the sum of the CPU utilization of the primary and supplementary containers on the instance. Units: Percent</td>
</tr>
<tr>
<td>MemoryUtilization</td>
<td>The percentage of memory that is used by the containers on an instance. This value range is 0%–100%. For endpoint variants, the value is the sum of the memory utilization of the primary and supplementary containers on the instance. Units: Percent</td>
</tr>
<tr>
<td>DiskUtilization</td>
<td>The percentage of disk space used by the containers on an instance. This value range is 0%–100%. For endpoint variants, the value is the sum of the disk space utilization of the primary and supplementary containers on the instance. Units: Percent</td>
</tr>
</tbody>
</table>

#### CloudWatch metrics for GPU multi-model endpoint deployments

You can monitor the following metrics on GPU backed multi-model endpoints.

The AWS/SageMaker namespace includes the following model loading metrics from calls to `InvokeEndpoint`.

Metrics are available at a 1-minute frequency.

For information about how long CloudWatch metrics are retained for, see `GetMetricStatistics` in the Amazon CloudWatch API Reference.

#### Multi-Model Endpoint Model Loading Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ModelLoadingWaitTime</td>
<td>The interval of time that an invocation request has waited for the target model to be downloaded, or loaded, or both in order to perform inference.</td>
</tr>
</tbody>
</table>
### Model Unloading Time

The interval of time that it took to unload the model through the container's UnloadModel API call.

- **Units:** Microseconds
- **Valid statistics:** Average, Sum, Min, Max, Sample Count

### Model Downloading Time

The interval of time that it took to download the model from Amazon Simple Storage Service (Amazon S3).

- **Units:** Microseconds
- **Valid statistics:** Average, Sum, Min, Max, Sample Count

### Model Loading Time

The interval of time that it took to load the model through the container's LoadModel API call.

- **Units:** Microseconds
- **Valid statistics:** Average, Sum, Min, Max, Sample Count

### Model Cache Hit

The number of `InvokeEndpoint` requests sent to the multi-model endpoint for which the model was already loaded.

- **The Average statistic shows the ratio of requests for which the model was already loaded.**
- **Units:** None
- **Valid statistics:** Average, Sum, Sample Count

### Dimensions for Multi-Model Endpoint Model Loading Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EndpointName,</td>
<td>Filters endpoint invocation metrics for a ProductionVariant of the specified endpoint and variant.</td>
</tr>
<tr>
<td>VariantName</td>
<td></td>
</tr>
</tbody>
</table>

The `/aws/sagemaker/Endpoints` namespaces include the following instance metrics from calls to `InvokeEndpoint`.

Metrics are available at a 1-minute frequency.

For information about how long CloudWatch metrics are retained for, see `GetMetricStatistics` in the `Amazon CloudWatch API Reference`.

### Multi-Model Endpoint Model Instance Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>LoadedModelCount</td>
<td>The number of models loaded in the containers of the multi-model endpoint. This metric is emitted per instance.</td>
</tr>
<tr>
<td>Metric</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Metric</td>
<td>Description</td>
</tr>
<tr>
<td>The Average statistic with a period of 1 minute tells you the average number of models loaded per instance.</td>
<td></td>
</tr>
<tr>
<td>The Sum statistic tells you the total number of models loaded across all instances in the endpoint.</td>
<td></td>
</tr>
<tr>
<td>The models that this metric tracks are not necessarily unique because a model might be loaded in multiple containers at the endpoint.</td>
<td></td>
</tr>
<tr>
<td>Units: None</td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>CPUUtilization</td>
<td>The sum of each individual CPU core's utilization. The CPU utilization of each core range is 0-100. For example, if there are four CPUs, the CPUUtilization range is 0%-400%.</td>
</tr>
<tr>
<td>For endpoint variants, the value is the sum of the CPU utilization of the primary and supplementary containers on the instance.</td>
<td></td>
</tr>
<tr>
<td>Units: Percent</td>
<td></td>
</tr>
<tr>
<td>MemoryUtilization</td>
<td>The percentage of memory that is used by the containers on an instance. This value range is 0%-100%.</td>
</tr>
<tr>
<td>For endpoint variants, the value is the sum of the memory utilization of the primary and supplementary containers on the instance.</td>
<td></td>
</tr>
<tr>
<td>Units: Percent</td>
<td></td>
</tr>
<tr>
<td>GPUUtilization</td>
<td>The percentage of GPU units that are used by the containers on an instance. The value can range between range is 0-100 and is multiplied by the number of GPUs. For example, if there are four GPUs, the GPUUtilization range is 0%-400%.</td>
</tr>
<tr>
<td>For endpoint variants, the value is the sum of the GPU utilization of the primary and supplementary containers on the instance.</td>
<td></td>
</tr>
<tr>
<td>Units: Percent</td>
<td></td>
</tr>
<tr>
<td>GPUMemoryUtilization</td>
<td>The percentage of GPU memory used by the containers on an instance. The value range is 0-100 and is multiplied by the number of GPUs. For example, if there are four GPUs, the GPUMemoryUtilization range is 0%-400%.</td>
</tr>
<tr>
<td>For endpoint variants, the value is the sum of the GPU memory utilization of the primary and supplementary containers on the instance.</td>
<td></td>
</tr>
<tr>
<td>Units: Percent</td>
<td></td>
</tr>
<tr>
<td>DiskUtilization</td>
<td>The percentage of disk space used by the containers on an instance. This value range is 0%-100%.</td>
</tr>
<tr>
<td>For endpoint variants, the value is the sum of the disk space utilization of the primary and supplementary containers on the instance.</td>
<td></td>
</tr>
<tr>
<td>Units: Percent</td>
<td></td>
</tr>
</tbody>
</table>
Set Auto Scaling Policies for Multi-Model Endpoint Deployments

SageMaker multi-model endpoints fully support automatic scaling, which manages replicas of models to ensure models scale based on traffic patterns. We recommend that you configure your multi-model endpoint and the size of your instances based on Instance recommendations for multi-model endpoint deployments (p. 2759) and also set up instance based auto scaling for your endpoint. The invocation rates used to trigger an auto-scale event are based on the aggregate set of predictions across the full set of models served by the endpoint. For additional details on setting up endpoint auto scaling, see Automate Scale Amazon SageMaker Models.

You can set up auto scaling policies with predefined and custom metrics on both CPU and GPU backed multi-model endpoints.

**Note**
SageMaker multi-model endpoint metrics are available at one-minute granularity.

**Define a scaling policy**

To specify the metrics and target values for a scaling policy, you can configure a target-tracking scaling policy. You can use either a predefined metric or a custom metric.

Scaling policy configuration is represented by a JSON block. You save your scaling policy configuration as a JSON block in a text file. You use that text file when invoking the AWS CLI or the Application Auto Scaling API. For more information about policy configuration syntax, see TargetTrackingScalingPolicyConfiguration in the Application Auto Scaling API Reference.

The following options are available for defining a target-tracking scaling policy configuration.

**Use a predefined metric**

To quickly define a target-tracking scaling policy for a variant, use the SageMakerVariantInvocationsPerInstance predefined metric. SageMakerVariantInvocationsPerInstance is the average number of times per minute that each instance for a variant is invoked. We strongly recommend using this metric.

To use a predefined metric in a scaling policy, create a target tracking configuration for your policy. In the target tracking configuration, include a PredefinedMetricSpecification for the predefined metric and a TargetValue for the target value of that metric.

The following example is a typical policy configuration for target-tracking scaling for a variant. In this configuration, we use the SageMakerVariantInvocationsPerInstance predefined metric to adjust the number of variant instances so that each instance has an InvocationsPerInstance metric of 70.

```json
{"TargetValue": 70.0,
 "PredefinedMetricSpecification":
 {  
  "PredefinedMetricType": "InvocationsPerInstance"
  
 }
}
```

**Note**
We recommend that you use InvocationsPerInstance while using multi-model endpoints. The TargetValue for this metric depends on your application’s latency requirements. We also recommend that you load test your endpoints to set up suitable scaling parameter values. To learn more about load testing and setting up autoscaling for your endpoints, see the blog Configuring autoscaling inference endpoints in Amazon SageMaker.
Use a custom metric

If you need to define a target-tracking scaling policy that meets your custom requirements, define a custom metric. You can define a custom metric based on any production variant metric that changes in proportion to scaling.

Not all SageMaker metrics work for target tracking. The metric must be a valid utilization metric, and it must describe how busy an instance is. The value of the metric must increase or decrease in inverse proportion to the number of variant instances. That is, the value of the metric should decrease when the number of instances increases.

**Important**
Before deploying automatic scaling in production, you must test automatic scaling with your custom metric.

Example custom metric for a CPU backed multi-model endpoint

The following example is a target-tracking configuration for a scaling policy. In this configuration, for a model named `my-model`, a custom metric of `CPUUtilization` adjusts the instance count on the endpoint based on an average CPU utilization of 50% across all instances.

```json
{"TargetValue": 50,  
 "CustomizedMetricSpecification": 
 {"MetricName": "CPUUtilization",  
  "Namespace": "/aws/sagemaker/Endpoints", 
  "Dimensions": [
  {"Name": "EndpointName", "Value": "my-endpoint" },
  {"Name": "ModelName","Value": "my-model"}
  ],
  "Statistic": "Average",
  "Unit": "Percent"
 }
}
```

Example custom metric for a GPU backed multi-model endpoint

The following example is a target-tracking configuration for a scaling policy. In this configuration, for a model named `my-model`, a custom metric of `GPUUtilization` adjusts the instance count on the endpoint based on an average GPU utilization of 50% across all instances.

```json
{"TargetValue": 50,  
 "CustomizedMetricSpecification": 
 {"MetricName": "GPUUtilization",  
  "Namespace": "/aws/sagemaker/Endpoints", 
  "Dimensions": [
  {"Name": "EndpointName", "Value": "my-endpoint" },
  {"Name": "ModelName","Value": "my-model"}
  ],
  "Statistic": "Average",
  "Unit": "Percent"
 }
}
```

Add a cooldown period

To add a cooldown period for scaling out your endpoint, specify a value, in seconds, for `ScaleOutCooldown`. Similarly, to add a cooldown period for scaling in your model, add a value, in seconds, for `ScaleInCooldown`. For more information about `ScaleInCooldown` and `ScaleOutCooldown`, see `TargetTrackingScalingPolicyConfiguration` in the Application Auto Scaling API Reference.
The following is an example target-tracking configuration for a scaling policy. In this configuration, the `SageMakerVariantInvocationsPerInstance` predefined metric is used to adjust scaling based on an average of 70 across all instances of that variant. The configuration provides a scale-in cooldown period of 10 minutes and a scale-out cooldown period of 5 minutes.

```json
{"TargetValue": 70.0,
 "PredefinedMetricSpecification":
 {"PredefinedMetricType": "SageMakerVariantInvocationsPerInstance"},
 "ScaleInCooldown": 600,
 "ScaleOutCooldown": 300
}
```

### Host multiple models which use different containers behind one endpoint

SageMaker multi-container endpoints enable customers to deploy multiple containers, that use different models or frameworks, on a single SageMaker endpoint. The containers can be run in a sequence as an inference pipeline, or each container can be accessed individually by using direct invocation to improve endpoint utilization and optimize costs.

For information about invoking the containers in a multi-container endpoint in sequence, see [Host models along with pre-processing logic as serial inference pipeline behind one endpoint](p. 2789).

For information about invoking a specific container in a multi-container endpoint, see [Use a multi-container endpoint with direct invocation](p. 2783)

### Topics
- Create a multi-container endpoint (Boto 3) (p. 2782)
- Update a multi-container endpoint (p. 2783)
- Delete a multi-container endpoint (p. 2783)
- Use a multi-container endpoint with direct invocation (p. 2783)

### Create a multi-container endpoint (Boto 3)

Create a Multi-container endpoint by calling `CreateModel`, `CreateEndpointConfig`, and `CreateEndpoint` APIs as you would to create any other endpoints. You can run these containers sequentially as an inference pipeline, or run each individual container by using direct invocation. Multi-container endpoints have the following requirements when you call `create_model`:

- Use the `Containers` parameter instead of `PrimaryContainer`, and include more than one container in the `Containers` parameter.
- The `ContainerHostname` parameter is required for each container in a multi-container endpoint with direct invocation.
- Set the `Mode` parameter of the `InferenceExecutionConfig` field to `Direct` for direct invocation of each container, or `Serial` to use containers as an inference pipeline. The default mode is `Serial`.

**Note**
Currently there is a limit of up to 15 containers supported on a multi-container endpoint.

The following example creates a multi-container model for direct invocation.

1. Create container elements and `InferenceExecutionConfig` with direct invocation.
container1 = {'Image': '123456789012.dkr.ecr.us-east-1.amazonaws.com/myimage1:mytag',
              'ContainerHostname': 'firstContainer'}

container2 = {'Image': '123456789012.dkr.ecr.us-east-1.amazonaws.com/myimage2:mytag',
              'ContainerHostname': 'secondContainer'}

inferenceExecutionConfig = {'Mode': 'Direct'}

2. Create the model with the container elements and set the InferenceExecutionConfig field.

```python
import boto3
sm_client = boto3.Session().client('sagemaker')
response = sm_client.create_model(
    ModelName = 'my-direct-mode-model-name',
    InferenceExecutionConfig = inferenceExecutionConfig,
    ExecutionRoleArn = role,
    Containers = [container1, container2])
```

To create an endpoint, you would then call `create_endpoint_config` and `create_endpoint` as you would to create any other endpoint.

**Update a multi-container endpoint**

To update a multi-container endpoint, complete the following steps.

1. Call `create_model` to create a new model with a new value for the Mode parameter in the InferenceExecutionConfig field.
2. Call `create_endpoint_config` to create a new endpoint config with a different name by using the new model you created in the previous step.
3. Call `update_endpoint` to update the endpoint with the new endpoint config you created in the previous step.

**Delete a multi-container endpoint**

To delete an endpoint, call `delete_endpoint`, and provide the name of the endpoint you want to delete as the EndpointName parameter.

**Use a multi-container endpoint with direct invocation**

SageMaker multi-container endpoints enable customers to deploy multiple containers to deploy different models on a SageMaker endpoint. You can host up to 15 different inference containers on a single endpoint. By using direct invocation, you can send a request to a specific inference container hosted on a multi-container endpoint.

**Topics**

- Invoke a multi-container endpoint with direct invocation (p. 2784)
- Security with multi-container endpoints with direct invocation (p. 2784)
- Metrics for multi-container endpoints with direct invocation (p. 2785)
- Autoscale multi-container endpoints (p. 2788)
- Troubleshoot multi-container endpoints (p. 2788)
Invoke a multi-container endpoint with direct invocation

To invoke a multi-container endpoint with direct invocation, call `invoke_endpoint` as you would invoke any other endpoint, and specify which container you want to invoke by using the `TargetContainerHostname` parameter.

The following example directly invokes the `secondContainer` of a multi-container endpoint to get a prediction.

```python
import boto3
runtime_sm_client = boto3.Session().client('sagemaker-runtime')
response = runtime_sm_client.invoke_endpoint(
    EndpointName='my-endpoint',
    ContentType='text/csv',
    TargetContainerHostname='secondContainer',
    Body=body)
```

For each direct invocation request to a multi-container endpoint, only the container with the `TargetContainerHostname` processes the invocation request. You will get validation errors if you do any of the following:

- Specify a `TargetContainerHostname` that does not exist in the endpoint
- Do not specify a value for `TargetContainerHostname` in a request to an endpoint configured for direct invocation
- Specify a value for `TargetContainerHostname` in a request to an endpoint that is not configured for direct invocation.

Security with multi-container endpoints with direct invocation

For multi-container endpoints with direct invocation, there are multiple containers hosted in a single instance by sharing memory and a storage volume. It's your responsibility to use secure containers, maintain the correct mapping of requests to target containers, and provide users with the correct access to target containers. SageMaker uses IAM roles to provide IAM identity-based policies that you use to specify whether access to a resource is allowed or denied to that role, and under what conditions. For information about IAM roles, see `IAM roles` in the `AWS Identity and Access Management User Guide`. For information about identity-based policies, see `Identity-based policies and resource-based policies`.

By default, an IAM principal with `InvokeEndpoint` permissions on a multi-container endpoint with direct invocation can invoke any container inside the endpoint with the endpoint name that you specify when you call `invoke_endpoint`. If you need to restrict `invoke_endpoint` access to a limited set of containers inside a multi-container endpoint, use the `sagemaker:TargetContainerHostname` IAM condition key. The following policies show how to limit calls to specific containers within an endpoint.

The following policy allows `invoke_endpoint` requests only when the value of the `TargetContainerHostname` field matches one of the specified regular expressions.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Action": ["sagemaker:InvokeEndpoint"],
            "Effect": "Allow",
```
The following policy denies `invoke_endpoint` requests when the value of the `TargetContainerHostname` field matches one of the specified regular expressions in the `Deny` statement.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Action": [
        "sagemaker:InvokeEndpoint"
      ],
      "Effect": "Allow",
      "Condition": {
        "StringLike": {
          "sagemaker:TargetContainerHostname": ["*"]
        }
      }
    },
    {
      "Action": [
        "sagemaker:InvokeEndpoint"
      ],
      "Effect": "Deny",
      "Condition": {
        "StringLike": {
          "sagemaker:TargetContainerHostname": ["special*"]
        }
      }
    }
  ]
}
```

For information about SageMaker condition keys, see [Condition Keys for SageMaker](#) in the AWS Identity and Access Management User Guide.

### Metrics for multi-container endpoints with direct invocation

In addition to the endpoint metrics that are listed in Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663), SageMaker also provides per-container metrics.

Per-container metrics for multi-container endpoints with direct invocation are located in CloudWatch and categorized into two namespaces: AWS/SageMaker and aws/sagemaker/Endpoints. The AWS/SageMaker namespace includes invocation-related metrics, and the aws/sagemaker/Endpoints namespace includes memory and CPU utilization metrics.

The following table lists the per-container metrics for multi-container endpoints with direct invocation. All the metrics use the [EndpointName, VariantName, ContainerName] dimension, which filters metrics at a specific endpoint, for a specific variant and corresponding to a specific container. These metrics share the same metric names as in those for inference pipelines, but at a per-container level [EndpointName, VariantName, ContainerName].
<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Dimension</th>
<th>NameSpace</th>
</tr>
</thead>
<tbody>
<tr>
<td>Invocations</td>
<td>The number of InvokeEndpoint requests sent to a container inside an endpoint. To get the total number of requests sent to that container, use the Sum statistic. Units: None Valid statistics: Sum, Sample Count</td>
<td>EndpointName, VariantName, ContainerName</td>
<td>AWS/SageMaker</td>
</tr>
<tr>
<td>Invocation4XX Errors</td>
<td>The number of InvokeEndpoint requests that the model returned a 4xx HTTP response code for on a specific container. For each 4xx response, SageMaker sends a 1. Units: None Valid statistics: Average, Sum</td>
<td>EndpointName, VariantName, ContainerName</td>
<td>AWS/SageMaker</td>
</tr>
<tr>
<td>Invocation5XX Errors</td>
<td>The number of InvokeEndpoint requests that the model returned a 5xx HTTP response code for on a specific container. For each 5xx response, SageMaker sends a 1. Units: None Valid statistics: Average, Sum</td>
<td>EndpointName, VariantName, ContainerName</td>
<td>AWS/SageMaker</td>
</tr>
<tr>
<td>ContainerLatency</td>
<td>The time it took for the target container to respond as viewed from SageMaker. ContainerLatency includes the time it took to send the request, to fetch the response from the model's container, and to complete inference in the container. Units: Microseconds Valid statistics: Average, Sum, Min, Max, Sample Count</td>
<td>EndpointName, VariantName, ContainerName</td>
<td>AWS/SageMaker</td>
</tr>
<tr>
<td>OverheadLatency</td>
<td>The time added to the time taken to respond to a client</td>
<td>EndpointName, VariantName, ContainerName</td>
<td>AWS/SageMaker</td>
</tr>
</tbody>
</table>
request by SageMaker for overhead. **OverheadLatency** is measured from the time that SageMaker receives the request until it returns a response to the client, minus the **ModelLatency**. Overhead latency can vary depending on request and response payload sizes, request frequency, and authentication or authorization of the request, among other factors. Units: Microseconds Valid statistics: Average, Sum, Min, Max, `Sample Count`

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPUUtilization</td>
<td>The percentage of CPU units that are used by each container running on an instance. The value ranges from 0% to 100%, and is multiplied by the number of CPUs. For example, if there are four CPUs, CPUUtilization can range from 0% to 400%. For endpoints with direct invocation, the number of CPUUtilization metrics equals the number of containers in that endpoint. Units: Percent</td>
<td>EndpointName, VariantName, ContainerName</td>
</tr>
</tbody>
</table>
MemoryUtilization | The percentage of memory that is used by each container running on an instance. This value ranges from 0% to 100%. Similar as CPUUtilization, in endpoints with direct invocation, the number of MemoryUtilization metrics equals the number of containers in that endpoint. Units: Percent | EndpointName, VariantName, ContainerName | aws/sagemaker/Endpoints

All the metrics in the previous table are specific to multi-container endpoints with direct invocation. Besides these special per-container metrics, there are also metrics at the variant level with dimension [EndpointName, VariantName] for all the metrics in the table expect ContainerLatency.

Autoscale multi-container endpoints

If you want to configure automatic scaling for a multi-container endpoint using the InvocationsPerInstance metric, we recommend that the model in each container exhibits similar CPU utilization and latency on each inference request. This is recommended because if traffic to the multi-container endpoint shifts from a low CPU utilization model to a high CPU utilization model, but the overall call volume remains the same, the endpoint does not scale out and there may not be enough instances to handle all the requests to the high CPU utilization model. For information about automatically scaling endpoints, see Automatically Scale Amazon SageMaker Models (p. 2803).

Troubleshoot multi-container endpoints

The following sections can help you troubleshoot errors with multi-container endpoints.

Ping Health Check Errors

With multiple containers, endpoint memory and CPU are under higher pressure during endpoint creation. Specifically, the MemoryUtilization and CPUUtilization metrics are higher than for single-container endpoints, because utilization pressure is proportional to the number of containers. Because of this, we recommend that you choose instance types with enough memory and CPU to ensure that there is enough memory on the instance to have all the models loaded (the same guidance applies to deploying an inference pipeline). Otherwise, your endpoint creation might fail with an error such as XXX did not pass the ping health check.

Missing accept-bind-to-port=true Docker label

The containers in a multi-container endpoints listen on the port specified in the SAGEMAKER_BIND_TO_PORT environment variable instead of port 8080. When a container runs in a multi-container endpoint, SageMaker automatically provides this environment variable to the container. If this environment variable isn't present, containers default to using port 8080. To indicate that your container complies with this requirement, use the following command to add a label to your Dockerfile:

```
LABEL com.amazonaws.sagemaker.capabilities.accept-bind-to-port=true
```

Otherwise, You will see an error message such as Your Ecr Image XXX does not contain required com.amazonaws.sagemaker.capabilities.accept-bind-to-port=true Docker label(s).
If your container needs to listen on a second port, choose a port in the range specified by the SAGEMAKER_SAFE_PORT_RANGE environment variable. Specify the value as an inclusive range in the format `XXXX-YYYY`, where XXXX and YYYY are multi-digit integers. SageMaker provides this value automatically when you run the container in a multi-container endpoint.

**Host models along with pre-processing logic as serial inference pipeline behind one endpoint**

An *inference pipeline* is a Amazon SageMaker model that is composed of a linear sequence of two to fifteen containers that process requests for inferences on data. You use an inference pipeline to define and deploy any combination of pretrained SageMaker built-in algorithms and your own custom algorithms packaged in Docker containers. You can use an inference pipeline to combine preprocessing, predictions, and post-processing data science tasks. Inference pipelines are fully managed.

You can add SageMaker Spark ML Serving and scikit-learn containers that reuse the data transformers developed for training models. The entire assembled inference pipeline can be considered as a SageMaker model that you can use to make either real-time predictions or to process batch transforms directly without any external preprocessing.

Within an inference pipeline model, SageMaker handles invocations as a sequence of HTTP requests. The first container in the pipeline handles the initial request, then the intermediate response is sent as a request to the second container, and so on, for each container in the pipeline. SageMaker returns the final response to the client.

When you deploy the pipeline model, SageMaker installs and runs all of the containers on each Amazon Elastic Compute Cloud (Amazon EC2) instance in the endpoint or transform job. Feature processing and inferences run with low latency because the containers are co-located on the same EC2 instances. You define the containers for a pipeline model using the `CreateModel` operation or from the console. Instead of setting one `PrimaryContainer`, you use the `Containers` parameter to set the containers that make up the pipeline. You also specify the order in which the containers are executed.

A pipeline model is immutable, but you can update an inference pipeline by deploying a new one using the `UpdateEndpoint` operation. This modularity supports greater flexibility during experimentation.

For information on how to create an inference pipeline with the SageMaker model registry, see Register and Deploy Models with Model Registry (p. 2982).

There are no additional costs for using this feature. You pay only for the instances running on an endpoint.

**Topics**

- Sample Notebooks for Inference Pipelines (p. 2789)
- Feature Processing with Spark ML and Scikit-learn (p. 2790)
- Create a Pipeline Model (p. 2790)
- Run Real-time Predictions with an Inference Pipeline (p. 2793)
- Run Batch Transforms with Inference Pipelines (p. 2795)
- Inference Pipeline Logs and Metrics (p. 2796)
- Troubleshoot Inference Pipelines (p. 2801)

**Sample Notebooks for Inference Pipelines**

For an example that shows how to create and deploy inference pipelines, see the Training using SparkML on EMR and hosting on SageMaker sample notebook. For instructions on creating and accessing Jupyter
notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291).

To see a list of all the SageMaker samples, after creating and opening a notebook instance, choose the SageMaker Examples tab. There are three inference pipeline notebooks. The first two inference pipeline notebooks just described are located in the advanced_functionality folder and the third notebook is in the sagemaker-python-sdk folder. To open a notebook, choose its Use tab, then choose Create copy.

**Feature Processing with Spark ML and Scikit-learn**

Before training a model with either Amazon SageMaker built-in algorithms or custom algorithms, you can use Spark and scikit-learn preprocessors to transform your data and engineer features.

**Feature Processing with Spark ML**

You can run Spark ML jobs with AWS Glue, a serverless ETL (extract, transform, load) service, from your SageMaker notebook. You can also connect to existing EMR clusters to run Spark ML jobs with Amazon EMR. To do this, you need an AWS Identity and Access Management (IAM) role that grants permission for making calls from your SageMaker notebook to AWS Glue.

**Note**

To see which Python and Spark versions AWS Glue supports, refer to AWS Glue Release Notes.

After engineering features, you package and serialize Spark ML jobs with MLeap into MLeap containers that you can add to an inference pipeline. You don't need to use externally managed Spark clusters. With this approach, you can seamlessly scale from a sample of rows to terabytes of data. The same transformers work for both training and inference, so you don't need to duplicate preprocessing and feature engineering logic or develop a one-time solution to make the models persist. With inference pipelines, you don't need to maintain outside infrastructure, and you can make predictions directly from data inputs.

When you run a Spark ML job on AWS Glue, a Spark ML pipeline is serialized into MLeap format. Then, you can use the job with the SparkML Model Serving Container in a SageMaker Inference Pipeline. MLeap is a serialization format and execution engine for machine learning pipelines. It supports Spark, Scikit-learn, and TensorFlow for training pipelines and exporting them to a serialized pipeline called an MLeap Bundle. You can deserialize Bundles back into Spark for batch-mode scoring or into the MLeap runtime to power real-time API services.

**Feature Processing with Scikit-Learn**

You can run and package scikit-learn jobs into containers directly in Amazon SageMaker. For an example of Python code for building a scikit-learn featurizer model that trains on Fisher's Iris flower data set and predicts the species of Iris based on morphological measurements, see IRIS Training and Prediction with Sagemaker Scikit-learn.

**Create a Pipeline Model**

To create a pipeline model that can be deployed to an endpoint or used for a batch transform job, use the Amazon SageMaker console or the CreateModel operation.

**To create an inference pipeline (console)**

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Choose Models, and then choose Create models from the Inference group.
3. On the Create model page, provide a model name, choose an IAM role, and, if you want to use a private VPC, specify VPC values.
4. To add information about the containers in the inference pipeline, choose Add container, then choose Next.

5. Complete the fields for each container in the order that you want to execute them, up to the maximum of fifteen. Complete the Container input options, Location of inference code image, and, optionally, Location of model artifacts, Container host name, and Environmental variables fields.
The **MyInferencePipelineModel** page summarizes the settings for the containers that provide input for the model. If you provided the environment variables in a corresponding container definition, SageMaker shows them in the **Environment variables** field.

### Run Real-time Predictions with an Inference Pipeline

You can use trained models in an inference pipeline to make real-time predictions directly without performing external preprocessing. When you configure the pipeline, you can choose to use the built-in feature transformers already available in Amazon SageMaker. Or, you can implement your own transformation logic using just a few lines of scikit-learn or Spark code.
**ML**eap, a serialization format and execution engine for machine learning pipelines, supports Spark, scikit-learn, and TensorFlow for training pipelines and exporting them to a serialized pipeline called an MLeap Bundle. You can deserialize Bundles back into Spark for batch-mode scoring or into the MLeap runtime to power real-time API services.

The containers in a pipeline listen on the port specified in the SAGEMAKER_BIND_TO_PORT environment variable (instead of 8080). When running in an inference pipeline, SageMaker automatically provides this environment variable to containers. If this environment variable isn't present, containers default to using port 8080. To indicate that your container complies with this requirement, use the following command to add a label to your Dockerfile:

```
LABEL com.amazonaws.sagemaker.capabilities.accept-bind-to-port=true
```

If your container needs to listen on a second port, choose a port in the range specified by the SAGEMAKER_SAFE_PORT_RANGE environment variable. Specify the value as an inclusive range in the format "XXXX-YYYY", where XXXX and YYYY are multi-digit integers. SageMaker provides this value automatically when you run the container in a multicontainer pipeline.

**Note**

To use custom Docker images in a pipeline that includes SageMaker built-in algorithms, you need an Amazon Elastic Container Registry (Amazon ECR) policy. Your Amazon ECR repository must grant SageMaker permission to pull the image. For more information, see Troubleshoot Amazon ECR Permissions for Inference Pipelines (p. 2801).

### Create and Deploy an Inference Pipeline Endpoint

The following code creates and deploys a real-time inference pipeline model with SparkML and XGBoost models in series using the SageMaker SDK.

```python
from sagemaker.model import Model
from sagemaker.pipeline_model import PipelineModel
from sagemaker.sparkml.model import SparkMLModel

sparkml_data = 's3://{}{}{}'.format(s3_model_bucket, s3_model_key_prefix, 'model.tar.gz')
sparkml_model = SparkMLModel(model_data=sparkml_data)
xgb_model = Model(model_data=xgb_model.model_data, image=training_image)

model_name = 'serial-inference-' + timestamp_prefix
endpoint_name = 'serial-inference-ep-' + timestamp_prefix
sm_model = PipelineModel(name=model_name, role=role, models=[sparkml_model, xgb_model])
sm_model.deploy(initial_instance_count=1, instance_type='ml.c4.xlarge',
endpoint_name=endpoint_name)
```

### Request Real-Time Inference from an Inference Pipeline Endpoint

The following example shows how to make real-time predictions by calling an inference endpoint and passing a request payload in JSON format:

```python
import sagemaker
from sagemaker.predictor import json_serializer, json_deserializer, Predictor

payload = {
    "input": [
    {
        "name": "Pclass",
        "type": "float",
        "val": "1.0"
    },
    {
        "name": "Embarked",
        "type": "string",
```
Hosting options

```python
import json

payload = [
    {
        "name": "Age",
        "type": "double",
        "val": "48.0"
    },
    {
        "name": "Fare",
        "type": "double",
        "val": "100.67"
    },
    {
        "name": "SibSp",
        "type": "double",
        "val": "1.0"
    },
    {
        "name": "Sex",
        "type": "string",
        "val": "male"
    }
],
"output": {
    "name": "features",
    "type": "double",
    "struct": "vector"
}

predictor = Predictor(endpoint=endpoint_name, sagemaker_session=sagemaker.Session(),
                       serializer=json_serializer, content_type='text/csv', accept='application/json')

print(predictor.predict(payload))
```

The response you get from `predictor.predict(payload)` is the model's inference result.

**Realtime inference pipeline example**

You can run this example notebook using the SKLearn predictor that shows how to deploy an endpoint, run an inference request, then deserialize the response. Find this notebook and more examples in the Amazon SageMaker example GitHub repository.

**Run Batch Transforms with Inference Pipelines**

To get inferences on an entire dataset you run a batch transform on a trained model. To run inferences on a full dataset, you can use the same inference pipeline model created and deployed to an endpoint for real-time processing in a batch transform job. To run a batch transform job in a pipeline, you download the input data from Amazon S3 and send it in one or more HTTP requests to the inference pipeline model. For an example that shows how to prepare data for a batch transform, see "Section 2 - Preprocess the raw housing data using Scikit Learn" of the Amazon SageMaker Multi-Model Endpoints using Linear Learner sample notebook. For information about Amazon SageMaker batch transforms, see Use Batch Transform (p. 2955).

**Note**

To use custom Docker images in a pipeline that includes Amazon SageMaker built-in algorithms, you need an Amazon Elastic Container Registry (ECR) policy. Your Amazon ECR repository must grant SageMaker permission to pull the image. For more information, see Troubleshoot Amazon ECR Permissions for Inference Pipelines (p. 2801).

The following example shows how to run a transform job using the Amazon SageMaker Python SDK. In this example, `model_name` is the inference pipeline that combines SparkML and XGBoost models.
(created in previous examples). The Amazon S3 location specified by `input_data_path` contains the input data, in CSV format, to be downloaded and sent to the Spark ML model. After the transform job has finished, the Amazon S3 location specified by `output_data_path` contains the output data returned by the XGBoost model in CSV format.

```python
import sagemaker
input_data_path = 's3://{{default_bucket}}/{{key}}/{{file_name}}'
output_data_path = 's3://{{default_bucket}}/{{key}}'
transform_job = sagemaker.transformer.Transformer(
    model_name = model_name,
    instance_count = 1,
    instance_type = 'ml.m4.xlarge',
    strategy = 'SingleRecord',
    assemble_with = 'Line',
    output_path = output_data_path,
    base_transform_job_name='inference-pipelines-batch',
    sagemaker_session=sagemaker.Session(),
    accept = CONTENT_TYPE_CSV)
transform_job.transform(data = input_data_path,
                         content_type = CONTENT_TYPE_CSV,
                         split_type = 'Line')
```

### Inference Pipeline Logs and Metrics

Monitoring is important for maintaining the reliability, availability, and performance of Amazon SageMaker resources. To monitor and troubleshoot inference pipeline performance, use Amazon CloudWatch logs and error messages. For information about the monitoring tools that SageMaker provides, see Monitor Amazon SageMaker (p. 3663).

#### Use Metrics to Monitor Multi-container Models

To monitor the multi-container models in Inference Pipelines, use Amazon CloudWatch. CloudWatch collects raw data and processes it into readable, near real-time metrics. SageMaker training jobs and endpoints write CloudWatch metrics and logs in the AWS/SageMaker namespace.

The following tables list the metrics and dimensions for the following:

- Endpoint invocations
- Training jobs, batch transform jobs, and endpoint instances

A *dimension* is a name/value pair that uniquely identifies a metric. You can assign up to 10 dimensions to a metric. For more information on monitoring with CloudWatch, see Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663).

#### Endpoint Invocation Metrics

The AWS/SageMaker namespace includes the following request metrics from calls to `InvokeEndpoint`.

Metrics are reported at a 1-minute intervals.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Invocation4XXErrors</td>
<td>The number of <code>InvokeEndpoint</code> requests that the model returned a 4xx HTTP response code for. For each 4xx response, SageMaker sends a 1.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
</tbody>
</table>

2796
<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Invocation5XXErrors</td>
<td>The number of InvokeEndpoint requests that the model returned a 5xx HTTP response code for. For each 5xx response, SageMaker sends a 1.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>Invocations</td>
<td>The number of InvokeEndpoint requests sent to a model endpoint. To get the total number of requests sent to a model endpoint, use the Sum statistic.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum, Sample Count</td>
</tr>
<tr>
<td>InvocationsPerInstance</td>
<td>The number of endpoint invocations sent to a model, normalized by InstanceCount in each ProductionVariant. SageMaker sends 1/numberOfInstances as the value for each request, where numberOfInstances is the number of active instances for the ProductionVariant at the endpoint at the time of the request.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>ModelLatency</td>
<td>The time the model or models took to respond. This includes the time it took to send the request, to fetch the response from the model container, and to complete the inference in the container. ModelLatency is the total time taken by all containers in an inference pipeline.</td>
</tr>
<tr>
<td></td>
<td>Units: Microseconds</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>OverheadLatency</td>
<td>The time added to the time taken to respond to a client request by SageMaker for overhead. OverheadLatency is measured from the time that SageMaker receives the request until it returns a response to the client, minus the ModelLatency. Overhead latency can vary depending on request and response payload sizes, request frequency, and authentication or authorization of the request, among other factors.</td>
</tr>
<tr>
<td></td>
<td>Units: Microseconds</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>ContainerLatency</td>
<td>The time it took for an Inference Pipelines container to respond as viewed from SageMaker. ContainerLatency includes the time it took to send the request, to fetch the response from the model's container, and to complete inference in the container.</td>
</tr>
<tr>
<td></td>
<td>Units: Microseconds</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>Dimension</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>EndpointName, VariantName, ContainerName</td>
<td>Filters endpoint invocation metrics for a ProductionVariant at the specified endpoint and for the specified variant.</td>
</tr>
</tbody>
</table>

For an inference pipeline endpoint, CloudWatch lists per-container latency metrics in your account as **Endpoint Container Metrics** and **Endpoint Variant Metrics** in the **SageMaker** namespace, as follows. The ContainerLatency metric appears only for inferences pipelines.

For each endpoint and each container, latency metrics display names for the container, endpoint, variant, and metric.

**Training Job, Batch Transform Job, and Endpoint Instance Metrics**

The namespaces /aws/sagemaker/TrainingJobs, /aws/sagemaker/TransformJobs, and /aws/sagemaker/Endpoints include the following metrics for training jobs and endpoint instances.

Metrics are reported at a 1-minute intervals.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPUUtilization</td>
<td>The percentage of CPU units that are used by the containers running on an instance. The value ranges from 0% to 100%, and is multiplied by the number of CPUs. For example, if there are four CPUs, CPUUtilization can range from 0% to 400%.</td>
</tr>
</tbody>
</table>

For training jobs, CPUUtilization is the CPU utilization of the algorithm container running on the instance.

For batch transform jobs, CPUUtilization is the CPU utilization of the transform container running on the instance.

For multi-container models, CPUUtilization is the sum of CPU utilization by all containers running on the instance.

For endpoint variants, CPUUtilization is the sum of CPU utilization by all of the containers running on the instance.

Units: Percent
<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MemoryUtilization</td>
<td>The percentage of memory that is used by the containers running on an instance. This value ranges from 0% to 100%. For training jobs, MemoryUtilization is the memory used by the algorithm container running on the instance.</td>
</tr>
<tr>
<td></td>
<td>For batch transform jobs, MemoryUtilization is the memory used by the transform container running on the instance. For multi-container models, MemoryUtilization is the sum of memory used by all containers running on the instance.</td>
</tr>
<tr>
<td></td>
<td>For endpoint variants, MemoryUtilization is the sum of memory used by all of the containers running on the instance. Units: Percent</td>
</tr>
<tr>
<td>GPUUtilization</td>
<td>The percentage of GPU units that are used by the containers running on an instance. GPUUtilization ranges from 0% to 100% and is multiplied by the number of GPUs. For example, if there are four GPUs, GPUUtilization can range from 0% to 400%.</td>
</tr>
<tr>
<td></td>
<td>For training jobs, GPUUtilization is the GPU used by the algorithm container running on the instance.</td>
</tr>
<tr>
<td></td>
<td>For batch transform jobs, GPUUtilization is the GPU used by the transform container running on the instance.</td>
</tr>
<tr>
<td></td>
<td>For multi-container models, GPUUtilization is the sum of GPU used by all containers running on the instance.</td>
</tr>
<tr>
<td></td>
<td>For endpoint variants, GPUUtilization is the sum of GPU used by all of the containers running on the instance. Units: Percent</td>
</tr>
<tr>
<td>GPUMemoryUtilization</td>
<td>The percentage of GPU memory used by the containers running on an instance. GPUMemoryUtilization ranges from 0% to 100% and is multiplied by the number of GPUs. For example, if there are four GPUs, GPUMemoryUtilization can range from 0% to 400%.</td>
</tr>
<tr>
<td></td>
<td>For training jobs, GPUMemoryUtilization is the GPU memory used by the algorithm container running on the instance.</td>
</tr>
<tr>
<td></td>
<td>For batch transform jobs, GPUMemoryUtilization is the GPU memory used by the transform container running on the instance.</td>
</tr>
<tr>
<td></td>
<td>For multi-container models, GPUMemoryUtilization is sum of GPU used by all containers running on the instance.</td>
</tr>
<tr>
<td></td>
<td>For endpoint variants, GPUMemoryUtilization is the sum of the GPU memory used by all of the containers running on the instance. Units: Percent</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>
## Hosting options

### Metric

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DiskUtilization</td>
<td>The percentage of disk space used by the containers running on an instance. DiskUtilization ranges from 0% to 100%. This metric is not supported for batch transform jobs. For training jobs, DiskUtilization is the disk space used by the algorithm container running on the instance. For endpoint variants, DiskUtilization is the sum of the disk space used by all of the provided containers running on the instance. Units: Percent</td>
</tr>
</tbody>
</table>

### Dimensions for Training Job, Batch Transform Job, and Endpoint Instance Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Host</td>
<td>For training jobs, Host has the format [training-job-name]/algo-[instance-number-in-cluster]. Use this dimension to filter instance metrics for the specified training job and instance. This dimension format is present only in the /aws/sagemaker/TrainingJobs namespace. For batch transform jobs, Host has the format [transform-job-name]/[instance-id]. Use this dimension to filter instance metrics for the specified batch transform job and instance. This dimension format is present only in the /aws/sagemaker/TransformJobs namespace. For endpoints, Host has the format [endpoint-name]/[production-variant-name]/[instance-id]. Use this dimension to filter instance metrics for the specified endpoint, variant, and instance. This dimension format is present only in the /aws/sagemaker/Endpoints namespace.</td>
</tr>
</tbody>
</table>

To help you debug your training jobs, endpoints, and notebook instance lifecycle configurations, SageMaker also sends anything an algorithm container, a model container, or a notebook instance lifecycle configuration sends to stdin or stdout to Amazon CloudWatch Logs. You can use this information for debugging and to analyze progress.

### Use Logs to Monitor an Inference Pipeline

The following table lists the log groups and log streams SageMaker sends to Amazon CloudWatch.

A log stream is a sequence of log events that share the same source. Each separate source of logs into CloudWatch makes up a separate log stream. A log group is a group of log streams that share the same retention, monitoring, and access control settings.

### Logs

<table>
<thead>
<tr>
<th>Log Group Name</th>
<th>Log Stream Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>/aws/sagemaker/TrainingJobs</td>
<td>[training-job-name]/algo-[instance-number-in-cluster]-[epoch_timestamp]</td>
</tr>
<tr>
<td>/aws/sagemaker/Endpoints/</td>
<td>[production-variant-name]/[instance-id]</td>
</tr>
<tr>
<td>[EndpointName]</td>
<td>[production-variant-name]/[instance-id]</td>
</tr>
<tr>
<td>Log Group Name</td>
<td>Log Stream Name</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>---------------------------------------------------------------------------------</td>
</tr>
<tr>
<td></td>
<td>[production-variant-name]/[instance-id]/[container-name provided in the SageMaker model] (For Inference Pipelines) For Inference Pipelines logs, if you don't provide container names, CloudWatch uses <strong>container-1, container-2</strong>, and so on, in the order that containers are provided in the model.</td>
</tr>
<tr>
<td>/aws/sagemaker/NotebookInstances</td>
<td>[notebook-instance-name]/[LifecycleConfigHook]</td>
</tr>
<tr>
<td>/aws/sagemaker/TransformJobs</td>
<td>[transform-job-name]/[instance-id]-[epoch_timestamp]</td>
</tr>
<tr>
<td></td>
<td>[transform-job-name]/[instance-id]-[epoch_timestamp]/data-log</td>
</tr>
<tr>
<td></td>
<td>[transform-job-name]/[instance-id]-[epoch_timestamp]/[container-name provided in the SageMaker model] (For Inference Pipelines) For Inference Pipelines logs, if you don't provide container names, CloudWatch uses <strong>container-1, container-2</strong>, and so on, in the order that containers are provided in the model.</td>
</tr>
</tbody>
</table>

**Note**

SageMaker creates the `/aws/sagemaker/NotebookInstances` log group when you create a notebook instance with a lifecycle configuration. For more information, see Customize a Notebook Instance Using a Lifecycle Configuration Script (p. 299).

For more information about SageMaker logging, see Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675).

### Troubleshoot Inference Pipelines

To troubleshoot inference pipeline issues, use CloudWatch logs and error messages. If you are using custom Docker images in a pipeline that includes Amazon SageMaker built-in algorithms, you might also encounter permissions problems. To grant the required permissions, create an Amazon Elastic Container Registry (Amazon ECR) policy.

**Topics**

- Troubleshoot Amazon ECR Permissions for Inference Pipelines (p. 2801)
- Use CloudWatch Logs to Troubleshoot SageMaker Inference Pipelines (p. 2802)
- Use Error Messages to Troubleshoot Inference Pipelines (p. 2803)

### Troubleshoot Amazon ECR Permissions for Inference Pipelines

When you use custom Docker images in a pipeline that includes SageMaker built-in algorithms, you need an Amazon ECR policy. The policy allows your Amazon ECR repository to grant permission for SageMaker to pull the image. The policy must add the following permissions:

```json
{
    "Version": "2008-10-17",
    "Statement": [
        {
            "Sid": "allowSageMakerToPull",
            "Effect": "Allow",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            }
        }
    ]
}
```
Use CloudWatch Logs to Troubleshoot SageMaker Inference Pipelines

SageMaker publishes the container logs for endpoints that deploy an inference pipeline to Amazon CloudWatch at the following path for each container.

/aws/sagemaker/Endpoints/{EndpointName}/{Variant}/{InstanceId}/{ContainerHostname}

For example, logs for this endpoint are published to the following log groups and streams:

- **EndpointName**: MyInferencePipelinesEndpoint
- **Variant**: MyInferencePipelinesVariant
- **InstanceId**: i-0179208609ff7e488
- **ContainerHostname**: MyContainerName1 and MyContainerName2

A **log stream** is a sequence of log events that share the same source. Each separate source of logs into CloudWatch makes up a separate log stream. A **log group** is a group of log streams that share the same retention, monitoring, and access control settings.

To see the log groups and streams

2. In the navigation page, choose Logs.
3. In Log Groups, filter on MyInferencePipelinesEndpoint:

4. To see the log streams, on the CloudWatch Log Groups page, choose MyInferencePipelinesEndpoint, and then Search Log Group.
Automatically Scale Amazon SageMaker Models

Amazon SageMaker supports automatic scaling (auto scaling) for your hosted models. Auto scaling dynamically adjusts the number of instances provisioned for a model in response to changes in your workload. When the workload increases, auto scaling brings more instances online. When the workload decreases, auto scaling removes unnecessary instances so that you don't pay for provisioned instances that you aren't using.

Topics

- Prerequisites (p. 2803)
- Configure model auto scaling with the console (p. 2806)
- Register a model (p. 2807)
- Define a scaling policy (p. 2808)
- Apply a scaling policy (p. 2811)
- Edit a scaling policy (p. 2812)
- Delete a scaling policy (p. 2813)
- Query Endpoint Auto scaling History (p. 2815)
- Update or delete endpoints that use automatic scaling (p. 2816)
- Load testing your auto scaling configuration (p. 2817)
- Use AWS CloudFormation to update auto scaling policies (p. 2818)

Prerequisites

Before you can use auto scaling, must have already created a Amazon SageMaker model deployment. Deployed models are referred to as a production variant. This includes information about the model and the resources used to host it.

For more information about deploying a model endpoint, see Deploy the Model to SageMaker Hosting Services (p. 85).

To activate auto scaling for a model, you can use the console, the AWS CLI, or the Application Auto Scaling API. It is recommended to try to Configure model auto scaling with the console (p. 2806) to get familiar with the requirements and to test your first auto scaling configuration. When using the AWS CLI or Application Auto Scaling the flow is to register the model, define the scaling policy, then apply it. The

For a list of the logs that SageMaker publishes, see Inference Pipeline Logs and Metrics (p. 2796).

Use Error Messages to Troubleshoot Inference Pipelines

The inference pipeline error messages indicate which containers failed.

If an error occurs while SageMaker is invoking an endpoint, the service returns a ModelError (error code 424), which indicates which container failed. If the request payload (the response from the previous container) exceeds the limit of 5 MB, SageMaker provides a detailed error message, such as:

Received response from MyContainerName1 with status code 200. However, the request payload from MyContainerName1 to MyContainerName2 is 6000000 bytes, which has exceeded the maximum limit of 5 MB.

If a container fails the ping health check while SageMaker is creating an endpoint, it returns a ClientError and indicates all of the containers that failed the ping check in the last health check.
following overview provides further details on the prerequisites and components used with Application Auto Scaling.

**Auto scaling policy overview**

To use automatic scaling, you define and apply a scaling policy that uses Amazon CloudWatch metrics and target values that you assign. Automatic scaling uses the policy to increase or decrease the number of instances in response to actual workloads.

You can use the AWS Management Console to apply a scaling policy based on a predefined metric. A *predefined metric* is defined in an enumeration so that you can specify it by name in code or use it in the AWS Management Console. Alternatively, you can use either the AWS Command Line Interface (AWS CLI) or the Application Auto Scaling API to apply a scaling policy based on a predefined or custom metric.

There are two types of supported scaling policies: target-tracking scaling and step scaling. It is recommended to use target-tracking scaling policies for your auto scaling configuration. You configure the *target-tracking scaling policy* by specifying a predefined or custom metric and a target value for the metric. For more information about using Application Auto Scaling target-tracking scaling policies, see [Target Tracking Scaling Policies](#).

You can use step scaling when you require an advanced configuration, such as specifying how many instances to deploy under what conditions. Otherwise, using target-tracking scaling is preferred as it will be fully automated. For more information about using Application Auto Scaling step scaling policies, see [Step Scaling Policies](#).

A scaling policy has the following components:

- **A target metric**—The Amazon CloudWatch metric that SageMaker automatic scaling uses to determine when and how much to scale.
- **Minimum and maximum capacity**—The minimum and maximum number of instances to use for scaling.
- **A cool down period**—The amount of time, in seconds, after a scale-in or scale-out activity completes before another scale-out activity can start.
- **Required permissions**—Permissions that are required to perform automatic scaling actions.
- **A service-linked role**—An AWS Identity and Access Management (IAM) role that is linked to a specific AWS service. A service-linked role includes all of the permissions that the service requires to call other AWS services on your behalf. SageMaker automatic scaling automatically generates this role, `AWSServiceRoleForApplicationAutoScaling_SageMakerEndpoint`, for you.

**Target metric for auto scaling**

Amazon CloudWatch alarms trigger the scaling policy, which calculate how to adjust scaling based on the metric and target value that you set. The scaling policy adds or removes endpoint instances as required to keep the metric at, or close to, the specified target value. In addition, a scaling policy also adjusts to fluctuations in the metric when a workload changes. The scaling policy minimizes rapid fluctuations in the number of available instances for your model.

For example, a scaling policy that uses the predefined `InvocationsPerInstance` metric with a target value of 70 can keep `InvocationsPerInstance` at, or close to 70.

**Minimum and maximum capacity**

You may specify the maximum number of endpoint instances for the model. The maximum value must be equal to or greater than the value specified for the minimum number of endpoint instances. SageMaker automatic scaling does not enforce a limit for this value.
You must also specify the minimum number of instances for the model. This value must be at least 1, and equal to or less than the value specified for the maximum number of endpoint instances.

To determine the minimum and maximum number of instances that you need for typical traffic, test your auto scaling configuration with the expected rate of traffic to your model.

**Important**
Scaling-in occurs when there is no traffic: if a variant’s traffic becomes zero, SageMaker automatically scales in to the minimum number of instances specified. In this case, SageMaker emits metrics with a value of zero. Minimum instance count is required to be 1 or higher.

**Cooldown period**

Tune the responsiveness of your scaling policy by adding a cooldown period. A **cooldown period** controls when your model is scaled-in (by reducing instances) or scaled-out (by increasing instances). It does this by blocking subsequent scale-in or scale-out requests until the period expires. This slows the deletion of instances for scale-in requests, and the creation of instances for scale-out requests. A cooldown period helps to ensure that the scaling policy doesn't launch or terminate additional instances before the previous scaling activity takes effect. After automatic scaling dynamically scales using a scaling policy, it waits for the cooldown period to complete before resuming scaling activities.

You configure the cooldown period in your automatic scaling policy. You can specify the following cooldown periods:

- A scale-in activity reduces the number of instances. A scale-in cooldown period specifies the amount of time, in seconds, after a scale-in activity completes before another scale-in activity can start.
- A scale-out activity increases the number of instances. A scale-out cooldown period specifies the amount of time, in seconds, after a scale-out activity completes before another scale-out activity can start.

If you don’t specify a scale-in or a scale-out cooldown period automatic scaling use the default, which is 300 seconds for each.

If instances are being added or removed too quickly when you test your automatic scaling configuration, consider increasing this value. You can see this behavior if the traffic to your model has a lot of spikes, or if you have multiple automatic scaling policies defined for a variant.

If instances are not being added quickly enough to address increased traffic, consider decreasing this value.

**Permissions**

The SagemakerFullAccessPolicy IAM policy has all of the IAM permissions required to perform auto scaling. For more information about SageMaker IAM permissions, see [SageMaker Roles (p. 3536)](https://docs.aws.amazon.com/sagemaker/latest/dg/sagemaker-roles.html).

If you are using a custom permission policy, you must include the following permissions:

```json
{
   "Effect": "Allow",
   "Action": [
      "sagemaker:DescribeEndpoint",
      "sagemaker:DescribeEndpointConfig",
      "sagemaker:UpdateEndpointWeightsAndCapacities"
   ],
   "Resource": "*"
}
```
Service-linked role

Auto scaling uses the AWSServiceRoleForApplicationAutoScaling_SageMakerEndpoint service-linked role; it created for you automatically. A service-linked role is a unique type of IAM role that is linked directly to an AWS service. Service-linked roles are predefined by the service and include all of the permissions that the service requires to call other AWS services on your behalf. For more information, see Service-Linked Roles.

Configure model auto scaling with the console

To configure auto scaling for a model using the console

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the navigation pane, open Inference and choose Endpoints.
3. Choose the endpoint that you want to configure.
4. For Endpoint runtime settings, choose the model variant that you want to configure.
5. For Endpoint runtime settings, choose Configure auto scaling.

The Configure variant automatic scaling page appears.

6. For Minimum capacity, type the minimum number of instances that you want the scaling policy to maintain. At least 1 instance is required.
7. For Maximum capacity, type the maximum number of instances that you want the scaling policy to maintain.
8. For the target value, type the average number of invocations per instance per minute for the model. To determine this value, follow the guidelines in Load testing (p. 2817).

Application Auto Scaling adds or removes instances to keep the metric close to the value that you specify.
9. For **Scale-in cool down (seconds)** and **Scale-out cool down (seconds)**, type the number seconds for each cool down period. Assuming that the order in the list is based on either most important to less important of first applied to last applied.

10. Select **Deactivate scale in** to prevent the scaling policy from deleting variant instances if you want to ensure that your variant scales out to address increased traffic, but are not concerned with removing instances to reduce costs when traffic decreases, deactivate scale-in activities.

Scale-out activities are always activated so that the scaling policy can create endpoint instances as needed.

11. Choose **Save**.

This procedure registers a model as a scalable target with Application Auto Scaling. When you register a model, Application Auto Scaling performs validation checks to ensure the following:

- The model exists
- The permissions are sufficient
- You aren't registering a variant with an instance that is a burstable performance instance such as T2

**Note**
SageMaker doesn't support auto scaling for burstable instances such as T2, because they already allow for increased capacity under increased workloads. For information about burstable performance instances, see [Amazon EC2 Instance Types](#).

### Register a model

You can add auto scaling for a model with the AWS CLI or the Application Auto Scaling API. You first must register the model, then you must define an auto scaling policy.

#### Register a model with the AWS CLI

With the AWS CLI, you can configure auto scaling based on either a predefined or a custom metric.

To register your endpoint, use the `register-scalable-target` AWS CLI command with the following parameters:

- `-service-namespace`—Set this value to `sagemaker`.
- `-resource-id`—The resource identifier for the model (specifically, the production variant). For this parameter, the resource type is endpoint and the unique identifier is the name of the production variant. For example, `endpoint/MyEndpoint/variant/MyVariant`.
- `-scalable-dimension`—Set this value to `sagemaker:variant:DesiredInstanceCount`.
- `-min-capacity`—The minimum number of instances that for this model. Set min-capacity to at least 1. It must be equal to or less than the value specified for max-capacity.
- `-max-capacity`—The maximum number of instances that Application Auto Scaling should manage. Set max-capacity to a minimum of 1, It must be equal to or greater than the value specified for min-capacity.

**Example**

The following example shows how to register a model named `MyVariant` that is dynamically scaled to have one to eight instances:

```
aws application-autoscaling register-scalable-target
   --service-namespace sagemaker
   --resource-id endpoint/MyEndpoint/variant/MyVariant
   --scalable-dimension sagemaker:variant:DesiredInstanceCount
   --min-capacity 1
   --max-capacity 8
```
Automatically scale models

```
--resource-id endpoint/MyEndPoint/variant/MyVariant 
--scalable-dimension sagemaker:variant:DesiredInstanceCount 
--min-capacity 1 
--max-capacity 8
```

Register a model with the Application Auto Scaling API

To define the scaling limits for the model, register your model with Application Auto Scaling. Application Auto Scaling dynamically scales the number of production variant instances.

To register your model with Application Auto Scaling, use the `RegisterScalableTarget` Application Auto Scaling API action with the following parameters:

- **ServiceNamespace**—Set this value to `sagemaker`.
- **ResourceId**—The resource identifier for the production variant. For this parameter, the resource type is endpoint and the unique identifier is the name of the variant, for example `endpoint/MyEndPoint/variant/MyVariant`.
- **ScalableDimension**—Set this value to `sagemaker:variant:DesiredInstanceCount`.
- **MinCapacity**—The minimum number of instances to be managed by Application Auto Scaling. This value must be set to at least 1 and must be equal to or less than the value specified for `MaxCapacity`.
- **MaxCapacity**—The maximum number of instances to be managed by Application Auto Scaling. This value must be set to at least 1 and must be equal to or greater than the value specified for `MinCapacity`.

**Example**

The following example shows how to register a SageMaker production variant that is dynamically scaled to use one to eight instances:

```
POST / HTTP/1.1
Host: autoscaling.us-east-2.amazonaws.com
Accept-Encoding: identity
X-Amz-Target: AnyScaleFrontendService.RegisterScalableTarget
X-Amz-Date: 20160506T182145Z
User-Agent: aws-cli/1.10.23 Python/2.7.11 Darwin/15.4.0 botocore/1.4.8
Content-Type: application/x-amz-json-1.1
Authorization: AUTHPARAMS

{
    "ServiceNamespace": "sagemaker",
    "ResourceId": "endpoint/MyEndPoint/variant/MyVariant",
    "ScalableDimension": "sagemaker:variant:DesiredInstanceCount",
    "MinCapacity": 1,
    "MaxCapacity": 8
}
```

Define a scaling policy

To specify the metrics and target values for a scaling policy, you configure a target-tracking scaling policy. You can use either a predefined metric or a custom metric.

Scaling policy configuration is represented by a JSON block. You save your scaling policy configuration as a JSON block in a text file. You use that text file when invoking the AWS CLI or the Application Auto Scaling API. For more information about policy configuration syntax, see [TargetTrackingScalingPolicyConfiguration](https://docs.aws.amazon.com/autoscaling/application/AutoScalingserviceDeveloperGuide/autoscaling-target-tracking-scaling-policy-reference.html) in the Application Auto Scaling API Reference.

The following options are available for defining a target-tracking scaling policy configuration.
Use a predefined metric

To quickly define a target-tracking scaling policy for a variant, use the SageMakerVariantInvocationsPerInstance predefined metric. SageMakerVariantInvocationsPerInstance is the average number of times per minute that each instance for a variant is invoked. We strongly recommend using this metric.

To use a predefined metric in a scaling policy, create a target tracking configuration for your policy. In the target tracking configuration, include a PredefinedMetricSpecification for the predefined metric and a TargetValue for the target value of that metric.

Example

The following example is a typical policy configuration for target-tracking scaling for a variant. In this configuration, we use the SageMakerVariantInvocationsPerInstance predefined metric to adjust the number of variant instances so that each instance has a InvocationsPerInstance metric of 70.

```
{
    "TargetValue": 70.0,
    "PredefinedMetricSpecification":
    {
        "PredefinedMetricType": "SageMakerVariantInvocationsPerInstance"
    }
}
```

Use a custom metric

If you need to define a target-tracking scaling policy that meets your custom requirements, define a custom metric. You can define a custom metric based on any production variant metric that changes in proportion to scaling.

Not all SageMaker metrics work for target tracking. The metric must be a valid utilization metric, and it must describe how busy an instance is. The value of the metric must increase or decrease in inverse proportion to the number of variant instances. That is, the value of the metric should decrease when the number of instances increases.

Important

Before deploying automatic scaling in production, you must test automatic scaling with your custom metric.

Example

The following example is a target-tracking configuration for a scaling policy. In this configuration, for a variant named my-variant, a custom metric adjusts the variant based on an average CPU utilization of 50 percent across all instances.

```
{
    "TargetValue": 50,
    "CustomizedMetricSpecification":
    {
        "MetricName": "CPUUtilization",
        "Namespace": "/aws/sagemaker/Endpoints",
        "Dimensions": [
            {"Name": "EndpointName", "Value": "my-endpoint" },
            {"Name": "VariantName","Value": "my-variant"}
        ],
        "Statistic": "Average",
        "Unit": "Percent"
    }
}
```
Use an online explainability metric

This guide shows how to use a metric to track the scaling of endpoints with online explainability. When an endpoint has online explainability activated, it emits a `ExplanationsPerInstance` metric that outputs the average number of records explained per minute, per instance, for a variant. The resource utilization of explaining records can be more different than that of predicting records. We strongly recommend using this metric for target-tracking scaling of endpoints with online explainability activated.

To use this online explainability metric inside a scaling policy, create a target tracking configuration. In the tracking configuration, include a `CustomizedMetricSpecification` for the custom metrics and a `TargetValue` for the target value.

The following is an example of a policy configuration that uses `ExplanationsPerInstance`. It is used to adjust the number of variant instances so that each instance has an `ExplanationsPerInstance` metric of 20.

```
{
    "TargetValue": 20,
    "CustomizedMetricSpecification": {
        "MetricName": "ExplanationsPerInstance",
        "Namespace": "AWS/SageMaker",
        "Dimensions": [
            {"Name": "EndpointName", "Value": "my-endpoint" },
            {"Name": "VariantName","Value": "my-variant"}
        ],
        "Statistic": "Sum"
    }
}
```

Application Auto Scaling allows multiple target tracking scaling policies for a scalable target. Consider adding the `InvocationsPerInstance` policy from the predefined metric section (in addition to the `ExplanationsPerInstance` policy). For example, if most invocations don't return an explanation because of the threshold value set in the `EnableExplanations` parameter, then the endpoint can choose the `InvocationsPerInstance` policy. If there is a large number of explanations, the endpoint can use the `ExplanationsPerInstance` policy.

Add a cooldown period

To add a cooldown period for scaling-out your model, specify a value, in seconds, for `ScaleOutCooldown`. Similarly, to add a cooldown period for scaling-in your model, add a value, in seconds, for `ScaleInCooldown`. For more information about `ScaleInCooldown` and `ScaleOutCooldown`, see the `TargetTrackingScalingPolicyConfiguration` in the Application Auto Scaling API Reference.

Example

The following is an example target-tracking configuration for a scaling policy. In this configuration, the SageMakerVariantInvocationsPerInstance predefined metric is used to adjust scaling based on an average of 70 across all instances of that variant. The configuration provides a scale-in cooldown period of 10 minutes and a scale-out cooldown period of 5 minutes.

```
{
    "TargetValue": 20,
    "CustomizedMetricSpecification": {
        "MetricName": "SageMakerVariantInvocationsPerInstance",
        "Namespace": "AWS/SageMaker",
        "Dimensions": [
            {"Name": "VariantName","Value": "my-variant"}
        ],
        "Statistic": "Sum"
    }
    "Cooldown": {
        "Seconds": 600,
        "Type": "ScaleIn"
    },
    "Cooldown": {
        "Seconds": 300,
        "Type": "ScaleOut"
    }
}
```
Apply a scaling policy

After registering your model and defining a scaling policy, apply the scaling policy to the registered model. To apply a scaling policy, you can use the AWS CLI or the Application Auto Scaling API.

Apply a scaling policy (Application Auto Scaling API)

To apply a scaling policy to your model, use the `put-scaling-policy` AWS CLI command with the following parameters:

- `--policy-name`—The name of the scaling policy.
- `--policy-type`—Set this value to `TargetTrackingScaling`.
- `--resource-id`—The resource identifier for the variant. For this parameter, the resource type is `endpoint` and the unique identifier is the name of the variant. For example, `endpoint/MyEndpoint/variant/MyVariant`.
- `--service-namespace`—Set this value to `sagemaker`.
- `--scalable-dimension`—Set this value to `sagemaker:variant:DesiredInstanceCount`.
- `--target-tracking-scaling-policy-configuration`—The target-tracking scaling policy configuration to use for the model.

Example

The following example uses with Application Auto Scaling to apply a target-tracking scaling policy named `myscalablepolicy` to a model (variant) named `myscalablevariant`. The policy configuration is saved in a file named `config.json`.

```bash
aws application-autoscaling put-scaling-policy \
  --policy-name myscalablepolicy \
  --policy-type TargetTrackingScaling \
  --resource-id endpoint/MyEndpoint/variant/MyVariant \
  --service-namespace sagemaker \
  --scalable-dimension sagemaker:variant:DesiredInstanceCount \
  --target-tracking-scaling-policy-configuration file://config.json
```

Apply a scaling policy (Application Auto Scaling API)

To apply a scaling policy to a variant with the Application Auto Scaling API, use the `PutScalingPolicy` Application Auto Scaling API action with the following parameters:

- `PolicyName`—The name of the scaling policy.
- `ServiceNamespace`—Set this value to `sagemaker`.
- `ResourceID`—The resource identifier for the variant. For this parameter, the resource type is `endpoint` and the unique identifier is the name of the variant. For example, `endpoint/MyEndpoint/variant/MyVariant`.
- `ScalableDimension`—Set this value to `sagemaker:variant:DesiredInstanceCount`.
• **PolicyType**—Set this value to TargetTrackingScaling.
• **TargetTrackingScalingPolicyConfiguration**—The target-tracking scaling policy configuration to use for the variant.

### Example

The following example uses Application Auto Scaling to apply a target-tracking scaling policy named myscalablepolicy to a variant named myscalablevariant. It uses a policy configuration based on the SageMakerVariantInvocationsPerInstance predefined metric.

```json
POST / HTTP/1.1
Host: autoscaling.us-east-2.amazonaws.com
Accept-Encoding: identity
X-Amz-Target: AnyScaleFrontendService.
X-Amz-Date: 20160506T182145Z
User-Agent: aws-cli/1.10.23 Python/2.7.11 Darwin/15.4.0 botocore/1.4.8
Content-Type: application/x-amz-json-1.1
Authorization: AUTHPARAMS

{
    "PolicyName": "myscalablepolicy",
    "ServiceNamespace": "sagemaker",
    "ResourceId": "endpoint/MyEndpoint/variant/MyVariant",
    "ScalableDimension": "sagemaker:variant:DesiredInstanceCount",
    "PolicyType": "TargetTrackingScaling",
    "TargetTrackingScalingPolicyConfiguration": {
        "TargetValue": 70.0,
        "PredefinedMetricSpecification": {
            "PredefinedMetricType": "SageMakerVariantInvocationsPerInstance"
        }
    }
}
```

### Edit a scaling policy

You can edit a scaling policy with the AWS Management Console, the AWS CLI, or the Application Auto Scaling API.

#### Scale-in

Scaling-in occurs when there is no traffic: if a variant's traffic becomes zero, SageMaker automatically scales in to the minimum number of instances specified. In this case, SageMaker emits metrics with a value of zero. Minimum instance count is required to be 1 or higher.

**Deactivate scale-in activity**

You can prevent the target-tracking scaling policy configuration from scaling in your variant by deactivating scale-in activity. Deactivating scale-in activity prevents the scaling policy from deleting instances, while still allowing it to create them as needed.

To activate or deactivate scale-in activity for your model, specify a Boolean value for DisableScaleIn. For more information about DisableScaleIn, see TargetTrackingScalingPolicyConfiguration in the Application Auto Scaling API Reference.

#### Example

The following is an example of a target-tracking configuration for a scaling policy where it will scale-out, but not scale-in. In this configuration, the SageMakerVariantInvocationsPerInstance predefined metric...
metric will scale-out based on an average of 70 invocations (inference requests) across all instances the
model is on. The configuration also deactivates scale-in activity for the scaling policy.

```
{
    "TargetValue": 70.0,
    "PredefinedMetricSpecification":
    {
        "PredefinedMetricType": "SageMakerVariantInvocationsPerInstance"
    },
    "DisableScaleIn": true
}
```

**Scale-out**

To manually scale-out, adjust the minimum capacity. You can use the console to update this value.
Alternatively, use the AWS CLI with the `--min-capacity` argument, or use the Application Auto Scaling
API's `MinCapacity` parameter.

**Deactivate scale-out activity**

To prevent scale-out, adjust the maximum capacity. You can use the console to update this value.
Alternatively, use the AWS CLI with the `--max-capacity` argument, or use the Application Auto Scaling
API's `MaxCapacity` parameter.

**Edit a scaling policy (Console)**

To edit a scaling policy with the AWS Management Console, use the same procedure that you used to
Configure model auto scaling with the console (p. 2806).

**Edit a scaling policy (AWS CLI or Application Auto Scaling API)**

You can use the AWS CLI or the Application Auto Scaling API to edit a scaling policy in the same way that
you apply a scaling policy:

- With the AWS CLI, specify the name of the policy that you want to edit in the `--policy-name`
  parameter. Specify new values for the parameters that you want to change.
- With the Application Auto Scaling API, specify the name of the policy that you want to edit in the
  `PolicyName` parameter. Specify new values for the parameters that you want to change.

For more information, see Apply a scaling policy (p. 2811).

**Delete a scaling policy**

You can delete a scaling policy with the AWS Management Console, the AWS CLI, or the Application Auto
Scaling API. You must delete a scaling policy if you wish to update a model's endpoint.

**Delete a scaling policy (Console)**

**To delete an automatic scaling policy (console)**

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the navigation pane, choose **Endpoints**.
3. Choose the endpoint for which you want to delete automatic scaling.
4. For **Endpoint runtime settings**, choose the variant that you want to configure.
5. Choose **Configure auto scaling**.
6. Choose **Deregister auto scaling**.

## Delete a scaling policy (AWS CLI or Application Auto Scaling API)

You can use the AWS CLI or the Application Auto Scaling API to delete a scaling policy from a variant.

### Delete a scaling policy with AWS CLI or Application Auto Scaling API

To delete a scaling policy from a variant, use the `delete-scaling-policy` AWS CLI command with the following parameters:

- **--policy-name**—The name of the scaling policy.
- **--resource-id**—The resource identifier for the variant. For this parameter, the resource type is `endpoint` and the unique identifier is the name of the variant. For example, `endpoint/MyEndpoint/variant/MyVariant`.
- **--service-namespace**—Set this value to `sagemaker`.
- **--scalable-dimension**—Set this value to `sagemaker:variant:DesiredInstanceCount`.

**Example**

The following example deletes a target-tracking scaling policy named `myscalablepolicy` from a variant named `myscalablevariant`.

```bash
aws application-autoscaling delete-scaling-policy
  --policy-name myscalablepolicy
  --resource-id endpoint/MyEndpoint/variant/MyVariant
  --service-namespace sagemaker
  --scalable-dimension sagemaker:variant:DesiredInstanceCount
```

### Delete a scaling policy (Application Auto Scaling API)

To delete a scaling policy from your variant, use the `DeleteScalingPolicy` Application Auto Scaling API action with the following parameters:

- **PolicyName**—The name of the scaling policy.
- **ServiceNamespace**—Set this value to `sagemaker`.
- **ResourceId**—The resource identifier for the variant. For this parameter, the resource type is `endpoint` and the unique identifier is the name of the variant. For example, `endpoint/MyEndpoint/variant/MyVariant`.
- **ScalableDimension**—Set this value to `sagemaker:variant:DesiredInstanceCount`.

**Example**

The following example uses the Application Auto Scaling API to delete a target-tracking scaling policy named `myscalablepolicy` from a variant named `myscalablevariant`.

```
POST / HTTP/1.1
Host: autoscaling.us-east-2.amazonaws.com
Accept-Encoding: identity
X-Amz-Target: AnyScaleFrontendService.DeleteScalingPolicy
X-Amz-Date: 20160506T182145Z
User-Agent: aws-cll/1.10.23 Python/2.7.11 Darwin/15.4.0 botocore/1.4.8
Content-Type: application/x-amz-json-1.1
Authorization: AUTHPARAMS
```
Query Endpoint Auto scaling History

You can view the status of scaling activities from your endpoint using `DescribeScalingActivities`. `DescribeScalingActivities` provides descriptive information about the scaling activities in the specified namespace from the previous six weeks.

How To Query Endpoint Auto Scaling Actions

Query your auto scaling endpoints with `DescribeScalingActivities`. To do so, specify `ServiceNamespace` parameter. `ServiceNamespace` is the name of the AWS service that provides the resource.

Valid service name values include the following:

- ecs
- elasticmapreduce
- ec2
- appstream
- dynamodb
- rds
- sagemaker
- custom-resource
- comprehend
- lambda
- cassandra

In this situation you need to set `ServiceNamespace` to `sagemaker`.

Use the following AWS CLI command to view details about all of your `sagemaker` endpoints that have a scaling policy:

```bash
aws application-autoscaling describe-scaling-activities --service-namespace sagemaker
```

You can search for a specific endpoint using `ResourceId`:

```bash
aws application-autoscaling describe-scaling-activities --service-namespace sagemaker --resource-id endpoint/<endpoint_name>/variant/<variant_name>
```

When you run this command, it returns the following output:

```json
{
    "ActivityId": "activity-id",
    "ServiceNamespace": "sagemaker",
    "ResourceId": "endpoint/<endpoint_name>/variant/<variant_name>",
    "ScalableDimension": "sagemaker:variant:DesiredInstanceCount",
    "Description": "string",
    "Cause": "string",
    "StartTime": timestamp,
    "EndTime": timestamp,
    "StatusCode": "string",
    "StatusMessage": "string"
}
```

Identify blocked auto scaling from instance quotas

When you scale out or add more instances, you might reach your account-level instance quota. You can use `DescribeScalingActivities` to check whether you have reached your instance quota. When you exceed your quota, automatic scaling is blocked.
To check if you have reached your instance quota, use the AWS CLI command as shown in the proceeding example where you specified the ResourceId:

```bash
aws application-autoscaling describe-scaling-activities 
  --service-namespace sagemaker 
  --resource-id endpoint/<endpoint_name>/variant/<variant_name>
```

Within the return syntax, check the `StatusCode` and `StatusMessage` keys and their associated values. `StatusCode` returns Failed. Within `StatusMessage` there is a message indicating that the account-level service quota was reached. The following is an example of what that message might look like:

```
{
  "ActivityId": "activity-id",
  "ServiceNamespace": "sagemaker",
  "ResourceId": "endpoint/<endpoint_name>/variant/<variant_name>",
  "ScalableDimension": "sagemaker:variant:DesiredInstanceCount",
  "Description": "string",
  "Cause": "minimum capacity was set to 110",
  "StartTime": timestamp,
  "EndTime": timestamp,
  "StatusCode": "Failed",
  "StatusMessage": "Failed to set desired instance count to 110. Reason: The account-level service limit 'ml.xx.xxxxx for endpoint usage' is 1000 Instances, with current utilization of 997 Instances and a request delta of 20 Instances. Please contact AWS support to request an increase for this limit. (Service: AmazonSageMaker; Status Code: 400; Error Code: ResourceLimitExceeded; Request ID: request-id)."
}
```

**Update or delete endpoints that use automatic scaling**

**Topics**
- Update endpoints that use automatic scaling (p. 2816)
- Delete endpoints configured for automatic scaling (p. 2817)

**Update endpoints that use automatic scaling**

When you update an endpoint, Application Auto Scaling checks to see whether any of the models on that endpoint are targets for automatic scaling. If the update would change the instance type for any model that is a target for automatic scaling, the update fails.

In the AWS Management Console, you see a warning that you must deregister the model from automatic scaling before you can update it. If you are trying to update the endpoint by calling the `UpdateEndpoint` API, the call fails. Before you update the endpoint, delete any scaling policies configured for it by calling the `DeleteScalingPolicy` Application Auto Scaling API action, then call `DeregisterScalableTarget` to deregister the variant as a scalable target. After you update the endpoint, you can register the variant as a scalable target and attach an automatic scaling policy to the updated variant.

There is one exception. If you change the model for a variant that is configured for automatic scaling, Amazon SageMaker automatic scaling allows the update. This is because changing the model doesn’t typically affect performance enough to change automatic scaling behavior. If you do update a model for a variant configured for automatic scaling, ensure that the change to the model doesn’t significantly affect performance and automatic scaling behavior.

When you update SageMaker endpoints that have automatic scaling applied, complete the following steps:
To update an endpoint that has automatic scaling applied

1. Deregister the endpoint as a scalable target by calling `DeregisterScalableTarget`.
2. Because automatic scaling is blocked while the update operation is in progress (or if you turned off automatic scaling in the previous step), you might want to take the additional precaution of increasing the number of instances for your endpoint during the update. To do this, update the instance counts for the production variants hosted at the endpoint by calling `UpdateEndpointWeightsAndCapacities`.
3. Call `DescribeEndpoint` repeatedly until the value of the `EndpointStatus` field of the response is `InService`.
4. Call `DescribeEndpointConfig` to get the values of the current endpoint config.
5. Create a new endpoint config by calling `CreateEndpointConfig`. For the production variants where you want to keep the existing instance count or weight, use the same variant name from the response from the call to `DescribeEndpointConfig` in the previous step. For all other values, use the values that you got as the response when you called `DescribeEndpointConfig` in the previous step.
6. Update the endpoint by calling `UpdateEndpoint`. Specify the endpoint config you created in the previous step as the `EndpointConfig` field. If you want to retain the variant properties like instance count or weight, set the value of the `RetainAllVariantProperties` parameter to True. This specifies that production variants with the same name will are updated with the most recent `DesiredInstanceCount` from the response from the call to `DescribeEndpoint`, regardless of the values of the `InitialInstanceCount` field in the new `EndpointConfig`.
7. (Optional) Re-activating automatic scaling by calling `RegisterScalableTarget`.

Note
Steps 1 and 7 are required only if you are updating an endpoint with the following changes:

- Changing the instance type for a production variant that has automatic scaling configured
- Removing a production variant that has automatic scaling configured.

Delete endpoints configured for automatic scaling

If you delete an endpoint, Application Auto Scaling checks to see whether any of the models on that endpoint are targets for automatic scaling. If any are and you have permission to deregister the model, Application Auto Scaling deregisters those models as scalable targets without notifying you. If you use a custom permission policy that doesn't provide permission for the `DeleteScalingPolicy` and `DeregisterScalableTarget` actions, you must delete automatic scaling policies and deregister scalable targets and before deleting the endpoint.

Note
You, as an IAM user, might not have sufficient permission to delete an endpoint if another IAM user configured automatic scaling for a variant on that endpoint.

Load testing your auto scaling configuration

Perform load tests to choose an automatic scaling configuration that works the way you want.

For an example of load testing to optimize automatic scaling for an Amazon SageMaker endpoint, see Load test and optimize an Amazon SageMaker endpoint using automatic scaling.

The following guidelines for load testing assume you are using an automatic scaling policy that uses the predefined target metric `SageMakerVariantInvocationsPerInstance`.

Topics

- Determine the performance characteristics (p. 2818)
Calculate the target load (p. 2818)

Determine the performance characteristics

Perform load testing to find the peak InvocationsPerInstance that your model's production variant can handle, and the latency of requests, as concurrency increases.

This value depends on the instance type chosen, payloads that clients of your model typically send, and the performance of any external dependencies your model has.

To find the peak requests-per-second (RPS) your model's production variant can handle and latency of requests

1. Set up an endpoint with your model using a single instance. For information about how to set up an endpoint, see Deploy the Model to SageMaker Hosting Services (p. 85).
2. Use a load testing tool to generate an increasing number of parallel requests, and monitor the RPS and model latency in the output of the load testing tool.

   Note
   You can also monitor requests-per-minute instead of RPS. In that case don't multiply by 60 in the equation to calculate SageMakerVariantInvocationsPerInstance shown below.

   When the model latency increases or the proportion of successful transactions decreases, this is the peak RPS that your model can handle.

Calculate the target load

After you find the performance characteristics of the variant, you can determine the maximum RPS we should allow to be sent to an instance. The threshold used for scaling must be less than this maximum value. Use the following equation in combination with load testing to determine the correct value for the SageMakerVariantInvocationsPerInstance target metric in your automatic scaling configuration.

\[
\text{SageMakerVariantInvocationsPerInstance} = (\text{MAX\_RPS} \times \text{SAFETY\_FACTOR}) \times 60
\]

Where MAX\_RPS is the maximum RPS that you determined previously, and SAFETY\_FACTOR is the safety factor that you chose to ensure that your clients don't exceed the maximum RPS. Multiply by 60 to convert from RPS to invocations-per-minute to match the per-minute CloudWatch metric that SageMaker uses to implement automatic scaling (you don't need to do this if you measured requests-per-minute instead of requests-per-second).

   Note
   SageMaker recommends that you start testing with a SAFETY\_FACTOR of 0.5. Test your automatic scaling configuration to ensure it operates in the way you expect with your model for both increasing and decreasing customer traffic on your endpoint.

Use AWS CloudFormation to update auto scaling policies

The following example shows how to activate Application Auto Scaling on an endpoint using AWS CloudFormation.

<table>
<thead>
<tr>
<th>Endpoint:</th>
</tr>
</thead>
<tbody>
<tr>
<td>Type: &quot;AWS::SageMaker::Endpoint&quot;</td>
</tr>
<tr>
<td>Properties:</td>
</tr>
<tr>
<td>EndpointName: yourEndpointName</td>
</tr>
<tr>
<td>EndpointConfigName: yourEndpointConfigName</td>
</tr>
</tbody>
</table>

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Host instance storage volumes

When you create an endpoint, Amazon SageMaker attaches an Amazon Elastic Block Store (Amazon EBS) storage volume to Amazon EC2 instances that hosts the endpoint. The size of the storage volume is scalable, and storage options are divided into two categories: SSD-backed storage and HDD-backed storage.

For more information about Amazon EBS storages and features, see the following pages.

- Amazon EBS Features
- Amazon EBS User Guide

For a full list of the host instance storage volumes, see Host Instance Storage Volumes Table

**Note**
Amazon SageMaker attaches an Amazon Elastic Block Store (Amazon EBS) storage volume to Amazon EC2 instances only when you create Asynchronous inference (p. 2939) or Real-time inference (p. 2744) endpoint types. For more information on customizing Amazon EBS storage volume, see Deploying large models with Amazon SageMaker (p. 2829).

Safely update models in production

In production ML workflows, data scientists and engineers frequently try to improve their models in various ways, such as by performing Perform Automatic Model Tuning with SageMaker (p. 2436), training on additional or more-recent data, and improving feature selection. Performing A/B testing between a new model and an old model with production traffic can be an effective final step in the validation process for a new model. In A/B testing, you test different variants of your models and compare how each variant performs. If the newer version of the model delivers better performance than the previously-existing version, replace the old version of the model with the new version in production.

Amazon SageMaker enables you to test multiple models or model versions behind the same endpoint using production variants. Each production variant identifies a machine learning (ML) model and the
resources deployed for hosting the model. By using production variants, you can test ML models that have been trained using different datasets, trained using different algorithms and ML frameworks, or are deployed to different instance type, or any combination of all of these. You can distribute endpoint invocation requests across multiple production variants by providing the traffic distribution for each variant, or you can invoke a specific variant directly for each request. In this topic, we look at both methods for testing ML models.

**Topics**
- Test models by specifying traffic distribution (p. 2820)
- Test models by invoking specific variants (p. 2820)
- Model A/B test example (p. 2821)

### Test models by specifying traffic distribution

To test multiple models by distributing traffic between them, specify the percentage of the traffic that gets routed to each model by specifying the weight for each production variant in the endpoint configuration. For information, see `CreateEndpointConfig`. The following diagram shows how this works in more detail.

![Diagram](image_url)

### Test models by invoking specific variants

To test multiple models by invoking specific models for each request, specify the specific version of the model you want to invoke by providing a value for the `TargetVariant` parameter when you call
InvokeEndpoint. SageMaker ensures that the request is processed by the production variant you specify. If you have already provided traffic distribution and specify a value for the TargetVariant parameter, the targeted routing overrides the random traffic distribution. The following diagram shows how this works in more detail.

Production Variants

Model A/B test example

The following example shows how to perform A/B model testing. For a sample notebook that implements this example, see "A/B Testing ML models in production."

Step 1: Create and deploy models

First, we define where our models are located in Amazon S3. These locations are used when we deploy our models in subsequent steps:

```python
model_url = f"s3://{path_to_model_1}"
model_url2 = f"s3://{path_to_model_2}"
```

Next, we create the model objects with the image and model data. These model objects are used to deploy production variants on an endpoint. The models are developed by training ML models on different data sets, different algorithms or ML frameworks, and different hyperparameters:

```python
from sagemaker.amazon.amazon_estimator import get_image_uri
```
model_name = f"DEMO-xgb-churn-pred-{datetime.now():%Y-%m-%d-%H-%M-%S}"
model_name2 = f"DEMO-xgb-churn-pred2-{datetime.now():%Y-%m-%d-%H-%M-%S}"
image_uri = get_image_uri(boto3.Session().region_name, 'xgboost', '0.90-1')
image_uri2 = get_image_uri(boto3.Session().region_name, 'xgboost', '0.90-2')
sm_session.create_model(name=model_name, role=role, container_defs={
    'Image': image_uri,
    'ModelDataUrl': model_url
})
sm_session.create_model(name=model_name2, role=role, container_defs={
    'Image': image_uri2,
    'ModelDataUrl': model_url2
})

We now create two production variants, each with its own different model and resource requirements (instance type and counts). This enables you to also test models on different instance types.

We set an initial_weight of 1 for both variants. This means that 50% of requests go to Variant1, and the remaining 50% of requests to Variant2. The sum of weights across both variants is 2 and each variant has weight assignment of 1. This means that each variant receives 1/2, or 50%, of the total traffic.

from sagemaker.session import production_variant
variant1 = production_variant(model_name=model_name,
instance_type="ml.m5.xlarge",
initial_instance_count=1,
variant_name='Variant1',
initial_weight=1)

variant2 = production_variant(model_name=model_name2,
instance_type="ml.m5.xlarge",
initial_instance_count=1,
variant_name='Variant2',
initial_weight=1)

Finally we’re ready to deploy these production variants on a SageMaker endpoint.

endpoint_name = f"DEMO-xgb-churn-pred-{datetime.now():%Y-%m-%d-%H-%M-%S}"
print(f"EndpointName={endpoint_name}")

sm_session.endpoint_from_production_variants(
    name=endpoint_name,
    production_variants=[variant1, variant2]
)

**Step 2: Invoke the deployed models**

Now we send requests to this endpoint to get inferences in real time. We use both traffic distribution and direct targeting.

First, we use traffic distribution that we configured in the previous step. Each inference response contains the name of the production variant that processes the request, so we can see that traffic to the two production variants is roughly equal.

# get a subset of test data for a quick test
!tail -120 test_data/test-dataset-input-cols.csv > test_data/test_sample_tail_input_cols.csv

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print(f"Sending test traffic to the endpoint {endpoint_name}. \nPlease wait...")

with open('test_data/test_sample_tail_input_cols.csv', 'r') as f:
    for row in f:
        print('.', end='', flush=True)
        payload = row.rstrip('
')
        sm_runtime.invoke_endpoint(EndpointName=endpoint_name,
                                ContentType="text/csv",
                                Body=payload)

    time.sleep(0.5)
print("Done!")

SageMaker emits metrics such as Latency and Invocations for each variant in Amazon CloudWatch. For a complete list of metrics that SageMaker emits, see Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663). Let's query CloudWatch to get the number of invocations per variant, to show how invocations are split across variants by default:

<table>
<thead>
<tr>
<th>Variant 1</th>
<th>Variant 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020-06-05 15:34:00+00:00</td>
<td>44.0</td>
</tr>
<tr>
<td>2020-06-05 15:35:00+00:00</td>
<td>7.0</td>
</tr>
</tbody>
</table>

Now let's invoke a specific version of the model by specifying Variant1 as the TargetVariant in the call to invoke_endpoint.

print(f"Sending test traffic to the endpoint {endpoint_name}. \nPlease wait...")
with open('test_data/test_sample_tail_input_cols.csv', 'r') as f:
    for row in f:
        print('.', end='', flush=True)
        payload = row.rstrip('
')
        sm_runtime.invoke_endpoint(EndpointName=endpoint_name,
                                ContentType="text/csv",
                                Body=payload,
                                TargetVariant="Variant1") # Notice the new parameter

    time.sleep(0.5)

To confirm that all new invocations were processed by Variant1, we can query CloudWatch to get the number of invocations per variant. We see that for the most recent invocations (latest timestamp), all requests were processed by Variant1, as we had specified. There were no invocations made for Variant2.
Step 3: Evaluate model performance

To see which model version performs better, let's evaluate the accuracy, precision, recall, F1 score, and Receiver operating characteristic/Area under the curve for each variant. First, let's look at these metrics for Variant1:

Accuracy: 0.958333333333334
Precision: 0.9411764705882353
Recall: 0.8
F1 Score: 0.8648648648648648
AUC is 0.895

Now let's look at the metrics for Variant2:
For most of our defined metrics, Variant2 is performing better, so this is the one that we want to use in production.

**Step 4: Increase traffic to the best model**

Now that we have determined that Variant2 performs better than Variant1, we shift more traffic to it. We can continue to use TargetVariant to invoke a specific model variant, but a simpler approach is to update the weights assigned to each variant by calling `UpdateEndpointWeightsAndCapacities`. This changes the traffic distribution to your production variants without requiring updates to your endpoint. Recall from the setup section that we set variant weights to split traffic 50/50. The CloudWatch metrics for the total invocations for each variant below show us the invocation patterns for each variant:

Now we shift 75% of the traffic to Variant2 by assigning new weights to each variant using `UpdateEndpointWeightsAndCapacities`. SageMaker now sends 75% of the inference requests to Variant2 and remaining 25% of requests to Variant1.

```python
sm.update_endpoint_weights_and_capacities(
    EndpointName=endpoint_name,
    DesiredWeightsAndCapacities=[
        {
            "DesiredWeight": 25,
            "VariantName": variant1["VariantName"]
        },
        {
            "DesiredWeight": 75,
            "VariantName": variant2["VariantName"]
        }
    ]
)
```
The CloudWatch metrics for total invocations for each variant shows us higher invocations for Variant2 than for Variant1:

![Graph showing CloudWatch metrics for total invocations]

We can continue to monitor our metrics, and when we're satisfied with a variant's performance, we can route 100% of the traffic to that variant. We use UpdateEndpointWeightsAndCapacities to update the traffic assignments for the variants. The weight for Variant1 is set to 0 and the weight for Variant2 is set to 1. SageMaker now sends 100% of all inference requests to Variant2.

```python
sm.update_endpoint_weights_and_capacities(
    EndpointName=endpoint_name,
    DesiredWeightsAndCapacities=[
        {
            "DesiredWeight": 0,
            "VariantName": variant1["VariantName"]
        },
        {
            "DesiredWeight": 1,
            "VariantName": variant2["VariantName"]
        }
    ]
)
```

The CloudWatch metrics for the total invocations for each variant show that all inference requests are being processed by Variant2 and there are no inference requests processed by Variant1.

![Graph showing CloudWatch metrics for total invocations]

You can now safely update your endpoint and delete Variant1 from your endpoint. You can also continue testing new models in production by adding new variants to your endpoint and following steps 2 - 4.

**Best practices**

This topic provides guidance on best practices for deploying machine learning models in Amazon SageMaker.
Best practices for deploying models on SageMaker Hosting Services

When hosting models using SageMaker hosting services, consider the following:

• Typically, a client application sends requests to the SageMaker HTTPS endpoint to obtain inferences from a deployed model. You can also send requests to this endpoint from your Jupyter notebook during testing.

• You can deploy a model trained with SageMaker to your own deployment target. To do that, you need to know the algorithm-specific format of the model artifacts that were generated by model training. For more information about output formats, see the section corresponding to the algorithm you are using in Common Data Formats for Training (p. 1959).

• You can deploy multiple variants of a model to the same SageMaker HTTPS endpoint. This is useful for testing variations of a model in production. For example, suppose that you’ve deployed a model into production. You want to test a variation of the model by directing a small amount of traffic, say 5%, to the new model. To do this, create an endpoint configuration that describes both variants of the model. You specify the ProductionVariant in your request to the CreateEndPointConfig. For more information, see ProductionVariant.

• You can configure a ProductionVariant to use Application Auto Scaling. For information about configuring automatic scaling, see Automatically Scale Amazon SageMaker Models (p. 2803).

• You can modify an endpoint without taking models that are already deployed into production out of service. For example, you can add new model variants, update the ML Compute instance configurations of existing model variants, or change the distribution of traffic among model variants. To modify an endpoint, you provide a new endpoint configuration. SageMaker implements the changes without any downtime. For more information see, UpdateEndpoint and UpdateEndpointWeightsAndCapacities.

• Changing or deleting model artifacts or changing inference code after deploying a model produces unpredictable results. If you need to change or delete model artifacts or change inference code, modify the endpoint by providing a new endpoint configuration. Once you provide the new endpoint configuration, you can change or delete the model artifacts corresponding to the old endpoint configuration.

• If you want to get inferences on entire datasets, consider using batch transform as an alternative to hosting services. For information, see Use Batch Transform (p. 2955)

Deploy Multiple Instances Across Availability Zones

Create robust endpoints when hosting your model. SageMaker endpoints can help protect your application from Availability Zone outages and instance failures. If an outage occurs or an instance fails, SageMaker automatically attempts to distribute your instances across Availability Zones. For this reason, we strongly recommended that you deploy multiple instances for each production endpoint.

If you are using an Amazon Virtual Private Cloud (VPC), configure the VPC with at least two Subnets, each in a different Availability Zone. If an outage occurs or an instance fails, Amazon SageMaker automatically attempts to distribute your instances across Availability Zones.
In general, to achieve more reliable performance, use more small instance types in different availability zones to host your endpoints.

**Low latency real-time inference with AWS PrivateLink**

Amazon SageMaker provides low latency for real-time inferences while maintaining high availability and resiliency using multi-AZ deployment. The end-to-end application latency is made up of two primary components: infrastructure or overhead latency and model inference latency. Reduction of overhead latency opens up new possibilities such as deploying more complex, deep, and accurate models or splitting monolithic applications into scalable and maintainable microservice modules. You can reduce the latency for real-time inferences with SageMaker using an AWS PrivateLink deployment. With AWS PrivateLink, you can privately access all SageMaker API operations from your Virtual Private Cloud (VPC) in a scalable manner by using interface VPC endpoints. An interface VPC endpoint is an elastic network interface in your subnet with private IP addresses that serves as an entry point for all SageMaker API calls.

By default, a SageMaker endpoint with 2 or more instances is deployed in at least 2 AWS Availability Zones (AZs) and instances in any AZ can process invocations. This results in one or more AZ “hops” that contribute to the overhead latency. An AWS PrivateLink deployment with the `privateDNSEnabled` option set as `true` alleviates this by achieving two objectives:

- It keeps all inference traffic within your VPC.
- It keeps invocation traffic in the same AZ as the client that originated it when using SageMaker. This avoids the “hops” between AZs reducing the overhead latency.

The following sections of this guide demonstrate how you can reduce the latency for real-time inferences with AWS PrivateLink deployment.

**Topics**
- Deploy AWS PrivateLink (p. 2828)
- Deploy SageMaker endpoint in a VPC (p. 2828)
- Invoke the SageMaker endpoint (p. 2829)

**Deploy AWS PrivateLink**

To deploy AWS PrivateLink first create an interface endpoint for the VPC from which you connect to the SageMaker endpoints. Please follow the steps in Access an AWS service using an interface VPC endpoint to create the interface endpoint. While creating the endpoint select the following settings in the console interface:

- Select `Enable DNS name` checkbox under Additional Settings
- Select the appropriate security groups and the subnets to be used with the SageMaker endpoints.

Also make sure that the VPC has DNS hostnames turned on. For more information on how to change DNS attributes for your VPC, see View and update DNS attributes for your VPC.

**Deploy SageMaker endpoint in a VPC**

To achieve low overhead latency, create a SageMaker endpoint using the same subnets that you specified when deploying AWS PrivateLink. These subnets should match the AZs of your client application, as shown in the following code snippet.

```python
model_name = '<the-name-of-your-model>'
vpc = 'vpc-0123456789abcdef0'
```
Create model response = sagemaker_client.create_model(
    ModelName = model_name,
    ExecutionRoleArn = sagemaker_role,
    PrimaryContainer = {
        'Image': container,
        'ModelDataUrl': model_url
    },
    VpcConfig = {
        'SecurityGroupIds': [security_group],
        'Subnets': [subnet_a, subnet_b],
    },
)

The aforementioned code snippet assumes that you have followed the steps in Before you begin (p. 2746).

Invoke the SageMaker endpoint

Finally, specify the SageMaker client and invoke the SageMaker endpoint as shown in the following code snippet.

endpoint_name = '<endpoint-name>'

runtime_client = boto3.client('sagemaker-runtime')
response = runtime_client.invoke_endpoint(EndpointName=endpoint_name,
    ContentType='text/csv',
    Body=payload)

For more information on endpoint configuration, see Create an Endpoint Configuration (p. 2749).

Deploying large models with Amazon SageMaker

State-of-the-art natural language processing (NLP) models are large, typically with billions of parameters. Empirical demonstrations show that larger models are more accurate. But these models are often too large to fit on single accelerators, making low-latency inference with them difficult. With SageMaker Hosting you can customize the following parameters to facilitate low-latency real-time inference with large models:

- **Maximum Amazon EBS volume size on the instance (VolumeSizeInGB)** – If the size of the model is larger than 30 GB and you are using an instance without a local disk, you should increase this parameter to be slightly larger than the size of your model.
- **Health check timeout quota (ContainerStartupHealthCheckTimeoutInSeconds)** – If your container is correctly setup and the CloudWatch logs indicate a health check timeout, you should increase this quota so the container has enough time to respond to health checks.
- **Model download timeout quota (ModelDataDownloadTimeoutInSeconds)** – If the size of your model is larger than 40 GB, then you should increase this quota to provide sufficient time to download the model from Amazon S3 to the instance.

For more information on low latency inference with large models, see Deploy large models on Amazon SageMaker using DJLServing and DeepSpeed model parallel inference. The following code snippet demonstrates how to programatically configure the aforementioned parameters. Replace the italicized placeholder text in the example with your own information.
import boto3
aws_region = "aws-region"
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# The name of the endpoint. The name must be unique within an AWS Region in your AWS account.
endpoint_name = "endpoint-name"

# Create an endpoint config name.
endpoint_config_name = "endpoint-config-name"

# The name of the model that you want to host.
model_name = "the-name-of-your-model"
instance_type = "instance-type"

sagemaker_client.create_endpoint_config(
    EndpointConfigName = endpoint_config_name
    ProductionVariants=[
        {
            "VariantName": "variant1", # The name of the production variant.
            "ModelName": model_name,
            "InstanceType": instance_type, # Specify the compute instance type.
            "InitialInstanceCount": 1, # Number of instances to launch initially.
            "VolumeSizeInGB": 256, # Specify the size of the Amazon EBS volume.
            "ModelDataDownloadTimeoutInSeconds": 1800, # Specify the model download timeout in seconds.
            "ContainerStartupHealthCheckTimeoutInSeconds": 1800, # Specify the health checkup timeout in seconds
        },
    ],
)

sagemaker_client.create_endpoint(EndpointName=endpoint_name,
    EndpointConfigName=endpoint_config_name)

For more information on the keys for ProductionVariants, see ProductionVariant and Create an Endpoint Configuration (p. 2749).

# Migrate inference workload from x86 to AWS Graviton

AWS Graviton is a series of ARM-based processors designed by AWS. They are more energy efficient than x86-based processors and offer a compelling price-performance ratio. Amazon SageMaker offers Graviton-based instances so that you can take advantage of these advanced processors for your inference needs.

You can migrate your existing inference workloads from x86-based instances to Graviton-based instances, by using either ARM compatible container images or multi-architecture container images. This guide assumes that you are either using AWS Deep Learning container images, or your own ARM compatible container images. For more information on building your own images, check Building your image.

At a high level, migrating inference workload from x86-based instances to Graviton-based instances is a four-step process:

1. Push container images to Amazon Elastic Container Registry (Amazon ECR), an AWS managed container registry.
2. Create a SageMaker Model.
3. Create an endpoint configuration.
4. Create an endpoint.

This process is very similar to how you would deploy models to x86-based instances. Check Create your endpoint and deploy your model (p. 2745), and particularly Before you begin (p. 2746), for details on deploying to x86-based instances.

The following sections of this guide provide more details regarding the above steps. Replace the user placeholder text in the code examples with your own information.

Topics
- Push container images to Amazon ECR (p. 2831)
- Create a SageMaker Model (p. 2832)
- Create an endpoint configuration (p. 2832)
- Create an endpoint (p. 2832)

Push container images to Amazon ECR

You can push your container images to Amazon ECR with the AWS CLI. When using an ARM compatible image, verify that it supports ARM architecture:

```
docker inspect deep-learning-container-uri
```

The response "Architecture": "arm64" indicates that the image supports ARM architecture. You can push it to Amazon ECR with the `docker push` command. For more information, check Pushing a Docker image.

Multi-architecture container images are fundamentally a set of container images supporting different architectures or operating systems, that you can refer to by a common manifest name. If you are using multi-architecture container images, then in addition to pushing the images to Amazon ECR, you will also have to push a manifest list to Amazon ECR. A manifest list allows for the nested inclusion of other image manifests, where each included image is specified by architecture, operating system and other platform attributes. The following example creates a manifest list, and pushes it to Amazon ECR.

1. Create a manifest list.

```
docker manifest create aws-account-id.dkr.ecr.aws-region.amazonaws.com/my-repository \ 
  aws-account-id.dkr.ecr.aws-account-id.amazonaws.com/my-repository:amd64 \ 
  aws-account-id.dkr.ecr.aws-region.amazonaws.com/my-repository:arm64
```

2. Annotate the manifest list, so that it correctly identifies which image is for which architecture.

```
docker manifest annotate --arch arm64 aws-account-id.dkr.ecr.aws-region.amazonaws.com/my-repository \ 
  aws-account-id.dkr.ecr.aws-region.amazonaws.com/my-repository:arm64
```

3. Push the manifest.

```
docker manifest push aws-account-id.dkr.ecr.aws-region.amazonaws.com/my-repository
```

For more information on creating and pushing manifest lists to Amazon ECR, check Introducing multi-architecture container images for Amazon ECR, and Pushing a multi-architecture image.
Create a SageMaker Model

Create a SageMaker Model by calling the `CreateModel` API.

```python
import boto3
from sagemaker import get_execution_role

aws_region = "aws-region"
sagemaker_client = boto3.client("sagemaker", region_name=aws_region)

role = get_execution_role()
sagemaker_client.create_model(
    ModelName = "model-name",
    PrimaryContainer = {
        "Image": "deep-learning-container-uri",
        "ModelDataUrl": "model-s3-location",
        "Environment": {
            "SAGEMAKER_PROGRAM": "inference.py",
            "SAGEMAKER_SUBMIT_DIRECTORY": "inference-script-s3-location",
            "SAGEMAKER_CONTAINER_LOG_LEVEL": "20",
            "SAGEMAKER_REGION": aws_region,
        }
    },
    ExecutionRoleArn = role
)
```

Create an endpoint configuration

Create an endpoint configuration by calling the `CreateEndpointConfig` API. For a list of Graviton-based instances, check the `Compute optimized instances`.

```python
sagemaker_client.create_endpoint_config(
    EndpointConfigName = "endpoint-config-name",
    ProductionVariants = [
        {  
            "VariantName": "variant-name",
            "ModelName": "model-name",
            "InitialInstanceCount": 1,
            "InstanceType": "ml.c7g.xlarge", # Graviton-based instance
        }
    ]
)
```

Create an endpoint

Create an endpoint by calling the `CreateEndpoint` API.

```python
sagemaker_client.create_endpoint(
    EndpointName = "endpoint-name",
    EndpointConfigName = "endpoint-config-name"
)
```

Troubleshoot Amazon SageMaker model deployments

If you encounter an issue when deploying machine learning models in Amazon SageMaker, see the following guidance.
Detection Errors in the Active CPU Count

If you deploy a SageMaker model with a Linux Java Virtual Machine (JVM), you might encounter detection errors that prevent using available CPU resources. This issue affects some JVMs that support Java 8 and Java 9, and most that support Java 10 and Java 11. These JVMs implement a mechanism that detects and handles the CPU count and the maximum memory available when running a model in a Docker container, and, more generally, within Linux `taskset` commands or control groups (cgroups). SageMaker deployments take advantage of some of the settings that the JVM uses for managing these resources. Currently, this causes the container to incorrectly detect the number of available CPUs.

SageMaker doesn't limit access to CPUs on an instance. However, the JVM might detect the CPU count as 1 when more CPUs are available for the container. As a result, the JVM adjusts all of its internal settings to run as if only 1 CPU core is available. These settings affect garbage collection, locks, compiler threads, and other JVM internals that negatively affect the concurrency, throughput, and latency of the container.

For an example of the misdetection, in a container configured for SageMaker that is deployed with a JVM that is based on Java8_191 and that has four available CPUs on the instance, run the following command to start your JVM:

```
java -XX:+UnlockDiagnosticVMOptions -XX:+PrintActiveCpus -version
```

This generates the following output:

```
active_processor_count: sched_getaffinity processor count: 4
active_processor_count: determined by OSContainer: 1
active_processor_count: sched_getaffinity processor count: 4
active_processor_count: determined by OSContainer: 1
active_processor_count: sched_getaffinity processor count: 4
active_processor_count: determined by OSContainer: 1
active_processor_count: sched_getaffinity processor count: 4
active_processor_count: determined by OSContainer: 1
openjdk version "1.8.0_191"
OpenJDK Runtime Environment (build 1.8.0_191-8u191-b12-2ubuntu0.16.04.1-b12)
OpenJDK 64-Bit Server VM (build 25.191-b12, mixed mode)
```

Many of the JVMs affected by this issue have an option to disable this behavior and reestablish full access to all of the CPUs on the instance. Disable the unwanted behavior and establish full access to all instance CPUs by including the `-XX:-UseContainerSupport` parameter when starting Java applications. For example, run the java command to start your JVM as follows:

```
java -XX:-UseContainerSupport -XX:+UnlockDiagnosticVMOptions -XX:+PrintActiveCpus -version
```

This generates the following output:

```
active_processor_count: sched_getaffinity processor count: 4
active_processor_count: sched_getaffinity processor count: 4
active_processor_count: sched_getaffinity processor count: 4
active_processor_count: sched_getaffinity processor count: 4
openjdk version "1.8.0_191"
OpenJDK Runtime Environment (build 1.8.0_191-8u191-b12-2ubuntu0.16.04.1-b12)
OpenJDK 64-Bit Server VM (build 25.191-b12, mixed mode)
```
Check whether the JVM used in your container supports the -XX:-UseContainerSupport parameter. If it does, always pass the parameter when you start your JVM. This provides access to all of the CPUs in your instances.

You might also encounter this issue when indirectly using a JVM in SageMaker containers. For example, when using a JVM to support SparkML Scala. The -XX:-UseContainerSupport parameter also affects the output returned by the Java Runtime.getRuntime().availableProcessors() API.

**Issues with deploying a model.tar.gz file**

When you deploy a model using a model.tar.gz file, the model tarball should not include any symlinks. Symlinks cause the model creation to fail. Also, we recommend that you do not include any unnecessary files in the tarball.

**Online Explainability with SageMaker Clarify**

This guide shows how to configure online explainability with SageMaker Clarify. With SageMaker real-time inference endpoints, you can analyze explainability in real time, continuously. The online explainability function fits into the **Deploy to production** part of the Amazon SageMaker Machine Learning workflow.

**How Clarify Online Explainability Works**

The following graphic shows SageMaker architecture for hosting an endpoint that serves explainability requests. It includes interactions between an endpoint, the model container, and the SageMaker Clarify explainer.
Here’s how Clarify online explainability works. The application sends a REST-style InvokeEndpoint request to the SageMaker Runtime Service. The service routes this request to a SageMaker endpoint to obtain predictions and explanations. Then, the service receives the response from the endpoint. Lastly, the service sends the response back to the application.

To increase the endpoint availability, SageMaker automatically attempts to distribute endpoint instances in multiple Availability Zones, according to the instance count in the endpoint configuration. On an endpoint instance, upon a new explainability request, the SageMaker Clarify explainer calls the model container for predictions. Then it computes and returns the feature attributions.

Here are the four steps to create an endpoint that uses SageMaker Clarify online explainability:

1. Check if your pre-trained SageMaker model is compatible with online explainability by following the pre-check steps.
2. Create an endpoint configuration with the SageMaker Clarify explainer configuration using the CreateEndpointConfig API.
3. Create an endpoint and provide the endpoint configuration to SageMaker using the CreateEndpoint API. The service launches the ML compute instance and deploys the model as specified in the configuration.
4. Invoke the endpoint: After the endpoint is in service, call the SageMaker Runtime API InvokeEndpoint to send requests to the endpoint. The endpoint then returns explanations and predictions.

Pre-check the model container

This section shows how to pre-check the model container inputs and outputs for compatibility before configuring an endpoint. The SageMaker Clarify explainer is model agnostic, but it has requirements for model container input and output.

Note
You can increase efficiency by configuring your container to support batch requests, which support two or more records in a single request. A record is a single line of CSV data.

Model container input

The model container supports input in CSV (MIME type:“text/csv”). The following table shows example inputs that SageMaker Clarify supports:

<table>
<thead>
<tr>
<th>Model container input (string representation)</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>’1,2,3,4’</td>
<td>Single record (four numerical features).</td>
</tr>
<tr>
<td>’1,2,3,4\n5,6,7,8’</td>
<td>Two records, separated by line break ‘\n’.</td>
</tr>
<tr>
<td>'&quot;This is a good product&quot;,5'</td>
<td>Single record (a text feature and a numerical feature)</td>
</tr>
<tr>
<td>'&quot;This is a good product&quot;,5\n&quot;Bad shopping experience&quot;,1'</td>
<td>Two records</td>
</tr>
</tbody>
</table>

SageMaker also supports input in JSON Lines dense format (MIME type:“application/jsonlines”):

<table>
<thead>
<tr>
<th>Model container input</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>{'data':{&quot;features&quot;:[1,2,3,4]}}</td>
<td>Single record, a list of features can be extracted by JMESPath expression 'data.features'.</td>
</tr>
</tbody>
</table>
Clarify online explainability

<table>
<thead>
<tr>
<th>Model container input</th>
<th>Comments</th>
</tr>
</thead>
</table>
| `{"data":{"features":[1,2,3,4]}}
{"data":{"features":[5,6,7,8]}}` | Two records |
| `{"features":"This is a good product",5]}` | Single record, a list of features can be extracted by JMESPath expression `features`. |
| `{"features":{"This is a good product",5]}
{"features":{"Bad shopping experience",1]}` | Two records |

## Model container output

Like the input, your model container output should also be in either CSV or JSON Lines dense format. Additionally the model container should include the probabilities of the input records, which SageMaker Clarify requires to compute feature attributions.

The following data examples are for model container outputs in **CSV format**.

### Probability only

For regression and binary classification problems, the model container outputs a single probability value (score) of the predicted label. These probabilities can be extracted using column index 0. For multi-class problems, the model container outputs a list of probabilities (scores). For multi-class problems, if no index is provided, all values are extracted.

<table>
<thead>
<tr>
<th>Model container input</th>
<th>Model container output (string representation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single record</td>
<td>'0.6'</td>
</tr>
<tr>
<td>Two records (results in one line)</td>
<td>'0.6,0.3'</td>
</tr>
<tr>
<td>Two records (results in two lines)</td>
<td>'0.6\n0.3'</td>
</tr>
<tr>
<td>Single record of a multi-class model (three classes)</td>
<td>'0.1,0.6,0.3'</td>
</tr>
<tr>
<td>Two records of a multi-class model (three classes)</td>
<td>'0.1,0.6,0.3\n0.2,0.5,0.3'</td>
</tr>
</tbody>
</table>

### Predicted label and probabilities

The model container outputs the predicted label followed by its probability in **CSV format**. The probabilities can be extracted using index 1.

<table>
<thead>
<tr>
<th>Model container input</th>
<th>Model container output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single record</td>
<td>'1,0.6'</td>
</tr>
<tr>
<td>Two records</td>
<td>'1,0.6\n0,0.3'</td>
</tr>
</tbody>
</table>
Predicted labels header and probabilities

A multi-class model container trained by Autopilot can be configured to output the string representation of the list of predicted labels and probabilities in CSV format. In the following example, the probabilities can be extracted by index 1 and the label headers can be extracted by index 1 and the label headers can be extracted using index 0.

<table>
<thead>
<tr>
<th>Model container input</th>
<th>Model container output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single record</td>
<td>&quot;[&quot;cat&quot;,&quot;dog&quot;,&quot;fish&quot;],\n&quot;[0.1,0.6,0.3]&quot;&quot;</td>
</tr>
<tr>
<td>Two records</td>
<td>&quot;[&quot;cat&quot;,&quot;dog&quot;,&quot;fish&quot;],\n&quot;[0.1,0.6,0.3]&quot;\n&quot;[&quot;cat&quot;,&quot;dog&quot;,&quot;fish&quot;],\n&quot;[0.2,0.5,0.3]&quot;&quot;</td>
</tr>
</tbody>
</table>

The following data examples are for model container outputs in JSON Lines format.

Probability only

In this example, the model container outputs the probability that can be extracted by be extracted by JMESPath expression 'score' in JSON Lines format.

<table>
<thead>
<tr>
<th>Model container input</th>
<th>Model container output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single record</td>
<td>'{&quot;score&quot;:0.6}'</td>
</tr>
<tr>
<td>Two records</td>
<td>'{&quot;score&quot;:0.6}\n{&quot;score&quot;:0.3}'</td>
</tr>
</tbody>
</table>

Predicted label and probabilities

In this example, a multi-class model container outputs a list of label headers along with a list of probabilities in JSON Lines format. The probabilities can be extracted by JMESPath expression 'probability', and the label headers can be extracted by JMESPath expression 'predicted labels'.

<table>
<thead>
<tr>
<th>Model container input</th>
<th>Model container output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single record</td>
<td>'{&quot;predicted_labels&quot;:\n[&quot;cat&quot;,&quot;dog&quot;,&quot;fish&quot;],&quot;probabilities&quot;:[0.1,0.6,0.3]}'</td>
</tr>
<tr>
<td>Two records</td>
<td>'{&quot;predicted_labels&quot;:\n[&quot;cat&quot;,&quot;dog&quot;,&quot;fish&quot;],&quot;probabilities&quot;:[0.1,0.6,0.3]\n&quot;predicted_labels&quot;:\n[&quot;cat&quot;,&quot;dog&quot;,&quot;fish&quot;],&quot;probabilities&quot;:[0.2,0.5,0.3]}'</td>
</tr>
</tbody>
</table>

Predicted labels header and probabilities

In this example, a multi-class model container outputs a list of label headers and probabilities in JSON Lines format. The probabilities can be extracted by JMESPath expression 'probability', and the label headers can be extracted by JMESPath expression 'predicted labels'.

<table>
<thead>
<tr>
<th>Model container input</th>
<th>Model container output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single record</td>
<td>'{&quot;predicted_labels&quot;:\n[&quot;cat&quot;,&quot;dog&quot;,&quot;fish&quot;],&quot;probabilities&quot;:[0.1,0.6,0.3]}'</td>
</tr>
</tbody>
</table>
## Model container validation

We recommend that you deploy your model to a SageMaker real-time inference endpoint, and send requests to the endpoint. Manually examine the requests (model container inputs) and responses (model container outputs) to make sure that both are compliant with the requirements in the **Model Container Input** section and **Model Container Output** section. If your model container supports batch requests, you can start with a single record request, and then try two or more records.

The following commands show how to request a response using the AWS CLI. The AWS CLI is pre-installed in SageMaker Studio, and SageMaker Notebook instances. If you need to install the AWS CLI, follow this [installation guide](#).

```
aws sagemaker-runtime invoke-endpoint \
   --endpoint-name $ENDPOINT_NAME \
   --content-type $CONTENT_TYPE \
   --accept $ACCEPT_TYPE \
   --body $REQUEST_DATA \n   $CLI_BINARY_FORMAT \n   /dev/stderr 1>/dev/null
```

The parameters are defined, as follows:

- **$ENDPOINT_NAME**: The name of the endpoint.
- **$CONTENT_TYPE**: The MIME type of the request (model container input).
- **$ACCEPT_TYPE**: The MIME type of the response (model container output).
- **$REQUEST_DATA**: The requested payload string.
- **$CLI_BINARY_FORMAT**: The format of the command line interface (CLI) parameter. For AWS CLI v1, this parameter should remain blank. For v2, this parameter should be set to `--cli-binary-format raw-in-base64-out`.

**Note**

AWS CLI v2 passes binary parameters as base64-encoded strings [default](#).

The following examples use AWS CLI v1:

### Request and response in CSV format

- The request consists of a single record and the response is its probability value.

```
aws sagemaker-runtime invoke-endpoint \
   --endpoint-name test-endpoint-sagemaker-xgboost-model \
   --content-type text/csv \
   --accept text/csv \n   --body '1,2,3,4' \n   /dev/stderr 1>/dev/null
```

Output:
0.6

- The request consists of two records, and the response includes their probabilities, and the model separates the probabilities by a comma. The `$content` expression in the `--body` tells the command to interpret `\n` in the content as a line break.

```bash
aws sagemaker-runtime invoke-endpoint \
  --endpoint-name test-endpoint-sagemaker-xgboost-model \
  --content-type text/csv \
  --accept text/csv \
  --body $'1,2,3,4\n5,6,7,8' \
/dev/stderr 1>/dev/null
```

Output:

0.6,0.3

- The request consists of two records, the response includes their probabilities, and the model separates the probabilities with a line break.

```bash
aws sagemaker-runtime invoke-endpoint \
  --endpoint-name test-endpoint-csv-1 \
  --content-type text/csv \
  --accept text/csv \
  --body $'1,2,3,4\n5,6,7,8' \
/dev/stderr 1>/dev/null
```

Output:

0.6

0.3

- The request consists of a single record, and the response is probability values (multi-class model, three classes).

```bash
aws sagemaker-runtime invoke-endpoint \
  --endpoint-name test-endpoint-csv-1 \
  --content-type text/csv \
  --accept text/csv \
  --body '1,2,3,4' \
/dev/stderr 1>/dev/null
```

Output:

0.1,0.6,0.3

- The request consists of two records, and the response includes their probability values (multi-class model, three classes).

```bash
aws sagemaker-runtime invoke-endpoint \
  --endpoint-name test-endpoint-csv-1 \
  --content-type text/csv \
  --accept text/csv \
  --body $'1,2,3,4\n5,6,7,8' \
/dev/stderr 1>/dev/null
```

Output:
The request consists of two records, and the response includes predicted label and probability.

```bash
aws sagemaker-runtime invoke-endpoint \
  --endpoint-name test-endpoint-csv-2 \
  --content-type text/csv \
  --accept text/csv \
  --body $'1,2,3,4
5,6,7,8' \
/dev/stderr 1>/dev/null
```

Output:

```
1,0.6
0,0.3
```

The request consists of two records and the response includes label headers and probabilities.

```bash
aws sagemaker-runtime invoke-endpoint \
  --endpoint-name test-endpoint-csv-3 \
  --content-type text/csv \
  --accept text/csv \
  --body $'1,2,3,4
5,6,7,8' \
/dev/stderr 1>/dev/null
```

Output:

```
"['cat','dog','fish']","[0.1,0.6,0.3]"
"['cat','dog','fish']","[0.2,0.5,0.3]"
```

Request and response in JSON Lines format

The request consists of a single record and the response is its probability value.

```bash
aws sagemaker-runtime invoke-endpoint \
  --endpoint-name test-endpoint-jsonlines \
  --content-type application/jsonlines \
  --accept application/jsonlines \
  --body '{"features":["This is a good product",5]}' \
/dev/stderr 1>/dev/null
```

Output:

```
{"score":0.6}
```

The request contains two records, and the response includes predicted label and probability.

```bash
aws sagemaker-runtime invoke-endpoint \
  --endpoint-name test-endpoint-jsonlines-2 \
  --content-type application/jsonlines \
  --accept application/jsonlines \
  --body $'{"features":[1,2,3,4]\n{"features":[5,6,7,8]}' \
/dev/stderr 1>/dev/null
```

Output:
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{"predicted_label":1,"probability":0.6}
{"predicted_label":0,"probability":0.3}
• The request contains two records and the response includes label headers and probabilities.
aws sagemaker-runtime invoke-endpoint \
--endpoint-name test-endpoint-jsonlines-3 \
--content-type application/jsonlines \
--accept application/jsonlines \
--body $'{"data":{"features":[1,2,3,4]}}\n{"data":{"features":[5,6,7,8]}}' \
/dev/stderr 1>/dev/null

Output:
{"predicted_labels":["cat","dog","fish"],"probabilities":[0.1,0.6,0.3]}
{"predicted_labels":["cat","dog","fish"],"probabilities":[0.2,0.5,0.3]}
Request and response in diﬀerent formats
• The request is in CSV format and the response is in JSON Lines format:
aws sagemaker-runtime invoke-endpoint \
--endpoint-name test-endpoint-csv-in-jsonlines-out \
--content-type text/csv \
--accept application/jsonlines \
--body $'1,2,3,4\n5,6,7,8' \
/dev/stderr 1>/dev/null

Output:
{"probability":0.6}
{"probability":0.3}
• The request is in JSON Lines format and the response is in CSV format:
aws sagemaker-runtime invoke-endpoint \
--endpoint-name test-endpoint-jsonlines-in-csv-out \
--content-type application/jsonlines \
--accept text/csv \
--body $'{"features":[1,2,3,4]}\n{"features":[5,6,7,8]}' \
/dev/stderr 1>/dev/null

Output:
0.6
0.3
After the validations are complete, delete the testing endpoint.

Conﬁgure and create an endpoint
Create a new endpoint conﬁguration to ﬁt your model, and use this conﬁguration to create the endpoint.
You can use the model container validated in the pre-check step to create an endpoint and enable the
SageMaker Clarify online explainability feature.

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Use the `sagemaker_client` object to create an endpoint using the `CreateEndpointConfig` API. Set the member `ClarifyExplainerConfig` inside the `ExplainerConfig` parameter as follows:

```python
sagemaker_client.create_endpoint_config(  
    EndpointConfigName='name-of-your-endpoint-config',  
    ExplainerConfig={  
        'ClarifyExplainerConfig': {  
            'EnableExplanations': 'true',  
            'InferenceConfig': {  
                ...  
            },  
            'ShapConfig': {  
                ...  
            }  
        },  
        ProductionVariants=[[  
            'VariantName': 'AllTraffic',  
            'ModelName': 'name-of-your-model',  
            'InitialInstanceCount': 1,  
            'InstanceType': 'ml.m5.xlarge',  
        ]],  
    }  
)
sagemaker_client.create_endpoint(  
    EndpointName='name-of-your-endpoint',  
    EndpointConfigName='name-of-your-endpoint-config'  
)
```

The first call to the `sagemaker_client` object creates a new endpoint configuration with the explainability feature enabled. The second call uses the endpoint configuration to launch the endpoint.

**The EnableExplanations expression**

The `EnableExplanations` parameter is a JMESPath Boolean expression string. It is evaluated for each record in the explainability request. If this parameter is evaluated to be `true`, then the record will be explained. If this parameter is evaluated to be `false`, then explanations are not be generated.

SageMaker Clarify deserializes the model container output for each record into a JSON compatible data structure, and then uses the `EnableExplanations` parameter to evaluate the data.

**Notes**

There are two options for records depending on the format of the model container output.

- If the model container output is in CSV format, then a record is loaded as a JSON array.
- If the model container output is in JSON Lines format, then a record is loaded as a JSON object.

The `EnableExplanations` parameter is a JMESPath expression that can be passed either during the `InvokeEndpoint` or `CreateEndpointConfig` operations. If the JMESPath expression that you supplied is not valid, the endpoint creation will fail. If the expression is valid, but the expression evaluation result is unexpected, then the endpoint will be created successfully, but an error will be generated when the endpoint is invoked. Test your `EnableExplanations` expression by using the `InvokeEndpoint` API, and then apply it to the endpoint configuration.

The following are some examples of valid `EnableExplanations` expression. In the examples, a JMESPath expression encloses a literal using backtick characters. For example, `true` means true.
### Clarify online explainability

<table>
<thead>
<tr>
<th>Expression (string representation)</th>
<th>Model container output (string representation)</th>
<th>Evaluation result (Boolean)</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>'true'</code></td>
<td>(N/A)</td>
<td>True</td>
<td>Activate online explainability unconditionally.</td>
</tr>
<tr>
<td><code>'false'</code></td>
<td>(N/A)</td>
<td>False</td>
<td>Deactivate online explainability unconditionally.</td>
</tr>
<tr>
<td>'[1]&gt; <code>0.5</code>'</td>
<td>'1,0.6'</td>
<td>True</td>
<td>For each record, the model container outputs its predicted label and probability. Explains a record if its probability (at index 1) is greater than 0.5.</td>
</tr>
<tr>
<td>'probability&gt; <code>0.5</code>'</td>
<td>'{&quot;predicted_label&quot;:1,&quot;probability&quot;:0.6}'</td>
<td></td>
<td>For each record, the model container outputs JSON data. Explain a record if its probability is greater than 0.5.</td>
</tr>
<tr>
<td>'!contains(probabilities[-1], max(probabilities))'</td>
<td>'{&quot;probabilities&quot;: [0.4, 0.1, 0.4], &quot;labels&quot;: [&quot;cat&quot;,&quot;dog&quot;,&quot;fish&quot;]}'</td>
<td>False</td>
<td>For a multi-class model: Explains a record if its predicted label (the class that has the max probability value) is the last class. Literally, the expression means that the max probability value is not in the list of probabilities excluding the last one.</td>
</tr>
</tbody>
</table>

### Synthetic dataset

SageMaker Clarify uses the Kernel SHAP algorithm. Given a record (also called a sample or an instance) and the SHAP configuration, the explainer first generates a synthetic dataset. SageMaker Clarify then queries the model container for the predictions of the dataset, and then computes and returns the feature attributions. The size of the synthetic dataset affects the runtime for the Clarify explainer. Larger synthetic datasets take more time to obtain model predictions than smaller ones.

The synthetic dataset size is determined by the following formula:

\[
\text{Synthetic dataset size} = \text{SHAP baseline size} \times \text{n_samples}
\]

The SHAP baseline size is the number of records in the SHAP baseline data. This information is taken from the ShapBaselineConfig.

The size of n_samples is set by the parameter NumberOfSamples in the explainer configuration and the number of features. If the number of features is n_features, then n_samples is the following:
n_samples = MIN(NumberOfSamples, 2^n_features - 2)

The following shows n_samples if NumberOfSamples is not provided.

n_samples = MIN(2*n_features + 2^11, 2^n_features - 2)

For example, a tabular record with 10 features has a SHAP baseline size of 1. If NumberOfSamples is not provided, the synthetic dataset contains 1022 records. If the record has 20 features, the synthetic dataset contains 2088 records.

For NLP problems, n_features is equal to the number of non-text features plus the number of text units.

Note
The InvokeEndpoint API has a request timeout limit. If the synthetic dataset is too large, the explainer may not be able to complete the computation within this limit. If necessary, use the previous information to understand and reduce the SHAP baseline size and NumberOfSamples. If your model container is set up to handle batch requests, then you can also adjust the value of MaxRecordCount.

Invoke the endpoint

After the endpoint is running, use the SageMaker Runtime InvokeEndpoint API in the SageMaker Runtime service to send requests to, or invoke the endpoint. In response, the requests are handled as explainability requests by the SageMaker Clarify explainer.

Note
To invoke an endpoint, choose one of the following options:

• For instructions to use Boto3 or the AWS CLI to invoke an endpoint, see real-time endpoints.
• To use the SageMaker SDK for Python to invoke an endpoint, see the Predictor API.

Request

The InvokeEndpoint API has an optional parameter EnableExplanations, which is mapped to the HTTP header X-Amzn-SageMaker-Enable-Explanations. If this parameter is provided, it overrides the EnableExplanations parameter of the ClarifyExplainerConfig.

Note
The ContentType and Accept parameters of the InvokeEndpoint API are required. Supported formats include MIME type text/csv and application/jsonlines.

Use the sagemaker_runtime_client to send a request to the endpoint, as follows:

```python
response = sagemaker_runtime_client.invoke_endpoint(
    EndpointName='name-of-your-endpoint',
    EnableExplanations='true',
    ContentType='text/csv',
    Accept='text/csv',
    Body='1,2,3,4',  # single record (of four numerical features)
)
```

Response

If the endpoint is created with ExplainerConfig, then a new response schema is used. This new schema is different from, and is not compatible with, an endpoint that lacks the ExplainerConfig parameter provided.
The MIME type of the response is "application/json", and the response payload can be decoded from UTF-8 bytes to a JSON object. The following shows the members of this JSON object are as follows:

- **version**: The version of the response schema in string format. For example, "1.0".
- **predictions**: The predictions that the request makes have the following:
  - **content_type**: The MIME type of the predictions, referring to the ContentType of the model container response.
  - **data**: The predictions data string delivered as the payload of the model container response for the request.
  - **label_headers**: The label headers from the LabelHeaders parameter. This is provided in either the explainer configuration or the model container output.
  - **explanations**: The explanations provided in the request payload. If no records are explained, then this member returns the empty object {}.
  - **kernel_shap**: A key that refers to an array of Kernel SHAP explanations for each record in the request. If a record is not explained, the corresponding explanation is null.

The kernel_shap element has the following members:

- **"feature_header"**: The header name of the features provided by the FeatureHeaders parameter in the explainer configuration ExplainerConfig.
- **feature_type**: The feature type inferred by explainer or provided in the FeatureTypes parameter in the ExplainerConfig. This element is only available for NLP explainability problems.
- **attributions**: An array of attribution objects. Text features can have multiple attribution objects, each for a unit. The attribution object has the following members:
  - **attribution**: A list of probability values, given for each class.
  - **description**: The description of the text units, available only for NLP explainability problems.
  - **partial_text**: The portion of the text explained by the explainer.
  - **start_idx**: A zero-based index to identify the array location of the beginning of the partial text fragment.

### Code examples: SDK for Python

This section provides sample code to create and invoke an endpoint that uses SageMaker Clarify online explainability. These code examples use the AWS SDK for Python.

#### Tabular data

The following example uses tabular data and a SageMaker model called model_name. In this example, the model container accepts data in CSV format, and each record has four numerical features. In this minimal configuration, for demonstration purposes only, the SHAP baseline data is set to zero. Refer to the SHAP Baselines for Explainability to choose more appropriate values for ShapBaseline.

Configure the endpoint, as follows:

```python
endpoint_config_name = 'tabular_explainer_endpoint_config'
response = sagemaker_client.create_endpoint_config(
    EndpointConfigName=endpoint_config_name,
    ProductionVariants=[
        {'VariantName': 'AllTraffic',
         'ModelName': model_name,
         'InitialInstanceCount': 1,
```
Use the endpoint configuration to create an endpoint, as follows:

```python
def create_endpoint(EndpointName, EndpointConfigName):
    return sagemaker_client.create_endpoint(EndpointName=EndpointName, EndpointConfigName=EndpointConfigName)
```

Use the `DescribeEndpoint` API to inspect the progress of creating an endpoint, as follows:

```python
def describe_endpoint(EndpointName):
    return sagemaker_client.describe_endpoint(EndpointName=EndpointName)
```

After the endpoint status is "InService", invoke the endpoint with a test record, as follows:

```python
def invoke_endpoint(EndpointName, ContentType='text/csv', Accept='text/csv', Body='1,2,3,4',)
```

Assume that the response has a status code of 200 (no error), and load the response body, as follows:

```python
import codecs
import json
json.loads(codecs.getreader('utf-8')(response['Body'])))
```

The default action for the endpoint is to explain the record. The following shows example output in the returned JSON object:

```json
{
    "version": "1.0",
    "predictions": {
        "content_type": "text/csv; charset=utf-8",
        "data": "0.0006380207487381"
    },
    "explanations": {
        "kernel_shap": [
            {
                "attributions": [
                    ...]
                ]
            }
        }
    }
```
Use the EnableExplanations parameter to enable on-demand explanations, as follows:

```python
response = sagemaker_runtime_client.invoke_endpoint(
    EndpointName=endpoint_name,
    ContentType='text/csv',
    Accept='text/csv',
    Body='1,2,3,4',
    EnableExplanations='[0]>`0.8`',
)
```

In this example, the prediction value is less than the threshold value of 0.8, so the record is not explained:

```json
{
    "version": "1.0",
    "predictions": {
        "content_type": "text/csv; charset=utf-8",
        "data": "0.6380207487381995"
    },
    "explanations": {}
}
```

Use visualization tools to help interpret the returned explanations. The following image shows how SHAP plots can be used to understand how each feature contributes to the prediction. The base value on the diagram, also called the expected value, is the mean predictions of the training dataset. Features that push the expected value higher are red, and features that push the expected value lower are blue. See [SHAP additive force layout](#) for additional information.
See the full example notebook for tabular data.

**Text data**

This section provides a code example to create and invoke an online explainability endpoint for text data. The code example uses SDK for Python.

The following example uses text data and a SageMaker model called `model_name`. In this example, the model container accepts data in CSV format, and each record is a single string.

```python
endpoint_config_name = 'text_explainer_endpoint_config'
response = sagemaker_client.create_endpoint_config(
    EndpointConfigName=endpoint_config_name,
    ProductionVariants=[
        {'VariantName': 'AllTraffic',
         'ModelName': model_name,
         'InitialInstanceCount': 1,
         'InstanceType': 'ml.m5.xlarge',
        },
    ],
    ExplainerConfig={
        'ClarifyExplainerConfig': {
            'InferenceConfig': {
                'FeatureTypes': ['text'],
                'MaxRecordCount': 100,
            },
            'ShapConfig': {
                'ShapBaselineConfig': {
                    'ShapBaseline': '"<MASK>"',
                },
                'TextConfig': {
                    'Granularity': 'token',
                    'Language': 'en',
                },
                'NumberOfSamples': 100,
            },
        },
    },
)
```

- **ShapBaseline**: A special token reserved for natural language processing (NLP) processing.
- **FeatureTypes**: Identifies the feature as text. If this parameter is not provided, the explainer will attempt to infer the feature type.
- **TextConfig**: Specifies the unit of granularity and language for the analysis of text features. In this example, the language is English, and granularity 'token' means a word in English text.
- **NumberOfSamples**: A limit to set the upper bounds of the size of the synthetic dataset.
- **MaxRecordCount**: The maximum number of records in a request that the model container can handle. This parameter is set to stabilize performance.

Use the endpoint configuration to create the endpoint, as follows:
endpoint_name = 'text_explainer_endpoint'
response = sagemaker_client.create_endpoint(
    EndpointName=endpoint_name,
    EndpointConfigName=endpoint_config_name,
)

After the status of the endpoint becomes InService, invoke the endpoint. The following code sample uses a test record as follows:

response = sagemaker_runtime_client.invoke_endpoint(
    EndpointName=endpoint_name,
    ContentType='text/csv',
    Accept='text/csv',
    Body='"This is a good product"',
)

If the request completes successfully, the response body will return a valid JSON object that's similar to the following:

```json
{
    "version": "1.0",
    "predictions": {
        "content_type": "text/csv",
        "data": "0.9766594\n"
    },
    "explanations": {
        "kernel_shap": [
            {
                "attributions": [
                    {
                        "attribution": [
                            -0.007270948666666712
                        ],
                        "description": {
                            "partial_text": "This",
                            "start_idx": 0
                        }
                    },
                    {
                        "attribution": [
                            -0.018199033666666628
                        ],
                        "description": {
                            "partial_text": "is",
                            "start_idx": 5
                        }
                    },
                    {
                        "attribution": [
                            0.01970993241666666
                        ],
                        "description": {
                            "partial_text": "a",
                            "start_idx": 8
                        }
                    },
                    {
                        "attribution": [
                            0.1253469515833334
                        ],
                        "description": {
```
Use visualization tools to help interpret the returned text attributions. The following image shows how the captum visualization utility can be used to understand how each word contributes to the prediction. The higher the color saturation, the higher the importance given to the word. In this example, a highly saturated bright red color indicates a strong negative contribution. A highly saturated green color indicates a strong positive contribution. The color white indicates that the word has a neutral contribution. See the captum library for additional information on parsing and rendering the attributions.

See the full example notebook for text data.

Troubleshooting guide

If you encounter errors using SageMaker Clarify online explainability, consult the topics in this section.

InvokeEndpoint API fails with the error "ReadTimeoutError:Read timeout on endpoint..."

This error means that the request could not be completed within the 60-second time limit set by the request timeout.

To reduce the request latency, try the following:

- Tune the model's performance during inference. For example, SageMaker Neo can optimize models for inference.
- Allow the model container to handle batch requests.
- Use a larger MaxRecordCount to reduce the number of calls from the explainer to the model container. This will reduce network latency and overhead.
- Use an instance type that has more resources allocated to it. Alternately, assign more instances to the endpoint to help balance the load.
- Reduce the number of records inside a single InvokeEndpoint request.
- Reduce the number of records in the baseline data.
• Use a smaller `NumberOfSamples` value to reduce the size of the synthetic dataset. For more information, see the **Synthetic dataset** section in **Configure and create an endpoint**.

## Invoke real-time endpoints

After you deploy your model using SageMaker hosting services, you can test your model on that endpoint by sending it test data. You can test your endpoints using Amazon SageMaker Studio, the AWS CLI, or AWS SDKs.

### Test Your Endpoint Using Amazon SageMaker Studio

After you deploy your model to an endpoint (see [Create your endpoint and deploy your model (p. 2745)](#)) you can check that endpoint with Amazon SageMaker Studio.

**Note**

Note: SageMaker only supports endpoint testing with Amazon SageMaker Studio for real-time endpoints.

1. Launch Amazon SageMaker Studio.
2. Select the **SageMaker Components and registries** icon on the left sidebar.
3. From the dropdown, choose **Endpoints**.
4. Search for your endpoint by name and double-click on the name of your endpoint. The endpoint names listed within the **SageMaker resources** panel are defined when you deploy a model. You can deploy your model in several ways:
   - The SageMaker Python SDK Model Class `sagemaker.model.Model.deploy`.
   - The AWS SDK for Python (Boto3) SageMaker Service Client API `CreateEndpoint`.
   - The SageMaker console. Select **Inference** in the left panel and then select **Endpoint configuration**. Provide an endpoint name within the **Endpoint name** field.
5. (Optional) You can optionally provide a custom URL to send your request to. In the **Configure endpoint URL and headers** field provide the URL of where your model is hosted. Leave this field blank if you are using a SageMaker endpoint. You can also optionally add multiple key-value headers to pass additional information to the inference request.
6. A new tab will populate in the Studio workspace. Select the **Test inference** tab.
7. Send a request to your endpoint by providing sample data in JSON format. Use the JSON editor to submit a request to your endpoint.
8. Select **Send Request**.
9. When you send the request an *Inference output card* will appear on the right-hand side of the console.

The top of the card will display the type of request that was sent to the endpoint (currently only JSON is accepted). Within the card there are four main fields: **Status**, **Execution Length**, **Request Time**, and **Result Time**.

- **Status**: displays the request status. There are three types of statuses:
  - Complete - If the request is successful, the status will display Complete and the execution length will be calculated by tracking the request time.
  - Failed - If the request fails for any reason. A failure response will appear within the **Failure Reason** accordion.
  - Pending - A spinning, circular icon will appear while the inference request is pending.
- **Execution Length**: How long the invocation takes (end time minus the start time) in milliseconds.
- **Request Time**: How many minutes have passed since the request was sent.
- **Result Time**: How many minutes have passed since the result was returned.
**Test Your Endpoint Using AWS SDKs**

After you deploy your model to an endpoint (see Create your endpoint and deploy your model (p. )), you can check your endpoint with the InvokeEndpoint API using one of the AWS SDKs. If the invocation is successful, SageMaker will return an HTTP 200 response. You can index the returned response dictionary object to find out more about the response headers. For more information, see InvokeEndpoint.

The following demonstrates how to use InvokeEndpoint to check the status of your endpoint using the AWS SDK for Python (Boto3). Provide the name of your endpoint. This is the name you specified for EndpointName when you created your endpoint with CreateEndpoint.

Provide input data in the Body field for SageMaker to pass to the model. The data must be in the same format that was used for training.

```python
import boto3

# Create a low-level client representing Amazon SageMaker Runtime
sagemaker_runtime = boto3.client("sagemaker-runtime", region_name=\<aws_region\>)

# The name of the endpoint. The name must be unique within an AWS Region in your AWS account.
endpoint_name=\'<endpoint-name>\'

# After you deploy a model into production using SageMaker hosting # services, your client applications use this API to get inferences # from the model hosted at the specified endpoint.
response = sagemaker_runtime.invoke_endpoint(  
    EndpointName=endpoin
```
Monitor models for data and model quality, bias, and explainability

Amazon SageMaker Model Monitor monitors the quality of Amazon SageMaker machine learning models in production. You can set up continuous monitoring with a real-time endpoint (or a batch transform job that runs regularly), or on-schedule monitoring for asynchronous batch transform jobs. With Model Monitor, you can set alerts that notify you when there are deviations in the model quality. Early and proactive detection of these deviations enables you to take corrective actions, such as retraining models, auditing upstream systems, or fixing quality issues without having to monitor models manually or build additional tooling. You can use Model Monitor prebuilt monitoring capabilities that do not require coding. You also have the flexibility to monitor models by coding to provide custom analysis.

Model Monitor provides the following types of monitoring:

- **Monitor data quality** - Monitor drift in data quality.
- **Monitor model quality** - Monitor drift in model quality metrics, such as accuracy.
- **Monitor Bias Drift for Models in Production** - Monitor bias in your model's predictions.
- **Monitor Feature Attribution Drift for Models in Production** - Monitor drift in feature attribution.

Topics

- How Model Monitor Works
- Capture data
- Monitor data quality
- Monitor model quality
- Monitor Bias Drift for Models in Production
- Monitor Feature Attribution Drift for Models in Production
- Schedule monitoring jobs
- Amazon SageMaker Model Monitor prebuilt container
- Interpret results
How Model Monitor Works

Amazon SageMaker Model Monitor automatically monitors machine learning (ML) models in production and notifies you when quality issues arise. Model Monitor uses rules to detect drift in your models and alerts you when it happens. The following figure shows how this process works in the case that your model is deployed to a real-time endpoint.

You can also use Model Monitor to monitor a batch transform job instead of a real-time endpoint. In this case, instead of receiving requests to an endpoint and tracking the predictions, Model Monitor will monitor inference inputs and outputs. The following figure diagrams the process of monitoring a batch transform job.
To enable model monitoring, you take the following steps, which follow the path of the data through the various data collection, monitoring, and analysis processes:

- For a real-time endpoint, enable the endpoint to capture data from incoming requests to a trained ML model and the resulting model predictions.
- For a batch transform job, enable data capture of the batch transform inputs and outputs.
- Create a baseline from the dataset that was used to train the model. The baseline computes metrics and suggests constraints for the metrics. Real-time or batch predictions from your model are compared to the constraints, and are reported as violations if they are outside the constrained values.
- Create a monitoring schedule specifying what data to collect, how often to collect it, how to analyze it, and which reports to produce.
- Inspect the reports, which compare the latest data with the baseline, and watch for any violations reported and for metrics and notifications from Amazon CloudWatch.

**Notes**

- Model Monitor computes model metrics and statistics on tabular data only. For example, an image classification model that takes images as input and outputs a label based on that image can still be monitored. Model Monitor would be able to calculate metrics and statistics for the output, not the input.
- Model Monitor currently supports only endpoints that host a single model and does not support monitoring multi-model endpoints. For information on using multi-model endpoints, see [Host multiple models in one container behind one endpoint](p. 2755).
- Model Monitor supports monitoring inference pipelines, but capturing and analyzing data is done for the entire pipeline, not for individual containers in the pipeline.
- To prevent impact to inference requests, Data Capture stops capturing requests at high levels of disk usage. It is recommended you keep your disk utilization below 75% in order to ensure data capture continues capturing requests.
- If you launch SageMaker Studio in a custom Amazon VPC, you need to create VPC endpoints to enable Model Monitor to communicate with Amazon S3 and CloudWatch. For information about VPC endpoints, see [VPC endpoints](p. 346) in the [Amazon Virtual Private Cloud User Guide](p. 2755). For information about launching SageMaker Studio in a custom VPC, see [Connect SageMaker Studio Notebooks in a VPC to External Resources](p. 3631).

**Model Monitor Sample Notebooks**

For a sample notebook that takes you through the full end-to-end workflow using Model Monitor with your real-time endpoint, see [Introduction to Amazon SageMaker Model Monitor](p. 2755).

For a sample notebook that visualizes the statistics.json file for a selected execution in a monitoring schedule, see the [Model Monitor Visualization](p. 2755).

For instructions that show you how to create and access Jupyter notebook instances that you can use to run the example in SageMaker, see [Use Amazon SageMaker Notebook Instances](p. 291). After you have created a notebook instance and opened it, choose the **SageMaker Examples** tab to see a list of all the SageMaker samples. To open a notebook, choose the notebook's **Use** tab and choose **Create copy**.

**Capture data**

To log the inputs to your endpoint and the inference outputs from your deployed model to Amazon S3, you can enable a feature called **Data Capture**. **Data Capture** is commonly used to record information that can be used for training, debugging, and monitoring. Amazon SageMaker Model Monitor automatically parses this captured data and compares metrics from this data with a baseline that you create for the
model. For more information about Model Monitor see Monitor models for data and model quality, bias, and explainability (p. 2853).

You can implement Data Capture for both real-time and batch model-monitor modes using the AWS SDK for Python (Boto) or the SageMaker Python SDK. For a real-time endpoint, you will specify your Data Capture configuration when you create your endpoint. Due to the persistent nature of your real-time endpoint, you can configure additional options to turn data capturing on or off at certain times, or change the sampling frequency. You can also choose to encrypt your inference data.

For a batch transform job, you can enable Data Capture if you want to run on-schedule model monitoring or continuous model-monitoring for regular, periodic batch transform jobs. You will specify your Data Capture configuration when you create your batch transform job. Within this configuration, you have the option to turn on encryption or generate the inference ID with your output, which helps you match your captured data to Ground Truth data.

Capture data from real-time endpoint

Note
To prevent impact to inference requests, Data Capture stops capturing requests at high levels of disk usage. It is recommended you keep your disk utilization below 75% in order to ensure data capture continues capturing requests.

To capture data for your real-time endpoint, you must deploy a model using SageMaker hosting services. This requires that you create a SageMaker model, define an endpoint configuration, and create an HTTPS endpoint.

The steps required to turn on data capture are similar whether you use the AWS SDK for Python (Boto) or the SageMaker Python SDK. If you use the AWS SDK, define the DataCaptureConfig dictionary, along with required fields, within the CreateEndpointConfig method to turn on data capture. If you use the SageMaker Python SDK, import the DataCaptureConfig Class and initialize an instance from this class. Then, pass this object to the DataCaptureConfig parameter in the sagemaker.model.Model.deploy() method.

To use the proceeding code snippets, replace the italicized placeholder text in the example code with your own information.

How to enable data capture

Specify a data capture configuration. You can capture the request payload, the response payload, or both with this configuration. The proceeding code snippet demonstrates how to enable data capture using the AWS SDK for Python (Boto) and the SageMaker Python SDK.

Note
You do not need to use Model Monitor to capture request or response payloads.

AWS SDK for Python (Boto)

Configure the data you want to capture with the DataCaptureConfig dictionary when you create an endpoint using the CreateEndpointConfig method. Set EnableCapture to the boolean value True. In addition, provide the following mandatory parameters:

- EndpointConfigName: the name of your endpoint configuration. You will use this name when you make a CreateEndpoint request.
- ProductionVariants: a list of models you want to host at this endpoint. Define a dictionary data type for each model.
- DataCaptureConfig: dictionary data type where you specify an integer value that corresponds to the initial percentage of data to sample (InitialSamplingPercentage), the Amazon S3 URI where you want captured data to be stored, and a capture options (CaptureOptions) list. Specify either Input or Output for CaptureMode within the CaptureOptions list.
You can optionally specify how SageMaker should encode captured data by passing key-value pair arguments to the CaptureContentTypeHeader dictionary.

```python
# Create an endpoint config name.
endpoint_config_name = '<endpoint-config-name>'

# The name of the production variant.
variant_name = '<name-of-production-variant>'

# The name of the model that you want to host. This is the name that you specified when creating the model.
model_name = '<The_name_of_your_model>'

instance_type = '<instance-type>'  # Specify the compute instance type.
initial_instance_count = <integer>  # Number of instances to launch initially.

# Sampling percentage. Choose an integer value between 0 and 100
initial_sampling_percentage = <integer>

# The S3 URI containing the captured data
s3_capture_upload_path = 's3://<bucket-name>/<data_capture_s3_key>'

# Specify either Input, Output, or both
capture_modes = ["Input", "Output"]  # Example - If you want to capture input only

endpoint_config_response = sagemaker_client.create_endpoint_config(
    EndpointConfigName=endpoint_config_name,
    ProductionVariants=[
        {
            "VariantName": variant_name,
            "ModelName": model_name,
            "InstanceType": instance_type,
            "InitialInstanceCount": initial_instance_count  # Number of instances to launch initially.
        }
    ],
    DataCaptureConfig={
        'EnableCapture': True,  # Whether data should be captured or not.
        'InitialSamplingPercentage': initial_sampling_percentage,
        'DestinationS3Uri': s3_capture_upload_path,
        'CaptureOptions': [{"CaptureMode": capture_mode} for capture_mode in capture_modes]  # Example - Use list comprehension to capture both Input and Output
    }
)
```

For more information about other endpoint configuration options, see the `CreateEndpointConfig` API in the Amazon SageMaker Service API Reference Guide.

**SageMaker Python SDK**

Import the `DataCaptureConfig` Class from `sagemaker.model_monitor` module. Enable data capture by setting `EnableCapture` to the boolean value `True`.

Optionally provide arguments for the following parameters:
• SamplingPercentage: an integer value that corresponds to percentage of data to sample. If you do not provide a sampling percentage, SageMaker will sample a default of 20 (20%) of your data.
• DestinationS3Uri: the Amazon S3 URI SageMaker will use to store captured data. If you do not provide one, SageMaker will store captured data in "s3://<default-session-bucket>/model-monitor/data-capture".

```python
from sagemaker.model_monitor import DataCaptureConfig

# Set to True to enable data capture
enable_capture = True

# Optional - Sampling percentage. Choose an integer value between 0 and 100
sampling_percentage = <int>
# sampling_percentage = 30 # Example 30%

# Optional - The S3 URI of stored captured-data location
s3_capture_upload_path = "s3://<bucket-name>/<data_capture_s3_key>"

# Specify either Input, Output or both.
capture_modes = ["REQUEST","RESPONSE"] # In this example, we specify both
# capture_mode = ["REQUEST"] # Example - If you want to only capture input.

data_capture_config = DataCaptureConfig(
enable_capture = enable_capture,
sampling_percentage = sampling_percentage, # Optional
destination_s3_uri = s3_capture_upload_path, # Optional
capture_options = ["CaptureMode": capture_mode for capture_mode in capture_modes])
```

Deploy your model

Deploy your model and create an HTTPS endpoint with DataCapture enabled.

AWS SDK for Python (Boto3)

Provide the endpoint configuration to SageMaker. The service launches the ML compute instances and deploys the model or models as specified in the configuration.

Once you have your model and endpoint configuration, use the CreateEndpoint API to create your endpoint. The endpoint name must be unique within an AWS Region in your AWS account.

The following creates an endpoint using the endpoint configuration specified in the request. Amazon SageMaker uses the endpoint to provision resources and deploy models.

```python
# The name of the endpoint. The name must be unique within an AWS Region in your AWS account.
endpoint_name = '<endpoint-name>'

# The name of the endpoint configuration associated with this endpoint.
endpoint_config_name='<endpoint-config-name>'

create_endpoint_response = sagemaker_client.create_endpoint(
    EndpointName=endpoint_name,
    EndpointConfigName=endpoint_config_name)
```

For more information, see the CreateEndpoint API.
SageMaker Python SDK

Define a name for your endpoint. This step is optional. If you do not provide one, SageMaker will create a unique name for you:

```python
from datetime import datetime
endpoint_name = f"DEMO-{datetime.utcnow():%Y-%m-%d-%H%M}"  
print("EndpointName =", endpoint_name)
```

Deploy your model to a real-time, HTTPS endpoint with the Model object's built-in `deploy()` method. Provide the name of the Amazon EC2 instance type to deploy this model to in the `instance_type` field along with the initial number of instances to run the endpoint on for the `initial_instance_count` field:

```python
initial_instance_count=<integer>  
# initial_instance_count=1 # Example
instance_type='<instance-type>'  
# instance_type='ml.m4.xlarge' # Example

# Uncomment if you did not define this variable in the previous step
#data_capture_config = <name-of-data-capture-configuration>

model.deploy(  
    initial_instance_count=initial_instance_count,  
    instance_type=instance_type,  
    endpoint_name=endpoint_name,  
    data_capture_config=data_capture_config
)
```

View Captured Data

Create a predictor object from the SageMaker Python SDK `Predictor` Class. You will use the object returned by the `Predictor` Class to invoke your endpoint in a future step. Provide the name of your endpoint (defined earlier as `endpoint_name`), along with serializer and deserializer objects for the serializer and deserializer, respectively. For information about serializer types, see the `Serializers` Class in the SageMaker Python SDK.

```python
from sagemaker.predictor import Predictor  
from sagemaker.serializers import <Serializer>  
from sagemaker.deserializers import <Deserializers>

predictor = Predictor(endpoint_name=endpoint_name,  
    serializer = <Serializer_Class>,  
    deserializer = <Deserializer_Class>)

# Example  
#from sagemaker.predictor import Predictor  
#from sagemaker.serializers import CSVSerializer  
#from sagemaker.deserializers import JSONDeserializer  

#predictor = Predictor(endpoint_name=endpoint_name,  
#    serializer=CSVSerializer(),  
#    deserializer=JSONDeserializer())
```

In the proceeding code example scenario we invoke the endpoint with sample validation data that we have stored locally in a CSV file named `validation_with_predictions`. Our sample validation set contains labels for each input.
Amazon SageMaker Developer Guide
Capture data

The ﬁrst few lines of the with statement ﬁrst opens the validation set CSV ﬁle, then splits each row
within the ﬁle by the comma character ",", and then stores the two returned objects into a label
and input_cols variables. For each row, the input (input_cols) is passed to the predictor variable's
(predictor) objects built-in method Predictor.predict().
Suppose the model returns a probability. Probabilities range between integer values of 0 and 1.0. If the
probability returned by the model is greater than 80% (0.8) we assign the prediction an integer value
label of 1. Otherwise, we assign the prediction an integer value label of 0.
from time import sleep
validate_dataset = "validation_with_predictions.csv"
# Cut off threshold of 80%
cutoff = 0.8
limit = 200 # Need at least 200 samples to compute standard deviations
i = 0
with open(f"test_data/{validate_dataset}", "w") as validation_file:
validation_file.write("probability,prediction,label\n") # CSV header
with open("test_data/validation.csv", "r") as f:
for row in f:
(label, input_cols) = row.split(",", 1)
probability = float(predictor.predict(input_cols))
prediction = "1" if probability > cutoff else "0"
baseline_file.write(f"{probability},{prediction},{label}\n")
i += 1
if i > limit:
break
print(".", end="", flush=True)
sleep(0.5)
print()
print("Done!")

Because you enabled the data capture in the previous steps, the request and response payload,
along with some additional meta data, is saved in the Amazon S3 location that you speciﬁed in
DataCaptureConfig. The delivery of capture data to Amazon S3 can require a couple of minutes.
View captured data by listing the data capture ﬁles stored in Amazon S3. The format of the Amazon S3
path is: s3:///{endpoint-name}/{variant-name}/yyyy/mm/dd/hh/filename.jsonl.
Expect to see diﬀerent ﬁles from diﬀerent time periods, organized based on the hour when the
invocation occurred. Run the following to print out the contents of a single capture ﬁle:
print("\n".join(capture_file[-3:-1]))

This will return a SageMaker speciﬁc JSON-line formatted ﬁle. The following is a response sample taken
from a real-time endpoint that we invoked using csv/text data:

{"captureData":{"endpointInput":{"observedContentType":"text/csv","mode":"INPUT",
"data":"69,0,153.7,109,194.0,105,256.1,114,14.1,6,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
"encoding":"CSV"},"endpointOutput":{"observedContentType":"text/csv;
charset=utf-8","mode":"OUTPUT","data":"0.0254181120544672","encoding":"CSV"}},
"eventMetadata":{"eventId":"aaaaaaaa-bbbb-cccc-ddddeeeeeeeeeeee","inferenceTime":"2022-02-14T17:25:49Z"},"eventVersion":"0"}
{"captureData":{"endpointInput":{"observedContentType":"text/csv","mode":"INPUT",
"data":"94,23,197.1,125,214.5,136,282.2,103,9.5,5,4,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
"encoding":"CSV"},"endpointOutput":{"observedContentType":"text/csv;
charset=utf-8","mode":"OUTPUT","data":"0.07675473392009735","encoding":"CSV"}},
"eventMetadata":{"eventId":"aaaaaaaa-bbbb-cccc-ddddeeeeeeeeeeee","inferenceTime":"2022-02-14T17:25:49Z"},"eventVersion":"0"}

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In the proceeding example, the capture_file object is a list type. Index the first element of the list to view a single inference request.

```python
# The capture_file object is a list. Index the first element to view a single inference request
print(json.dumps(json.loads(capture_file[0]), indent=2))
```

This will return a response similar to the following. The values returned will differ based on your endpoint configuration, SageMaker model, and captured data:

```json
{
    "captureData": {
        "endpointInput": {
            "observedContentType": "text/csv", # data MIME type
            "mode": "INPUT",
            "data": "50,0,188.9,203.9,104,151.8,124,11.6,8,3,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,1,1,0,1,0",
            "encoding": "CSV"
        },
        "endpointOutput": {
            "observedContentType": "text/csv; charset=character-encoding",
            "mode": "OUTPUT",
            "data": "0.023190177977085114",
            "encoding": "CSV"
        }
    },
    "eventMetadata": {
        "eventId": "aaaaaaaa-bbbb-cccc-dddd-eeeeeeeeeeee",
        "inferenceTime": "2022-02-14T17:25:06Z"
    },
    "eventVersion": "0"
}
```

**Capture data from batch transform job**

The steps required to turn on data capture for your batch transform job are similar whether you use the AWS SDK for Python (Boto) or the SageMaker Python SDK. If you use the AWS SDK, define the DataCaptureConfig dictionary, along with required fields, within the CreateTransformJob method to turn on data capture. If you use the SageMaker Python SDK, import the BatchDataCaptureConfig class and initialize an instance from this class. Then, pass this object to the batch_transform_data_capture_config parameter of your transform job instance.

To use the proceeding code snippets, replace the *italicized placeholder text* in the example code with your own information.

**How to enable data capture**

Specify a data capture configuration when you launch a transform job. Whether you use the AWS SDK for Python (Boto3) or the SageMaker Python SDK, you must provide the DestinationS3Uri argument, which is the directory where you want the transform job to log the captured data. Optionally, you can also set the following parameters:

- **KmsKeyId**: The AWS KMS key used to encrypt the captured data.
- **GenerateInferenceId**: A Boolean flag that, when capturing the data, indicates if you want the transform job to append the inference ID and time to your output. This is useful for model quality monitoring, where you need to ingest the Ground Truth data. The inference ID and time help to match the captured data with your Ground Truth data.
AWS SDK for Python (Boto3)

Configure the data you want to capture with the `DataCaptureConfig` dictionary when you create a transform job using the `CreateTransformJob` method.

```python
input_data_s3_uri = "s3://<input_S3_uri>"
output_data_s3_uri = "s3://<output_S3_uri>"
data_capture_destination = "s3://<captured_data_S3_uri>"
model_name = "<model_name>"

sm_client.create_transform_job(  
    TransformJobName="<transform_job_name>",  
    MaxConcurrentTransforms=2,  
    ModelName=model_name,  
    TransformInput={  
        'DataSource': {  
            'S3DataSource': {  
                'S3DataType': "S3Prefix",  
                'S3Uri': input_data_s3_uri,  
            }  
        },  
        'ContentType': 'text/csv',  
        'CompressionType': 'None',  
        'SplitType': 'Line',  
    },  
    TransformOutput={  
        'S3OutputPath': output_data_s3_uri,  
        'Accept': 'text/csv',  
        'AssembleWith': 'Line',  
    },  
    TransformResources={  
        "InstanceType": "ml.m4.xlarge",  
        "InstanceCount": 1,  
    },  
    DataCaptureConfig={  
        "DestinationS3Uri": data_capture_destination,  
        "KmsKeyId": "<kms_key>",  
        "GenerateInferenceId": True,  
    }
)
```

SageMaker Python SDK

Import the `BatchDataCaptureConfig` class from the `sagemaker.model_monitor`.

```python
from sagemaker.transformer import Transformer
from sagemaker.inputs import BatchDataCaptureConfig

# Optional - The S3 URI of where to store captured data in S3
data_capture_destination = 's3://<bucket_name>'

model_name = "<inference_model_name>"

transformer = Transformer(  
    model_name=model_name,  
    ...  
    batch_transform_data_capture_config=BatchDataCaptureConfig(  
        destination_s3_uri=data_capture_destination,  
        kms_key_id="<kms_key>",  
        generate_inference_id=True,  
    )))
...  
)
```
How to view data captured

Once the transform job completes, the captured data gets logged under the DestinationS3Uri you provided with the data capture configuration. There are two subdirectories under DestinationS3Uri, /input and /output. If DestinationS3Uri is s3://my-data-capture, then the transform job creates the following directories:

- s3://my-data-capture/input: The captured input data for the transform job.
- s3://my-data-capture/output: The captured output data for the transform job.

To avoid data duplication, the captured data under the preceding two directories are manifests. Each manifest is a JSONL file that contains the Amazon S3 locations of the source objects. A manifest file may look like the following example:

```
// under "input" directory
[
  {
    "prefix":"s3://<input_S3_uri>",
    "dummy_0.csv",
    "dummy_1.csv",
    "dummy_2.csv",
    ...
  }

// under "output" directory
[
  {
    "prefix":"s3://<output_S3_uri>",
    "dummy_0.csv.out",
    "dummy_1.csv.out",
    "dummy_2.csv.out",
    ...
  }
```

The transform job organizes and labels these manifests with a yyyy/mm/dd/hh S3 prefix to indicate when they were captured. This helps the model monitor determine the appropriate portion of data to analyze. For example, if you start your transform job at 2022-08-26 13PM UTC, then the captured data is labeled with a 2022/08/26/13/ prefix string.

InferenceId Generation

When you configure DataCaptureConfig for a transform job, you can turn on the Boolean flag GenerateInferenceId. This is particularly useful when you need to run model quality and model bias monitoring jobs, for which you need user-ingested Ground Truth data. Model monitor relies on an inference ID to match the captured data and the Ground Truth data. For addition details about Ground Truth ingestion, see Ingest Ground Truth Labels and Merge Them With Predictions (p. 2874). When GenerateInferenceId is on, the transform output appends an inference ID (a random UUID) as well as the transform job start time in UTC for each record. You need these two values to run model quality and model bias monitoring. When you construct the Ground Truth data, you need to provide the same inference ID to match the output data. Currently, this feature supports transform outputs in CSV, JSON, and JSONL formats.

If your transform output is in CSV format, the output file looks like the following example:

```
0, 1f1d57b1-2e6f-488c-8c30-db4e6d757861,2022-08-30T00:49:15Z
1, 22445434-0c67-45e9-bb4d-bd1bf26561e6,2022-08-30T00:49:15Z
```
Monitor data quality

Data quality monitoring automatically monitors machine learning (ML) models in production and notifies you when data quality issues arise. ML models in production have to make predictions on real-life data that is not carefully curated like most training datasets. If the statistical nature of the data that your model receives while in production drifts away from the nature of the baseline data it was trained on, the model begins to lose accuracy in its predictions. Amazon SageMaker Model Monitor uses rules to detect data drift and alerts you when it happens. To monitor data quality, follow these steps:

- Enable data capture. This captures inference input and output from a real-time inference endpoint or batch transform job and stores the data in Amazon S3. For more information, see Capture data (p. 2855).
- Create a baseline. In this step, you run a baseline job that analyzes an input dataset that you provide. The baseline computes baseline schema constraints and statistics for each feature using Deequ, an open source library built on Apache Spark, which is used to measure data quality in large datasets. For more information, see Create a Baseline (p. 2865).
- Define and schedule data quality monitoring jobs. For specific information and code samples of data quality monitoring jobs, see Schedule data quality monitoring jobs (p. 2866). For general information about monitoring jobs, see Schedule monitoring jobs (p. 2897).
- Optionally use preprocessing and postprocessing scripts to transform the data coming out of your data quality analysis. For more information, see Preprocessing and Postprocessing (p. 2908).
- View data quality metrics. For more information, see Schema for Statistics (statistics.json file) (p. 2867).
- Integrate data quality monitoring with Amazon CloudWatch. For more information, see CloudWatch Metrics (p. 2868).
- Interpret the results of a monitoring job. For more information, see Interpret results (p. 2900).
- Use SageMaker Studio to enable data quality monitoring and visualize results if you are using a real-time endpoint. For more information, see Visualize results for real-time endpoints in Amazon SageMaker Studio (p. 2902).

**Note**
Model Monitor computes model metrics and statistics on tabular data only. For example, an image classification model that takes images as input and outputs a label based on that image can still be monitored. Model Monitor would be able to calculate metrics and statistics for the output, not the input.
Monitor data quality

- Create a Baseline (p. 2865)
- Schedule data quality monitoring jobs (p. 2866)
- Schema for Statistics (statistics.json file) (p. 2867)
- CloudWatch Metrics (p. 2868)
- Schema for Violations (constraint_violations.json file) (p. 2869)

Create a Baseline

The baseline calculations of statistics and constraints are needed as a standard against which data drift and other data quality issues can be detected. Model Monitor provides a built-in container that provides the ability to suggest the constraints automatically for CSV and flat JSON input. This sagemaker-model-monitor-analyzer container also provides you with a range of model monitoring capabilities, including constraint validation against a baseline, and emitting Amazon CloudWatch metrics. This container is based on Spark and is built with Deequ. All column names in your baseline dataset must be compliant with Spark. For column names, use only lowercase characters, and _ as the only special character.

The training dataset that you used to trained the model is usually a good baseline dataset. The training dataset data schema and the inference dataset schema should exactly match (the number and order of the features). Note that the prediction/output columns are assumed to be the first columns in the training dataset. From the training dataset, you can ask SageMaker to suggest a set of baseline constraints and generate descriptive statistics to explore the data. For this example, upload the training dataset that was used to train the pretrained model included in this example. If you already stored the training dataset in Amazon S3, you can point to it directly.

To Create a baseline from a training dataset

When you have your training data ready and stored in Amazon S3, start a baseline processing job with DefaultModelMonitor.suggest_baseline(..) using the Amazon SageMaker Python SDK. This uses an Amazon SageMaker Model Monitor prebuilt container (p. 2899) that generates baseline statistics and suggests baseline constraints for the dataset and writes them to the output_s3_uri location that you specify.

```python
from sagemaker.model_monitor import DefaultModelMonitor
from sagemaker.model_monitor.dataset_format import DatasetFormat

my_default_monitor = DefaultModelMonitor(
    role=role,
    instance_count=1,
    instance_type='ml.m5.xlarge',
    volume_size_in_gb=20,
    max_runtime_in_seconds=3600,
)

my_default_monitor.suggest_baseline(
    baseline_dataset=baseline_data_uri+'/training-dataset-with-header.csv',
    dataset_format=DatasetFormat.csv(header=True),
    output_s3_uri=baseline_results_uri,
    wait=True
)
```

**Note**

If you provide the feature/column names in the training dataset as the first row and set the header=True option as shown in the previous code sample, SageMaker uses the feature name in the constraints and statistics file.

The baseline statistics for the dataset are contained in the statistics.json file and the suggested baseline constraints are contained in the constraints.json file in the location you specify with output_s3_uri.
Output Files for Tabular Dataset Statistics and Constraints

<table>
<thead>
<tr>
<th>File Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>statistics.json</td>
<td>This file is expected to have columnar statistics for each feature in the dataset that is analyzed. For more information about the schema for this file, see Schema for Statistics (statistics.json file) (p. 2915).</td>
</tr>
<tr>
<td>constraints.json</td>
<td>This file is expected to have the constraints on the features observed. For more information about the schema for this file, see Schema for Constraints (constraints.json file) (p. 2917).</td>
</tr>
</tbody>
</table>

The Amazon SageMaker Python SDK provides convenience functions described to generate the baseline statistics and constraints. But if you want to call processing job directly for this purpose instead, you need to set the Environment map as shown in the following example:

```
"Environment": {
    "dataset_format": "{\"csv\": { \"header\": true}}",
    "dataset_source": "\./opt/ml/processing/sm_input",
    "output_path": "\./opt/ml/processing/sm_output",
    "publish_cloudwatch_metrics": "Disabled",
}
```

Schedule data quality monitoring jobs

After you create your baseline, you can call the create_monitoring_schedule() method of your DefaultModelMonitor class instance to schedule an hourly data quality monitor. The following sections show you how to create a data quality monitor for a model deployed to a real-time endpoint as well as for a batch transform job.

Data quality monitoring for models deployed to real-time endpoints

To schedule a data quality monitor for a real-time endpoint, pass your EndpointInput instance to the endpoint_input argument of your DefaultModelMonitor instance, as shown in the following code sample:

```
from sagemaker.model_monitor import CronExpressionGenerator

data_quality_model_monitor = DefaultModelMonitor(
    role=sagemaker.get_execution_role(),
    ...
)

schedule = data_quality_model_monitor.create_monitoring_schedule(
    monitor_schedule_name=schedule_name,
    post_analytics_processor_script=s3_code_postprocessor_uri,
    output_s3_uri=s3_report_path,
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    statistics=data_quality_model_monitor.baseline_statistics(),
    constraints=data_quality_model_monitor.suggested_constraints(),
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
    endpoint_input=EndpointInput(
        endpoint_name=endpoint_name,
        destination="\./opt/ml/processing/input/endpoint",
    )
)```
Data quality monitoring for batch transform jobs

To schedule a data quality monitor for a batch transform job, pass your BatchTransformInput instance to the batch_transform_input argument of your DefaultModelMonitor instance, as shown in the following code sample:

```python
from sagemaker.model_monitor import CronExpressionGenerator
data_quality_model_monitor = DefaultModelMonitor(
    role=sagemaker.get_execution_role(),
    ...
)
schedule = data_quality_model_monitor.create_monitoring_schedule(
    monitor_schedule_name=mon_schedule_name,
    batch_transform_input=BatchTransformInput(
        data_captured_destination_s3_uri=s3_capture_upload_path,
        destination="/opt/ml/processing/input",
        dataset_format=MonitoringDatasetFormat.csv(header=False),
    ),
    output_s3_uri=s3_report_path,
    statistics= statistics_path,
    constraints = constraints_path,
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
)
```

Schema for Statistics (statistics.json file)

Amazon SageMaker Model Monitor prebuilt container computes per column/feature statistics. The statistics are calculated for the baseline dataset and also for the current dataset that is being analyzed.

```json
{
    "version": 0,
    # dataset level stats
    "dataset": {
        "item_count": number
    },
    # feature level stats
    "features": [
        {
            "name": "feature-name",
            "inferred_type": "Fractional" | "Integral",
            "numerical_statistics": {
                "common": {
                    "num_present": number,
                    "num_missing": number
                },
                "mean": number,
                "sum": number,
                "std_dev": number,
                "min": number,
                "max": number,
                "distribution": {
                    "kll": {
                        "buckets": [
                            {
                                "lower_bound": number,
                                "upper_bound": number,
                                "count": number
                            }
                        ]
                    }
                }
            }
        }
    }
}
```
Note the following:

- The prebuilt containers compute **KLL sketch**, which is a compact quantiles sketch.
- By default, we materialize the distribution in 10 buckets. This is not currently configurable.

### CloudWatch Metrics

You can use the built-in Amazon SageMaker Model Monitor container for CloudWatch metrics. When the `emit_metrics` option is `Enabled` in the baseline constraints file, SageMaker emits these metrics for each feature/column observed in the dataset in the following namespace:
Monitor data quality

- For real-time endpoints: /aws/sagemaker/Endpoints/data-metric namespace with EndpointName and ScheduleName dimensions.
- For batch transform jobs: /aws/sagemaker/ModelMonitoring/data-metric namespace with MonitoringSchedule dimension.

For numerical fields, the built-in container emits the following CloudWatch metrics:

- Metric: Max → query for MetricName: feature_data_{feature_name}, Stat: Max
- Metric: Min → query for MetricName: feature_data_{feature_name}, Stat: Min
- Metric: Sum → query for MetricName: feature_data_{feature_name}, Stat: Sum
- Metric: SampleCount → query for MetricName: feature_data_{feature_name}, Stat: SampleCount
- Metric: Average → query for MetricName: feature_data_{feature_name}, Stat: Average

For both numerical and string fields, the built-in container emits the following CloudWatch metrics:

- Metric: Completeness → query for MetricName: feature_non_null_{feature_name}, Stat: Sum
- Metric: Baseline Drift → query for MetricName: feature_baseline_drift_{feature_name}, Stat: Sum

Schema for Violations (constraintViolations.json file)

The violations file is generated as the output of a MonitoringExecution, which lists the results of evaluating the constraints (specified in the constraints.json file) against the current dataset that was analyzed. The Amazon SageMaker Model Monitor prebuilt container provides the following violation checks.

```json
{
   "violations": [{
      "feature_name" : "string",
      "constraint_check_type" :
         "data_type_check",
         | "completeness_check",
         | "baseline_drift_check",
         | "missing_column_check",
         | "extra_column_check",
         | "categorical_values_check"
      "description" : "string"
    ]
}
```

Types of Violations Monitored

<table>
<thead>
<tr>
<th>Violation Check Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>data_type_check</td>
<td>If the data types in the current execution are not the same as in the baseline dataset, this violation is flagged. During the baseline step, the generated constraints suggest the inferred data type for each column. The monitoring_config.datatype_check_threshold...</td>
</tr>
</tbody>
</table>
Monitor model quality

Model quality monitoring jobs monitor the performance of a model by comparing the predictions that the model makes with the actual Ground Truth labels that the model attempts to predict. To do this, model quality monitoring merges data that is captured from real-time or batch inference with actual labels that you store in an Amazon S3 bucket, and then compares the predictions with the actual labels.

To measure model quality, model monitor uses metrics that depend on the ML problem type. For example, if your model is for a regression problem, one of the metrics evaluated is mean square error (mse). For information about all of the metrics used for the different ML problem types, see Model Quality Metrics (p. 2875).

Model quality monitoring follows the same steps as data quality monitoring, but adds the additional step of merging the actual labels from Amazon S3 with the predictions captured from the real-time inference endpoint or batch transform job. To monitor model quality, follow these steps:

- Enable data capture. This captures inference input and output from a real-time inference endpoint or batch transform job and stores the data in Amazon S3. For more information, see Capture data (p. 2855).
- Create a baseline. In this step, you run a baseline job that compares predictions from the model with Ground Truth labels in a baseline dataset. The baseline job automatically creates baseline statistical rules and constraints that define thresholds against which the model performance is evaluated. For more information, see Create a Model Quality Baseline (p. 2871).
Monitor model quality

- Define and schedule model quality monitoring jobs. For specific information and code samples of model quality monitoring jobs, see Schedule Model Quality Monitoring Jobs (p. 2872). For general information about monitoring jobs, see Schedule monitoring jobs (p. 2897).
- Ingest Ground Truth labels that model monitor merges with captured prediction data from a real-time inference endpoint or batch transform job. For more information, see Ingest Ground Truth Labels and Merge Them With Predictions (p. 2874).
- Integrate model quality monitoring with Amazon CloudWatch. For more information, see Model Quality CloudWatch Metrics (p. 2878).
- Interpret the results of a monitoring job. For more information, see Interpret results (p. 2900).
- Use SageMaker Studio to enable model quality monitoring and visualize results. For more information, see Visualize results for real-time endpoints in Amazon SageMaker Studio (p. 2902).

Topics

- Create a Model Quality Baseline (p. 2871)
- Schedule Model Quality Monitoring Jobs (p. 2872)
- Ingest Ground Truth Labels and Merge Them With Predictions (p. 2874)
- Model Quality Metrics (p. 2875)
- Model Quality CloudWatch Metrics (p. 2878)

Create a Model Quality Baseline

Create a baseline job that compares your model predictions with ground truth labels in a baseline dataset that you have stored in Amazon S3. Typically, you use a training dataset as the baseline dataset. The baseline job calculates metrics for the model and suggests constraints to use to monitor model quality drift.

To create a baseline job, you need to have a dataset that contains predictions from your model along with labels that represent the Ground Truth for your data.

To create a baseline job use the ModelQualityMonitor class provided by the SageMaker Python SDK, and complete the following steps.

To create a model quality baseline job

1. First, create an instance of the ModelQualityMonitor class. The following code snippet shows how to do this.

```python
from sagemaker import get_execution_role, session, Session
from sagemaker.model_monitor import ModelQualityMonitor

role = get_execution_role()
session = Session()

model_quality_monitor = ModelQualityMonitor(
    role=role,
    instance_count=1,
    instance_type='ml.m5.xlarge',
    volume_size_in_gb=20,
    max_runtime_in_seconds=1800,
    sagemaker_session=session
)
```

2. Now call the suggest_baseline method of the ModelQualityMonitor object to run a baseline job. The following code snippet assumes that you have a baseline dataset that contains both predictions and labels stored in Amazon S3.
baseline_job_name = "MyBaselineJob"
job = model_quality_monitor.suggest_baseline(
    job_name=baseline_job_name,
    baseline_dataset=baseline_dataset_uri, # The S3 location of the validation dataset.
    dataset_format=DatasetFormat.csv(header=True),
    output_s3_uri = baseline_results_uri, # The S3 location to store the results.
    problem_type='BinaryClassification',
    inference_attribute= "prediction", # The column in the dataset that contains predictions.
    probability_attribute= "probability", # The column in the dataset that contains probabilities.
    ground_truth_attribute= "label" # The column in the dataset that contains ground truth labels.
)  
job.wait(logs=False)

3. After the baseline job finishes, you can see the constraints that the job generated. First, get
the results of the baseline job by calling the latest_baselining_job method of the
ModelQualityMonitor object.

```python
baseline_job = model_quality_monitor.latest_baselining_job
```

4. The baseline job suggests constraints, which are thresholds for metrics that model monitor
measures. If a metric goes beyond the suggested threshold, Model Monitor reports a violation. To
view the constraints that the baseline job generated, call the suggested_constraints method of
the baseline job. The following code snippet loads the constraints for a binary classification model
into a Pandas dataframe.

```python
import pandas as pd
pd.DataFrame(baseline_job.suggested_constraints().body_dict["binary_classification_constraints"]).T
```

We recommend that you view the generated constraints and modify them as necessary before using
them for monitoring. For example, if a constraint is too aggressive, you might get more alerts for
violations than you want.

5. When you are satisfied with the constraints, pass them as the constraints parameter when
you create a monitoring schedule. For more information, see Schedule Model Quality Monitoring
Jobs (p. 2872).

The suggested baseline constraints are contained in the constraints.json file in the location you specify
with output_s3_uri. For information about the schema for this file in the Schema for Constraints
(constraints.json file) (p. 2917).

**Schedule Model Quality Monitoring Jobs**

After you create your baseline, you can call the create_monitoring_schedule() method of your
ModelQualityMonitor class instance to schedule an hourly model quality monitor. The following
sections show you how to create a model quality monitor for a model deployed to a real-time endpoint
as well as for a batch transform job.

Unlike data quality monitoring, you need to supply Ground Truth labels if you want to monitor model
quality. However, Ground Truth labels could be delayed. To address this, specify offsets when you create
your monitoring schedule.
Model monitor offsets

Model quality jobs include StartTimeOffset and EndTimeOffset, which are fields of the ModelQualityJobInput parameter of the create_model_quality_job_definition method that work as follows:

- **StartTimeOffset** - If specified, jobs subtract this time from the start time.
- **EndTimeOffset** - If specified, jobs subtract this time from the end time.

The format of the offsets are, for example, -PT7H, where 7H is 7 hours. You can use -PT#H or -P#D, where H=hours, D=days, and M=minutes, and # is the number. In addition, the offset should be in ISO 8601 duration format.

For example, if your Ground Truth starts coming in after 1 day, but is not complete for a week, set StartTimeOffset to -P8D and EndTimeOffset to -P1D. Then, if you schedule a job to run at 2020-01-09T13:00, it analyzes data from between 2020-01-01T13:00 and 2020-01-08T13:00.

**Important**

- The schedule cadence should be such that one execution finishes before the next execution starts, which allows the Ground Truth merge job and monitoring job from the execution to complete. The maximum runtime of an execution is divided between the two jobs, so for an hourly model quality monitoring job, the value of MaxRuntimeInSeconds specified as part of StoppingCondition should be no more than 1800.

Model quality monitoring for models deployed to real-time endpoints

To schedule a model quality monitor for a real-time endpoint, pass your EndpointInput instance to the endpoint_input argument of your ModelQualityMonitor instance, as shown in the following code sample:

```python
from sagemaker.model_monitor import CronExpressionGenerator

model_quality_model_monitor = ModelQualityMonitor(
    role=sagemaker.get_execution_role(),
    ...)

schedule = model_quality_model_monitor.create_monitoring_schedule(
    monitor_schedule_name=schedule_name,
    post_analytics_processor_script=s3_code_postprocessor_uri,
    output_s3_uri=s3_report_path,
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    statistics=model_quality_model_monitor.baseline_statistics(),
    constraints=model_quality_model_monitor.suggested_constraints(),
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
    endpoint_input=EndpointInput(
        endpoint_name=endpoint_name,
        destination="/opt/ml/processing/input/endpoint",
        start_time_offset="-PT2D",
        end_time_offset="-PT1D",
    )
)
```

Model quality monitoring for batch transform jobs

To schedule a model quality monitor for a batch transform job, pass your BatchTransformInput instance to the batch_transform_input argument of your ModelQualityMonitor instance, as shown in the following code sample:
from sagemaker.model_monitor import CronExpressionGenerator

model_quality_model_monitor = ModelQualityMonitor(
    role=sagemaker.get_execution_role(),
    ...
)

schedule = model_quality_model_monitor.create_monitoring_schedule(
    monitor_schedule_name=mon_schedule_name,
    batch_transform_input=BatchTransformInput(
        data_captured_destination_s3_uri=s3_capture_upload_path,
        destination=f'/opt/ml/processing/input',
        dataset_format=MonitoringDatasetFormat.csv(header=False),
        # the column index of the output representing the inference probability
        probability_attribute='0',
        # the threshold to classify the inference probability to class 0 or 1 in
        # binary classification problem
        probability_threshold_attribute=0.5,
        # look back 6 hour for transform job outputs.
        start_time_offset='-PT6H',
        end_time_offset='-PT0H'
    ),
    ground_truth_input=gt_s3_uri,
    output_s3_uri=s3_report_path,
    problem_type="BinaryClassification",
    constraints = constraints_path,
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
)

Ingest Ground Truth Labels and Merge Them With Predictions

Model quality monitoring compares the predictions your model makes with ground truth labels to measure the quality of the model. For this to work, you periodically label data captured by your endpoint or batch transform job and upload it to Amazon S3.

To match Ground Truth labels with captured prediction data, there must be a unique identifier for each record in the dataset. The structure of each record for ground truth data is as follows:

```json
{
    "groundTruthData": {
        "data": "1",
        "encoding": "CSV" # only CSV supported at launch, we assume "data" only consists of label
    },
    "eventMetadata": {
        "eventId": "aaaa-bbbb-cccc"
    },
    "eventVersion": "0"
}
```

In the groundTruthData structure, eventId can be one of the following:

- eventId – This ID is automatically generated when a user invokes the endpoint.
- inferenceId – The caller supplies this ID when they invoke the endpoint.

If inferenceId is present in captured data records, Model Monitor uses it to merge captured data with Ground Truth records. You are responsible for making sure that the inferenceId in the Ground Truth records match the inferenceId in the captured records. If inferenceId is not present in captured
data, model monitor uses eventId from the captured data records to match them with a Ground Truth record.

You must upload Ground Truth data to an Amazon S3 bucket that has the same path format as captured data, which is of the following form:

```
s3://bucket/prefix/yyyy/mm/dd/hh
```

The date in this path is the date when the Ground Truth label is collected, and does not have to match the date when the inference was generated.

After you create and upload the Ground Truth labels, include the location of the labels as a parameter when you create the monitoring job. If you are using AWS SDK for Python (Boto3), do this by specifying the location of Ground Truth labels as the S3Uri field of the GroundTruthS3Input parameter in a call to the `create_model_quality_job_definition` method. If you are using the SageMaker Python SDK, specify the location of the Ground Truth labels as the `ground_truth_input` parameter in the call to the `create_monitoring_schedule` of the `ModelQualityMonitor` object.

## Model Quality Metrics

Model quality monitoring jobs compute different metrics depending on the ML problem type. The following sections list the metrics analyzed for each ML problem type.

**Note**
Standard deviation for metrics are provided only when at least 200 samples are available. Model Monitor computes standard deviation by randomly sampling 80% of the data 5 times, computing the metric, and taking the standard deviation for those results.

### Regression Metrics

The following shows an example of the metrics that model quality monitor computes for a regression problem.

```
"regression_metrics" : {
   "mae" : {
      "value" : 0.3711832061068702,
      "standard_deviation" : 0.0037566388129940394
   },
   "mse" : {
      "value" : 0.3711832061068702,
      "standard_deviation" : 0.0037566388129940524
   },
   "rmse" : {
      "value" : 0.609248066149471,
      "standard_deviation" : 0.003079253267651125
   },
   "r2" : {
      "value" : -1.3766111872212665,
      "standard_deviation" : 0.022653980022771227
   }
}
```

### Binary Classification Metrics

The following shows an example of the metrics that model quality monitor computes for a binary classification problem.

```
"binary_classification_metrics" : {
```

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"confusion_matrix" : {
    "0" : {
        "0" : 1,
        "1" : 2
    },
    "1" : {
        "0" : 0,
        "1" : 1
    }
},
"recall" : {
    "value" : 1.0,
    "standard_deviation" : "NaN"
},
"precision" : {
    "value" : 0.3333333333333333,
    "standard_deviation" : "NaN"
},
"accuracy" : {
    "value" : 0.5,
    "standard_deviation" : "NaN"
},
"recall_best_constant_classifier" : {
    "value" : 1.0,
    "standard_deviation" : "NaN"
},
"precision_best_constant_classifier" : {
    "value" : 0.25,
    "standard_deviation" : "NaN"
},
"accuracy_best_constant_classifier" : {
    "value" : 0.25,
    "standard_deviation" : "NaN"
},
"true_positive_rate" : {
    "value" : 1.0,
    "standard_deviation" : "NaN"
},
"true_negative_rate" : {
    "value" : 0.33333333333333337,
    "standard_deviation" : "NaN"
},
"false_positive_rate" : {
    "value" : 0.6666666666666666,
    "standard_deviation" : "NaN"
},
"false_negative_rate" : {
    "value" : 0.0,
    "standard_deviation" : "NaN"
},
"receiver_operating_characteristic_curve" : {
    "false_positive_rates" : [ 0.0, 0.0, 0.0, 0.0, 0.0, 1.0 ],
    "true_positive_rates" : [ 0.0, 0.25, 0.5, 0.75, 1.0, 1.0 ]
},
"precision_recall_curve" : {
    "precisions" : [ 1.0, 1.0, 1.0, 1.0, 1.0 ],
    "recalls" : [ 0.0, 0.25, 0.5, 0.75, 1.0 ]
},
"auc" : {
    "value" : 1.0,
    "standard_deviation" : "NaN"
},
"f0_5" : {
    "value" : 0.3846153846153846,
    "standard_deviation" : "NaN"
}
"f1" : {
    "value" : 0.5,
    "standard_deviation" : "NaN"
},
"f2" : {
    "value" : 0.7142857142857143,
    "standard_deviation" : "NaN"
},
"f0_5_best_constant_classifier" : {
    "value" : 0.29411764705882354,
    "standard_deviation" : "NaN"
},
"f1_best_constant_classifier" : {
    "value" : 0.4,
    "standard_deviation" : "NaN"
},
"f2_best_constant_classifier" : {
    "value" : 0.625,
    "standard_deviation" : "NaN"
}
}

**Multiclass Metrics**

The following shows an example of the metrics that model quality monitor computes for a multiclass classification problem.

"multiclass_classification_metrics" : {
    "confusion_matrix" : {
        "0" : {
            "0" : 1180,
            "1" : 510
        },
        "1" : {
            "0" : 268,
            "1" : 138
        }
    },
    "accuracy" : {
        "value" : 0.6288167938931297,
        "standard_deviation" : 0.003756638812994008
    },
    "weighted_recall" : {
        "value" : 0.6288167938931297,
        "standard_deviation" : 0.003756638812994008
    },
    "weighted_precision" : {
        "value" : 0.6983172269629505,
        "standard_deviation" : 0.006195912915307507
    },
    "weighted_f0_5" : {
        "value" : 0.6803947317178771,
        "standard_deviation" : 0.005328406973561699
    },
    "weighted_f1" : {
        "value" : 0.6571162346664904,
        "standard_deviation" : 0.004385008075019733
    },
    "weighted_f2" : {
        "value" : 0.6384024354394601,
        "standard_deviation" : 0.003867109755267757
    },
    "accuracy_best_constant_classifier" : {
        "value" : 0.19370229007633588,
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Model Quality CloudWatch Metrics

If you set the value of the `enable_cloudwatch_metrics` to True when you create the monitoring schedule, model quality monitoring jobs send all metrics to Amazon CloudWatch.

Model quality metrics appear in the following namespace:

- For real-time endpoints: `aws/sagemaker/Endpoints/model-metrics`
- For batch transform jobs: `aws/sagemaker/ModelMonitoring/model-metrics`

For a list of the metrics that are emitted, see Model Quality Metrics (p. 2875).

You can use CloudWatch metrics to create an alarm when a specific metric doesn't meet the threshold you specify. For instructions about how to create CloudWatch alarms, see Create a CloudWatch Alarm Based on a Static Threshold in the Amazon CloudWatch User Guide.

Monitor Bias Drift for Models in Production

Amazon SageMaker Clarify bias monitoring helps data scientists and ML engineers monitor predictions for bias on a regular basis. As the model is monitored, customers can view exportable reports and graphs detailing bias in SageMaker Studio and configure alerts in Amazon CloudWatch to receive notifications if bias beyond a certain threshold is detected. Bias can be introduced or exacerbated in deployed ML models when the training data differs from the data that the model sees during deployment (that is, the live data). These kinds of changes in the live data distribution might be temporary (for example, due to some short-lived, real-world events) or permanent. In either case, it might be important to detect these changes. For example, the outputs of a model for predicting home prices can become biased if the mortgage rates used to train the model differ from current, real-world mortgage rates.

With bias detection capabilities in Model Monitor, when SageMaker detects bias beyond a certain threshold, it automatically generates metrics that you can view in SageMaker Studio and through Amazon CloudWatch alerts.

In general, measuring bias only during the train-and-deploy phase might not be sufficient. It is possible that after the model has been deployed, the distribution of the data that the deployed model sees (that is, the live data) is different from data distribution in the training dataset. This change might introduce
bias in a model over time. The change in the live data distribution might be temporary (for example, due to some short-lived behavior like the holiday season) or permanent. In either case, it might be important to detect these changes and take steps to reduce the bias when appropriate.

To detect these changes, SageMaker Clarify provides functionality to monitor the bias metrics of a deployed model continuously and raise automated alerts if the metrics exceed a threshold. For example, consider the DPPL bias metric. Specify an allowed range of values $A=(a_{\text{min}},a_{\text{max}})$, for instance an interval of $(-0.1, 0.1)$, that DPPL should belong to during deployment. Any deviation from this range should raise a \textit{bias detected} alert. With SageMaker Clarify, you can perform these checks at regular intervals.

For example, you can set the frequency of the checks to 2 days. This means that SageMaker Clarify computes the DPPL metric on data collected during a 2-day window. In this example, $D_{\text{win}}$ is the data that the model processed during last 2-day window. An alert is issued if the DPPL value $b_{\text{win}}$ computed on $D_{\text{win}}$ falls outside of an allowed range $A$. This approach to checking if $b_{\text{win}}$ is outside of $A$ can be somewhat noisy. $D_{\text{win}}$ might consist of very few samples and might not be representative of the live data distribution. The small sample size means that the value of bias $b_{\text{win}}$ computed over $D_{\text{win}}$ might not be a very robust estimate. In fact, very high (or low) values of $b_{\text{win}}$ may be observed purely due to chance. To ensure that the conclusions drawn from the observed data $D_{\text{win}}$ are statistically significant, SageMaker Clarify makes use of confidence intervals. Specifically, it uses the Normal Bootstrap Interval method to construct an interval $C=(c_{\text{min}},c_{\text{max}})$ such that SageMaker Clarify is confident that the true bias value computed over the full live data is contained in $C$ with high probability. Now, if the confidence interval $C$ overlaps with the allowed range $A$, SageMaker Clarify interprets it as "it is likely that the bias metric value of the live data distribution falls within the allowed range". If $C$ and $A$ are disjoint, SageMaker Clarify is confident that the bias metric does not lie in $A$ and raises an alert.

Model Monitor Sample Notebook

Amazon SageMaker Clarify provides the following sample notebook that shows how to capture inference data for a real-time endpoint, create a baseline to monitor evolving bias against, and inspect the results:

- Monitoring bias drift and feature attribution drift Amazon SageMaker Clarify – Use Amazon SageMaker Model Monitor to monitor bias drift and feature attribution drift over time.

This notebook has been verified to run in Amazon SageMaker Studio only. If you need instructions on how to open a notebook in Amazon SageMaker Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133). If you're prompted to choose a kernel, choose Python 3 (Data Science). The following topics contain the highlights from the last two steps, and they contain code examples from the example notebook.

Topics

- Create a Bias Drift Baseline (p. 2879)
- Bias Drift Violations (p. 2881)
- Configure Parameters to Monitor Bias Drift (p. 2882)
- Schedule Bias Drift Monitoring Jobs (p. 2885)
- Inspect Reports for Data Bias Drift (p. 2886)
- CloudWatch Metrics for Bias Drift Analysis (p. 2887)

Create a Bias Drift Baseline

After you have configured your application to capture real-time or batch transform inference data, the first task to monitor for bias drift is to create a baseline. This involves configuring the data inputs, which groups are sensitive, how the predictions are captured, and the model and its posttraining bias metrics. Then you need to start the baselining job.
Model bias monitor can detect bias drift of ML models on a regular basis. Similar to the other monitoring types, the standard procedure of creating a model bias monitor is first baselining and then establishing a monitoring schedule.

```python
model_bias_monitor = ModelBiasMonitor(
    role=role,
    sagemaker_session=sagemaker_session,
    max_runtime_in_seconds=1800,
)
```

DataConfig stores information about the dataset to be analyzed (for example, the dataset file), its format (that is, CSV or JSON Lines), headers (if any) and label.

```python
model_bias_baselining_job_result_uri = f"{baseline_results_uri}/model_bias"
model_bias_data_config = DataConfig(
    s3_data_input_path=validation_dataset,
    s3_output_path=model_bias_baselining_job_result_uri,
    label=label_header,
    headers=all_headers,
    dataset_type=dataset_type,
)
```

BiasConfig is the configuration of the sensitive groups in the dataset. Typically, bias is measured by computing a metric and comparing it across groups. The group of interest is called the facet. For postraining bias, you should also take the positive label into account.

```python
model_bias_config = BiasConfig(
    label_values_or_threshold=[1],
    facet_name="Account Length",
    facet_values_or_threshold=[100],
)
```

ModelPredictedLabelConfig specifies how to extract a predicted label from the model output. In this example, the 0.8 cutoff has been chosen in anticipation that customers will turn over frequently. For more complicated outputs, there are a few more options, like "label" is the index, name, or JSONPath to locate predicted label in endpoint response payload.

```python
model_predicted_label_config = ModelPredictedLabelConfig(
    probability_threshold=0.8,
)
```

ModelConfig is the configuration related to the model to be used for inferencing. In order to compute postraining bias metrics, the computation needs to get inferences for the model name provided. To accomplish this, the processing job uses the model to create an ephemeral endpoint (also known as shadow endpoint). The processing job deletes the shadow endpoint after the computations are completed. This configuration is also used by the explainability monitor.

```python
model_config = ModelConfig(
    model_name=model_name,
    instance_count=endpoint_instance_count,
    instance_type=endpoint_instance_type,
    content_type=dataset_type,
    accept_type=dataset_type,
)
```

Now you can start the baselining job.
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```python
model_bias_monitor.suggest_baseline(
    model_config=model_config,
    data_config=model_bias_data_config,
    bias_config=model_bias_config,
    model_predicted_label_config=model_predicted_label_config,
)
print(f"ModelBiasMonitor baselining job: {model_bias_monitor.latest_baselining_job_name}"
)
```

The scheduled monitor automatically picks up baselining job name and waits for it before monitoring begins.

**Bias Drift Violations**

Bias drift jobs evaluate the baseline constraints provided by the baseline configuration against the analysis results of current MonitoringExecution. If violations are detected, the job lists them to the constraint_violations.json file in the execution output location, and marks the execution status as Interpret results (p. 2900).

Here is the schema of the bias drift violations file.

- **facet** – The name of the facet, provided by the monitoring job analysis configuration facet name_or_index.
- **facet_value** – The value of the facet, provided by the monitoring job analysis configuration facet value_or_threshold.
- **metric_name** – The short name of the bias metric. For example, "CI" for class imbalance. See Measure Pretraining Bias (p. 801) for the short names of each of the pretraining bias metrics and Measure Posttraining Data and Model Bias (p. 2631) for the short names of each of the posttraining bias metrics.
- **constraint_check_type** – The type of violation monitored. Currently only bias_drift_check is supported.
- **description** – A descriptive message to explain the violation.

```json
{
    "version": "1.0",
    "violations": [[
        "facet": "string",
        "facet_value": "string",
        "metric_name": "string",
        "constraint_check_type": "string",
        "description": "string"
    ]]
}
```

If the value of a bias metric in the baseline constraints file is different from its peer in the job analysis results file (analysis.json), the monitoring jobs log a violation. The following output provides an example of several logged violations.

```json
{
    "version": "1.0",
    "violations": [[
        "facet": "Age",
        "facet_value": "40",
        "metric_name": "CI",
        "constraint_check_type": "bias_drift_check",
        "description": "Value 0.0751544567666083 does not meet the constraint requirement"
    ],
```
Configure Parameters to Monitor Bias Drift

Amazon SageMaker Clarify bias monitoring reuses a subset of the parameters used in the analysis configuration of Configure the Analysis (p. 2620). After describing the configuration parameters, this topic provides examples of JSON files. These files are used to configure CSV and JSON Lines datasets to monitor them for bias drift when machine learning models are in production.

The following parameters must be provided in a JSON file. The path to this JSON file must be provided in the ConfigUri parameter of the ModelBiasAppSpecification API.

- **version** – (Optional) Schema version of the configuration file. If not provided, the latest supported version is used.
- **headers** – (Optional) A list of column names in the dataset. If the dataset_type is “application/jsonlines” and “label” is specified, then the last header becomes the header of the label column.
- **label** – (Optional) Target attribute for the model to be used for bias metrics. Specified either as a column name, or an index (if dataset format is CSV), or as a JSONPath (if dataset format is JSON Lines).
- **label_values_or_threshold** – (Optional) List of label values or threshold. Indicates positive outcome used for bias metrics.
- **facet** – (Optional) A list of features that are sensitive attributes, referred to as facets. Facets are used for bias metrics in the form of pairs, and include the following:
  - **name_or_index** – Facet column name or index.
  - **value_or_threshold** – (Optional) List of values or threshold that the facet column can take. Indicates the sensitive group, such as the group that is used to measure bias against. If not provided, bias metrics are computed as one group for every unique value (rather than all values). If the facet column is numeric, this threshold value is applied as the lower bound to select the sensitive group.
- **group_variable** – (Optional) A column name or index to indicate the group variable to be used for the bias metric Conditional Demographic Disparity.

The other parameters should be provided in EndpointInput (for real-time endpoints) or BatchTransformInput (for batch transform jobs) of the ModelBiasJobInput API.

- **FeaturesAttribute** – This parameter is required if endpoint input data format is "application/jsonlines". It is the JSONPath used to locate the feature columns if the dataset format is JSON Lines.
- **InferenceAttribute** – Index or JSONPath location in the model output for the target attribute to be used for monitored for bias using bias metrics. If it is not provided in the CSV accept_type case, then it is assumed that the model output is a single numeric value corresponding to a score or probability.
- **ProbabilityAttribute** – Index or JSONPath location in the model output for probabilities. If the model output is JSON Lines with a list of labels and probabilities, for example, then the label that corresponds to the maximum probability is selected for bias computations.
- **ProbabilityThresholdAttribute** – (Optional) A float value to indicate the threshold to select the binary label, in the case of binary classification. The default value is 0.5.
Example JSON Configuration Files for CSV and JSON Lines Datasets

Here are examples of the JSON files used to configure CSV and JSON Lines datasets to monitor them for bias drift.

Topics
• CSV Datasets (p. 2883)
• JSON Lines Datasets (p. 2884)

CSV Datasets

Consider a dataset that has four feature columns and one label column, where the first feature and the label are binary, as in the following example.

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.58145668701544718</td>
<td>0.6651538910132964</td>
<td>0.3158080342665499</td>
<td>0</td>
</tr>
<tr>
<td>1</td>
<td>0.6711642728531724</td>
<td>0.7466687034026017</td>
<td>0.1215477472819713</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0.84532565438053371</td>
<td>0.63774580803264152</td>
<td>0.3558625219713576</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0.4785191813363956</td>
<td>0.0265841045263860</td>
<td>0.0376935084990697</td>
<td>1</td>
</tr>
</tbody>
</table>

Assume that the model output has two columns, where the first one is the predicted label and the second one is the probability, as in the following example.

1, 0.5385257417814224

Then the following JSON configuration file shows an example of how this CSV dataset can be configured.

```json
{
  "headers": [
    "feature_0",
    "feature_1",
    "feature_2",
    "feature_3",
    "target"
  ],
  "label": "target",
  "label_values_or_threshold": [1],
  "facet": [
    {
      "name_or_index": "feature_1",
      "value_or_threshold": [1]
    }
  ]
}
```

The predicted label is selected by the "InferenceAttribute" parameter. Zero-based numbering is used, so 0 indicates the first column of the model output,

```json
"EndpointInput": {
  "...":
  "InferenceAttribute": 0
  "..."
}
```

Alternatively, you can use different parameters to convert probability values to binary predicted labels. Zero-based numbering is used: 1 indicates the second column; the ProbabilityThresholdAttribute value of 0.6 indicates that a probability greater than 0.6 predicts the binary label as 1.

```json
"EndpointInput": {
  "...
  "ProbabilityAttribute": 1,
  "..."
}
```
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}

"ProbabilityThresholdAttribute": 0.6
...

JSON Lines Datasets
Consider a dataset that has four feature columns and one label column, where the ﬁrst feature and the
label are binary, as in the following example.
{"features":[0,
{"features":[1,
{"features":[0,
{"features":[1,

0.5814568701544718,
0.6711642728531724,
0.0453256543003371,
0.4785191813363956,

0.6651538910132964,
0.7466687034026017,
0.6377430803264152,
0.0265841045263860,

0.3138080342665499],
0.1215477472819713],
0.3558625219713576],
0.0376935084990697],

"label":0}
"label":1}
"label":1}
"label":1}

Assume that the model output has two columns, where the ﬁrst is a predicted label and the second is a
probability.
{"predicted_label":1, "probability":0.5385257417814224}

The following JSON conﬁguration ﬁle shows an example of how this JSON Lines dataset can be
conﬁgured.
{

}

"headers": [
"feature_0",
"feature_1",
"feature_2",
"feature_3",
"target"
],
"label": "label",
"label_values_or_threshold": [1],
"facet": [{
"name_or_index": "feature_1",
"value_or_threshold": [1]
}]

Then, the "features" parameter value in EndpointInput (for real-time endpoints) or
BatchTransformInput (for batch transform jobs) is used to locate the features in the dataset, and the
"predicted_label" parameter value selects the predicted label from the model output.
"EndpointInput": {
...
"FeaturesAttribute": "features",
"InferenceAttribute": "predicted_label"
...
}

Alternatively, you can convert probability values to predicted binary labels using the
ProbabilityThresholdAttribute parameter value. A value of 0.6, for example, indicates that a
probability greater than 0.6 predicts the binary label as 1.
"EndpointInput": {
...
"FeaturesAttribute": "features",
"ProbabilityAttribute": "probability",
"ProbabilityThresholdAttribute": 0.6
...

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Schedule Bias Drift Monitoring Jobs

After you create your baseline, you can call the `create_monitoring_schedule()` method of your `ModelBiasModelMonitor` class instance to schedule an hourly bias drift monitor. The following sections show you how to create bias drift monitor for a model deployed to a real-time endpoint as well as for a batch transform job.

Unlike data quality monitoring, you need to supply Ground Truth labels if you want to monitor model quality. However, Ground Truth labels could be delayed. To address this, specify offsets when you create your monitoring schedule. For details about how to create time offsets, see ??? (p. 2873).

If you have submitted a baselining job, the monitor automatically picks up analysis configuration from the baselining job. If you skip the baselining step or the capture dataset has a different nature from the training dataset, you must provide the analysis configuration.

Bias drift monitoring for models deployed to real-time endpoint

To schedule a bias drift monitor for a real-time endpoint, pass your `EndpointInput` instance to the `endpoint_input` argument of your `ModelBiasModelMonitor` instance, as shown in the following code sample:

```python
from sagemaker.model_monitor import CronExpressionGenerator

model_bias_monitor = ModelBiasModelMonitor(
    role=sagemaker.get_execution_role(),
    ...
)

model_bias_analysis_config = None
if not model_bias_monitor.latest_baselining_job:
    model_bias_analysis_config = BiasAnalysisConfig(
        model_bias_config,
        headers=all_headers,
        label=label_header,
    )

model_bias_monitor.create_monitoring_schedule(
    monitor_schedule_name=schedule_name,
    post_analytics_processor_script=s3_code_postprocessor_uri,
    output_s3_uri=s3_report_path,
    statistics=model_bias_monitor.baseline_statistics(),
    constraints=model_bias_monitor.suggested_constraints(),
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
    analysis_config=model_bias_analysis_config,
    endpoint_input=EndpointInput(
        endpoint_name=endpoint_name,
        destination="/opt/ml/processing/input/endpoint",
        start_time_offset="-PT1H",
        end_time_offset="-PT0H",
        probability_threshold_attribute=0.8,
    ),
)
```

Bias drift monitoring for batch transform jobs

To schedule a bias drift monitor for a batch transform job, pass your `BatchTransformInput` instance to the `batch_transform_input` argument of your `ModelBiasModelMonitor` instance, as shown in the following code sample:
from sagemaker.model_monitor import CronExpressionGenerator

model_bias_monitor = ModelBiasModelMonitor(
    role=sagemaker.get_execution_role(),
    ...
)

model_bias_analysis_config = None
if not model_bias_monitor.latest_baselining_job:
    model_bias_analysis_config = BiasAnalysisConfig(
        model_bias_config,
        headers=all_headers,
        label=label_header,
    )

schedule = model_bias_monitor.create_monitoring_schedule(
    monitor_schedule_name=schedule_name,
    post_analytics_processor_script=s3_code_postprocessor_uri,
    output_s3_uri=s3_report_path,
    statistics=model_bias_monitor.baseline_statistics(),
    constraints=model_bias_monitor.suggested_constraints(),
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
    analysis_config=model_bias_analysis_config,
    batch_transform_input=BatchTransformInput(
        destination="opt/ml/processing/input",
        data_captured_destination_s3_uri=s3_capture_path,
        start_time_offset="-PT1H",
        end_time_offset="-PT0H",
        probability_threshold_attribute=0.8
    ),
)

Inspect Reports for Data Bias Drift

If you are not able to inspect the results of the monitoring in the generated reports in SageMaker Studio, you can print them out as follows:

schedule_desc = model_bias_monitor.describe_schedule()
execution_summary = schedule_desc.get("LastMonitoringExecutionSummary")
if execution_summary and execution_summary["MonitoringExecutionStatus"] in ["Completed", "CompletedWithViolations"]:
    last_model_bias_monitor_execution = model_bias_monitor.list_executions()[-1]
    last_model_bias_monitor_execution_report_uri = last_model_bias_monitor_execution.output.destination
    print(f"Report URI: {last_model_bias_monitor_execution_report_uri}")
    last_model_bias_monitor_execution_report_files = sorted(S3Downloader.list(last_model_bias_monitor_execution_report_uri))
    print("Found Report Files:")
    print("\n ".join(last_model_bias_monitor_execution_report_files))
else:
    last_model_bias_monitor_execution = None
    print("=====STOP==== \n No completed executions to inspect further. Please wait till an execution completes or investigate previously reported failures.")

If there are violations compared to the baseline, they are listed here:

if last_model_bias_monitor_execution:
    model_bias_violations = last_model_bias_monitor_execution.constraint_violations()
    if model_bias_violations:
        print(model_bias_violations.body_dict)
If your model is deployed to a real-time endpoint, you can see visualizations in SageMaker Studio of the analysis results and CloudWatch metrics by choosing the **Endpoints** tab, and then double-clicking the endpoint.

### CloudWatch Metrics for Bias Drift Analysis

This guide shows CloudWatch metrics and their properties that you can use for bias drift analysis in SageMaker Clarify. Bias drift monitoring jobs compute both **pretraining bias metrics** and **posttraining bias metrics**, and publish them to the following CloudWatch namespace:

- For real-time endpoints: `aws/sagemaker/Endpoints/bias-metrics`
- For batch transform jobs: `aws/sagemaker/ModelMonitoring/bias-metrics`

The CloudWatch metric name appends the metric's short name to `bias_metric`.

For example, `bias_metric_CI` is the bias metric for class imbalance (CI).

**Note**

- `+/- \infty` is published as the floating point number `+/- 2.348543e108`, and errors including null values are not published.

Each metric has the following properties:

- **Endpoint**: The name of the monitored endpoint, if applicable.
- **MonitoringSchedule**: The name of the schedule for the monitoring job.
- **BiasStage**: The name of the stage of the bias drift monitoring job. Choose either **Pre-training** or **Post-Training**.
- **Label**: The name of the target feature, provided by the monitoring job analysis configuration `label`.
- **LabelValue**: The value of the target feature, provided by the monitoring job analysis configuration `label_values_or_threshold`.
- **Facet**: The name of the facet, provided by the monitoring job analysis configuration `facet_name_of_index`.
- **FacetValue**: The value of the facet, provided by the monitoring job analysis configuration `facet_nvalue_or_threshold`.

To stop the monitoring jobs from publishing metrics, set `publish_cloudwatch_metrics` to `Disabled` in the `Environment` map of **model bias job** definition.

### Monitor Feature Attribution Drift for Models in Production

A drift in the distribution of live data for models in production can result in a corresponding drift in the feature attribution values, just as it could cause a drift in bias when monitoring bias metrics. Amazon SageMaker Clarify feature attribution monitoring helps data scientists and ML engineers monitor predictions for feature attribution drift on a regular basis. As the model is monitored, customers can view exportable reports and graphs detailing feature attributions in SageMaker Studio and configure alerts in Amazon CloudWatch to receive notifications if it is detected that the attribution values drift beyond a certain threshold.

To illustrate this with a specific situation, consider a hypothetical scenario for college admissions. Assume that we observe the following (aggregated) feature attribution values in the training data and in the live data:
College Admission Hypothetical Scenario

<table>
<thead>
<tr>
<th>Feature</th>
<th>Attribution in training data</th>
<th>Attribution in live data</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAT score</td>
<td>0.70</td>
<td>0.10</td>
</tr>
<tr>
<td>GPA</td>
<td>0.50</td>
<td>0.20</td>
</tr>
<tr>
<td>Class rank</td>
<td>0.05</td>
<td>0.70</td>
</tr>
</tbody>
</table>

The change from training data to live data appears significant. The feature ranking has completely reversed. Similar to the bias drift, the feature attribution drifts might be caused by a change in the live data distribution and warrant a closer look into the model behavior on the live data. Again, the first step in these scenarios is to raise an alarm that a drift has happened.

We can detect the drift by comparing how the ranking of the individual features changed from training data to live data. In addition to being sensitive to changes in ranking order, we also want to be sensitive to the raw attribution score of the features. For instance, given two features that fall in the ranking by the same number of positions going from training to live data, we want to be more sensitive to the feature that had a higher attribution score in the training data. With these properties in mind, we use the Normalized Discounted Cumulative Gain (NDCG) score for comparing the feature attributions rankings of training and live data.

Specifically, assume we have the following:

- \( F = [f_1, \ldots, f_m] \) is the list of features sorted with respect to their attribution scores in the training data where \( m \) is the total number of features. For instance, in our case, \( F = [\text{SAT Score, GPA, Class Rank}] \).
- \( a(f) \) is a function that returns the feature attribution score on the training data given a feature \( f \). For example, \( a(\text{SAT Score}) = 0.70 \).
- \( F' = [f'_1, \ldots, f'_m] \) is the list of features sorted with respect to their attribution scores in the live data. For example, \( F' = [\text{Class Rank, GPA, SAT Score}] \).

Then, we can compute the NDCG as:

\[
\text{NDCG} = \frac{\text{DCG}}{\text{iDCG}}
\]

with

- \( \text{DCG} = \sum_1^m a(f'_i) / \log_2(i+1) \)
- \( \text{iDCG} = \sum_1^m a(f_i) / \log_2(i+1) \)

The quantity DCG measures whether features with high attribution in the training data are also ranked higher in the feature attribution computed on the live data. The quantity iDCG measures the ideal score and it's just a normalizing factor to ensure that the final quantity resides in the range \([0, 1]\), with 1 being the best possible value. A NDCG value of 1 means that the feature attribution ranking in the live data is the same as the one in the training data. In this particular example, because the ranking changed by quite a bit, the NDCG value is 0.69.

In SageMaker Clarify, if the NDCG value is below 0.90, we automatically raise an alert.

Model Monitor Example Notebook

SageMaker Clarify provides the following example notebook that shows how to capture inference data for a real-time endpoint, create a baseline to monitor evolving bias against, and inspect the results:

- Monitoring bias drift and feature attribution drift Amazon SageMaker Clarify – Use Amazon SageMaker Model Monitor to monitor bias drift and feature attribution drift over time.

2888
This notebook has been verified to run in SageMaker Studio only. If you need instructions on how to open a notebook in SageMaker Studio, see Create or Open an Amazon SageMaker Studio Notebook (p. 133). If you're prompted to choose a kernel, choose Python 3 (Data Science). The following topics contain the highlights from the last two steps, and they contain code examples from the example notebook.

**Topics**

- Create a SHAP Baseline for Models in Production (p. 2889)
- Model Feature Attribution Drift Violations (p. 2890)
- Configure Parameters to Monitor Attribution Drift (p. 2891)
- Schedule Feature Attribute Drift Monitoring Jobs (p. 2894)
- Inspect Reports for Feature Attribute Drift in Production Models (p. 2895)
- CloudWatch Metrics for Feature Drift Analysis (p. 2896)

### Create a SHAP Baseline for Models in Production

Explanations are typically contrastive, that is, they account for deviations from a baseline. For information on explainability baselines, see SHAP Baselines for Explainability (p. 2654).

In addition to providing explanations for per-instance inferences, SageMaker Clarify also supports global explanation for ML models that helps you understand the behavior of a model as a whole in terms of its features. SageMaker Clarify generates a global explanation of an ML model by aggregating the Shapley values over multiple instances. SageMaker Clarify supports the following different ways of aggregation, which you can use to define baselines:

- `mean_abs` – Mean of absolute SHAP values for all instances.
- `median` – Median of SHAP values for all instances.
- `mean_sq` – Mean of squared SHAP values for all instances.

After you have configured your application to capture real-time or batch transform inference data, the first task to monitor for drift in feature attribution is to create a baseline to compare against. This involves configuring the data inputs, which groups are sensitive, how the predictions are captured, and the model and its posttraining bias metrics. Then you need to start the baselining job. Model explainability monitor can explain the predictions of a deployed model that's producing inferences and detect feature attribution drift on a regular basis.

```python
model_explainability_monitor = ModelExplainabilityMonitor(
    role=role,
    sagemaker_session=sagemaker_session,
    max_runtime_in_seconds=1800,
)
```

In this example, the explainability baselining job shares the test dataset with the bias baselining job, so it uses the same `DataConfig`, and the only difference is the job output URI.

```python
model_explainability_baselining_job_result_uri = f"{baseline_results_uri}/model_explainability"
model_explainability_data_config = DataConfig(
    s3_data_input_path=validation_dataset,
    s3_output_path=model_explainability_baselining_job_result_uri,
    label=label_header,
    headers=all_headers,
    dataset_type=dataset_type,
)```
Currently the SageMaker Clarify explainer offers a scalable and efficient implementation of SHAP, so the explainability config is SHAPConfig, including the following:

- **baseline** – A list of rows (at least one) or S3 object URI to be used as the baseline dataset in the Kernel SHAP algorithm. The format should be the same as the dataset format. Each row should contain only the feature columns/values and omit the label column/values.
- **num_samples** – Number of samples to be used in the Kernel SHAP algorithm. This number determines the size of the generated synthetic dataset to compute the SHAP values.
- **agg_method** – Aggregation method for global SHAP values. Following are valid values:
  - **mean_abs** – Mean of absolute SHAP values for all instances.
  - **median** – Median of SHAP values for all instances.
  - **mean_sq** – Mean of squared SHAP values for all instances.
- **use_logit** – Indicator of whether the logit function is to be applied to the model predictions. Default is False. If use_logit is True, the SHAP values will have log-odds units.
- **save_local_shap_values** (bool) – Indicator of whether to save the local SHAP values in the output location. Default is False.

```python
# Here use the mean value of test dataset as SHAP baseline
test_dataframe = pd.read_csv(test_dataset, header=None)
shap_baseline = [list(test_dataframe.mean())]
shap_config = SHAPConfig(
    baseline=shap_baseline,
    num_samples=100,
    agg_method="mean_abs",
    save_local_shap_values=False,
)
```

Start a baselining job. The same model_config is required because the explainability baselining job needs to create a shadow endpoint to get predictions for the generated synthetic dataset.

```python
model_explainability_monitor.suggest_baseline(
    data_config=model_explainability_data_config,
    model_config=model_config,
    explainability_config=shap_config,
)
print(f"ModelExplainabilityMonitor baselining job: 
{model_explainability_monitor.latest_baselining_job_name}")
```

### Model Feature Attribution Drift Violations

Feature attribution drift jobs evaluate the baseline constraints provided by the baseline configuration against the analysis results of current MonitoringExecution. If violations are detected, the job lists them to the constraint_violations.json file in the execution output location, and marks the execution status as Interpret results (p. 2900).

Here is the schema of the feature attribution drift violations file.

- **label** – The name of the label, job analysis configuration label_headers or a placeholder such as "label0".
- **metric_name** – The name of the explainability analysis method. Currently only shap is supported.
- **constraint_check_type** – The type of violation monitored. Currently only feature_attribution_drift_check is supported.
- **description** – A descriptive message to explain the violation.
For each label in the explanations section, the monitoring jobs calculate the nDCG score of its global SHAP values in the baseline constraints file and in the job analysis results file (analysis.json). If the score is less than 0.9, then a violation is logged. The combined global SHAP value is evaluated, so there are no “feature” fields in the violation entry. The following output provides an example of several logged violations.

```json
{
    "version": "1.0",
    "violations": [
        {
            "label": "label0",
            "metric_name": "shap",
            "constraint_check_type": "feature_attribution_drift_check",
            "description": "Feature attribution drift 0.7639720923277322 exceeds threshold 0.9"
        },
        {
            "label": "label1",
            "metric_name": "shap",
            "constraint_check_type": "feature_attribution_drift_check",
            "description": "Feature attribution drift 0.7323763972092327 exceeds threshold 0.9"
        }
    ]
}
```

## Configure Parameters to Monitor Attribution Drift

Amazon SageMaker Clarify explainability monitor reuses a subset of the parameters used in the analysis configuration of [Configure the Analysis](p. 2620). The following parameters must be provided in a JSON file and the path must be provided in the ConfigUri parameter of ModelExplainabilityAppSpecification.

- **"version"** – (Optional) Schema version of the configuration file. If not provided, the latest supported version is used.
- **"headers"** – (Optional) A list of feature names in the dataset. Explainability analysis does not require labels.
- **"methods"** – A list of methods and their parameters for the analyses and reports. If any section is omitted, then it is not computed.
  - **"shap"** – (Optional) Section on SHAP value computation.
    - **"baseline"** – (Optional) A list of rows (at least one), or an Amazon Simple Storage Service Amazon S3 object URI. To be used as the baseline dataset (also known as a background dataset) in the Kernel SHAP algorithm. The format should be the same as the dataset format. Each row should contain only the feature columns (or values). Before you send each row to the model, omit any column that must be excluded.
    - **"num_samples"** – Number of samples to be used in the Kernel SHAP algorithm. This number determines the size of the generated synthetic dataset to compute the SHAP values. If not provided, then a SageMaker Clarify job chooses the value based on a count of features.
    - **"agg_method"** – Aggregation method for global SHAP values. Valid values are as follows:
      - **"mean_abs"** – Mean of absolute SHAP values for all instances.
      - **"median"** – Median of SHAP values for all instances.
Monitor Feature Attribution Drift

- "mean_sq" – Mean of squared SHAP values for all instances.
- "use_logit" – (Optional) Boolean value to indicate if the logit function is to be applied to the model predictions. If "use_logit" is true, then the SHAP values have log-odds units. The default value is false.
- "save_local_shap_values" – (Optional) Boolean value to indicate if local SHAP values are to be saved in the output location. Use false to save them. Use true to save them. The default is false.

- "predictor" – (Optional for real-time endpoint, required for batch transform) Section on model parameters, required if "shap" and "post_training_bias" sections are present.

- "model_name" – Model name created by CreateModel API, with container mode as SingleModel.
- "instance_type" – Instance type for the shadow endpoint.
- "initial_instance_count" – Instance count for the shadow endpoint.
- "content_type" – (Optional) The model input format to be used for getting inferences with the shadow endpoint. Valid values are "text/csv" for CSV, "application/jsonlines" for JSON Lines, application/x-parquet for Apache Parquet, and application/x-image to enable Computer Vision explainability. The default value is the same as the dataset_type format.
- "accept_type" – (Optional) The model output format to be used for getting inferences with the shadow endpoint. Valid values are "text/csv" for CSV, "application/jsonlines" for JSON Lines. If omitted, SageMaker Clarify uses the response data type of the captured data.
- "content_template" – (Optional) A template string used to construct the model input from dataset instances. It is only used when "content_type" is "application/jsonlines". The template should have only one placeholder, $features, which is replaced by the features list at runtime. For example, given "content_template": "{\"myfeatures\":$features}" if an instance (no label) is 1,2,3, then model input becomes JSON Lines '{"myfeatures":[1,2,3]}'.
- "label_headers" – (Optional) A list of values that the "label" takes in the dataset. Associates the scores returned by the model endpoint or batch transform job with their corresponding label values. If it is provided, then the analysis report uses the headers instead of placeholders like "label0".

The other parameters should be provided in EndpointInput (for real-time endpoints) or BatchTransformInput (for batch transform jobs) of the ModelExplainabilityJobInput API.

- FeaturesAttribute – This parameter is required if endpoint or batch job input data format is "application/jsonlines". It is the JSONPath used to locate the feature columns if the dataset format is JSON Lines.
- ProbabilityAttribute – Index or JSONPath location in the model output for probabilities. If the model output is JSON Lines with a list of labels and probabilities, for example, then the label that corresponds to the maximum probability is selected for bias computations.

Example JSON Configuration Files for CSV and JSON Lines Datasets

Here are examples of the JSON files used to configure CSV and JSON Lines datasets to monitor them for feature attribution drift.

Topics
- CSV Datasets (p. 2892)
- JSON Lines Datasets (p. 2893)

CSV Datasets

Consider a dataset that has three numerical feature columns, as in the following example.
Assume that the model output has two columns, where the first one is the predicted label and the second one is the probability, as in the following example.

1, 0.5385257417814224

The following example JSON configuration file shows how this CSV dataset can be configured.

```json
{
    "headers": [
        "feature_1",
        "feature_2",
        "feature_3"
    ],
    "methods": {
        "shap": {
            "baseline": [
                [0.4441164946610942, 0.5190374448171748, 0.20722795300473712]
            ],
            "num_samples": 100,
            "agg_method": "mean_abs"
        }
    },
    "predictor": {
        "model_name": "my_model",
        "instance_type": "ml.m5.xlarge",
        "initial_instance_count": 1
    }
}
```

The predicted label is selected by the "ProbabilityAttribute" parameter. Zero-based numbering is used, so 1 indicates the second column of the model output.

"EndpointInput": {
    ...
    "ProbabilityAttribute": 1
    ...
}

**JSON Lines Datasets**

Consider a dataset that has four feature columns and one label column, where the first feature and the label are binary, as in the following example.

```json
{"features":[0, 0.5814568701544718, 0.6651538910132964, 0.313800342665499], "label":0}
{"features":[1, 0.6711642728531724, 0.74666687034026017, 0.12154774178219713], "label":1}
{"features":[0, 0.0453256543003371, 0.6377430803264152, 0.3558625219713576], "label":1}
{"features":[1, 0.4785191853136956, 0.0265841045263860, 0.0376935084990697], "label":1}
```

The model input is the same as the dataset format, and the model output are JSON Lines, as in the following example.

{"predicted_label":1, "probability":0.5385257417814224}
In the following example, the JSON configuration file shows how this JSON Lines dataset can be configured.

```json
{
  "headers": [
    "feature_1",
    "feature_2",
    "feature_3"
  ],
  "methods": {
    "shap": {
      "baseline": [
        "features": [0.4441164946610942, 0.5190374448171748, 0.20722795300473712]
      ],
      "num_samples": 100,
      "agg_method": "mean_abs"
    }
  },
  "predictor": {
    "model_name": "my_model",
    "instance_type": "ml.m5.xlarge",
    "initial_instance_count": 1,
    "content_template": "{"features":$features}"
  }
}
```

Then the "features" parameter value in EndpointInput (for real-time endpoints) or BatchTransformInput (for batch transform jobs) is used to locate the features in the dataset, and the "probability" parameter value selects the probability value from model output.

```json
"EndpointInput": {
  ...
  "FeaturesAttribute": "features",
  "ProbabilityAttribute": "probability",
  ...
}
```

**Schedule Feature Attribute Drift Monitoring Jobs**

After you create your SHAP baseline, you can call the `create_monitoring_schedule()` method of your `ModelExplainabilityMonitor` class instance to schedule an hourly model explainability monitor. The following sections show you how to create a model explainability monitor for a model deployed to a real-time endpoint as well as for a batch transform job.

If a baselining job has been submitted, the monitor automatically picks up analysis configuration from the baselining job. However, if you skip the baselining step or the capture dataset has a different nature from the training dataset, you have to provide the analysis configuration. `ModelConfig` is required by `ExplainabilityAnalysisConfig` for the same reason that it's required for the baselining job. Note that only features are required for computing feature attribution, so you should exclude Ground Truth labeling.

**Feature attribution drift monitoring for models deployed to real-time endpoint**

To schedule a model explainability monitor for a real-time endpoint, pass your `EndpointInput` instance to the `endpoint_input` argument of your `ModelExplainabilityMonitor` instance, as shown in the following code sample:

```python
from sagemaker.model_monitor import CronExpressionGenerator
```
model_exp_model_monitor = ModelExplainabilityMonitor(
    role=sagemaker.get_execution_role(),
    ...)

schedule = model_exp_model_monitor.create_monitoring_schedule(
    monitor_schedule_name=monitor_schedule_name,
    post_analytics_processor_script=s3_code_postprocessor_uri,
    output_s3_uri=s3_report_path,
    statistics=model_exp_model_monitor.baseline_statistics(),
    constraints=model_exp_model_monitor.suggested_constraints(),
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
    endpoint_input=EndpointInput(
        endpoint_name=endpoint_name,
        destination="/opt/ml/processing/input/endpoint",
    )
)

Feature attribution drift monitoring for batch transform jobs

To schedule a model explainability monitor for a batch transform job, pass your BatchTransformInput instance to the batch_transform_input argument of your ModelExplainabilityMonitor instance, as shown in the following code sample:

from sagemaker.model_monitor import CronExpressionGenerator

model_exp_model_monitor = ModelExplainabilityMonitor(
    role=sagemaker.get_execution_role(),
    ...)

schedule = model_exp_model_monitor.create_monitoring_schedule(
    monitor_schedule_name=monitor_schedule_name,
    post_analytics_processor_script=s3_code_postprocessor_uri,
    output_s3_uri=s3_report_path,
    statistics=model_exp_model_monitor.baseline_statistics(),
    constraints=model_exp_model_monitor.suggested_constraints(),
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
    batch_transform_input=BatchTransformInput(
        destination="/opt/ml/processing/data",
        model_name="batch-fraud-detection-model",
        input_manifests_s3_uri="s3://my-bucket/batch-fraud-detection/on-schedule-monitoring/in/",
        excludeFeatures="0",
    )
)

Inspect Reports for Feature Attribute Drift in Production Models

After the schedule that you set up is started by default, you need to wait for the its first execution to start, and then stop the schedule to avoid incurring charges.

To inspect the reports, use the following code:

schedule_desc = model_explainability_monitor.describe_schedule()
execution_summary = schedule_desc.get("LastMonitoringExecutionSummary")
if execution_summary and execution_summary["MonitoringExecutionStatus"] in ["Completed", "CompletedWithViolations"]:
Monitor Feature Attribution Drift

```python
last_model_explainability_monitor_execution = 
model_explainability_monitor.list_executions()[-1]
last_model_explainability_monitor_execution_report_uri = 
last_model_explainability_monitor_execution.output.destination
print(f'Report URI: {last_model_explainability_monitor_execution_report_uri}')
last_model_explainability_monitor_execution_report_files = 
sorted(S3Downloader.list(last_model_explainability_monitor_execution_report_uri))
print(f'Found Report Files: {last_model_explainability_monitor_execution_report_files}"
else:
    last_model_explainability_monitor_execution = None
    print("====STOP==== \n No completed executions to inspect further. Please wait till an 
execution completes or investigate previously reported failures.")

If there are any violations compared to the baseline, they are listed here:

```python
if last_model_explainability_monitor_execution: 
    model_explainability_violations = 
    last_model_explainability_monitor_execution.constraint_violations()
    if model_explainability_violations:
        print(model_explainability_violations.body_dict)
```  
If your model is deployed to a real-time endpoint, you can see visualizations in SageMaker Studio of the analysis results and CloudWatch metrics by choosing the Endpoints tab, and then double-clicking the endpoint.

**CloudWatch Metrics for Feature Drift Analysis**

This guide shows CloudWatch metrics and their properties that you can use for feature attribute drift analysis in SageMaker Clarify. Feature attribute drift monitoring jobs compute and publish two types of metrics:

1. The global SHAP value of each feature.
   
   **Note**
   The name of this metric appends the feature name provided by the job analysis configuration to feature_. For example, feature_X is the global SHAP value for feature X.
2. The ExpectedValue of the metric.

These metrics are published to the following CloudWatch namespace:

- For real-time endpoints: aws/sagemaker/Endpoints/explainability-metrics
- For batch transform jobs: aws/sagemaker/ModelMonitoring/explainability-metrics

Each metric has the following properties:

- **Endpoint**: The name of the monitored endpoint, if applicable.
- **MonitoringSchedule**: The name of the schedule for the monitoring job.
- **ExplainabilityMethod**: The method used to compute Shapley values. Choose KernelShap.
- **Label**: The name provided by job analysis configuration label_headers, or a placeholder like label0.
- **ValueType**: The type of the value returned by the metric. Choose either GlobalShapValues or ExpectedValue.

To stop the monitoring jobs from publishing metrics, set publish_cloudwatch_metrics to Disabled in the Environment map of model explainability job definition.
Schedule monitoring jobs

Amazon SageMaker Model Monitor provides you the ability to monitor the data collected from your real-time endpoints on a continuous schedule or from your batch transform jobs on a specific schedule. You can create a monitoring schedule with the `CreateMonitoringSchedule` API with a predefined periodic interval. For example, every x hours (x can range from 1 to 23).

With a monitoring schedule, SageMaker can kick off processing jobs at a specified frequency to analyze the data collected during a given period. SageMaker provides a prebuilt container for performing analysis on tabular datasets. In the processing job, SageMaker compares the dataset for the current analysis with the baseline statistics, constraints provided and generate a violations report. In addition, CloudWatch metrics are emitted for each feature under analysis. Alternatively, you could choose to bring your own container as outlined in the Bring Your Own Containers (p. 2912) topic.

You can create a model monitoring schedule for your real-time endpoint or batch transform job. Use the baseline resources (constraints and statistics) to compare against the real-time traffic or batch job inputs. In the following example, the training dataset used to train the model was uploaded to Amazon S3. If you already have it in Amazon S3, you can point to it directly.

```python
# copy over the training dataset to Amazon S3 (if you already have it in Amazon S3, you could reuse it)
baseline_prefix = prefix + '/baselining'
baseline_data_prefix = baseline_prefix + '/data'
baseline_results_prefix = baseline_prefix + '/results'

baseline_data_uri = 's3://{}/{}'.format(bucket,baseline_data_prefix)
baseline_results_uri = 's3://{}/{}'.format(bucket, baseline_results_prefix)
print('Baseline data uri: {}'.format(baseline_data_uri))
print('Baseline results uri: {}'.format(baseline_results_uri))

training_data_file = open("test_data/training-dataset-with-header.csv", 'rb')
s3_key = os.path.join(baseline_prefix, 'data', 'training-dataset-with-header.csv')
boto3.Session().resource('s3').Bucket(bucket).Object(s3_key).upload_fileobj(training_data_file)
```

If you are scheduling a model monitor for a real-time endpoint, use the baseline constraints and statistics to compare against real-time traffic. The following code snippet shows the general format you use to create a model monitor for a real-time endpoint.

```python
from sagemaker.model_monitor import CronExpressionGenerator
from time import gmtime, strftime

mon_schedule_name = 'DEMO-xgb-churn-pred-model-monitor-schedule-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
my_default_monitor.create_monitoring_schedule(
    monitor_schedule_name=mon_schedule_name,
    endpoint_input=EndpointInput(
        endpoint_name=endpoint_name,
        destination="/opt/ml/processing/input/endpoint"
    ),
    post_analytics_processor_script=s3_code_postprocessor_uri,
    output_s3_uri=s3_report_path,
    statistics=my_default_monitor.baseline_statistics(),
    constraints=my_default_monitor.suggested_constraints(),
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
)
```

The following code snippet shows the general format you use to schedule a model monitor for a batch transform job.
from sagemaker.model_monitor import (  
    CronExpressionGenerator,  
    BatchTransformInput,  
    MonitoringDatasetFormat,  
)  
from time import gmtime, strftime  

mon_schedule_name = 'DEMO-xgb-churn-pred-model-monitor-schedule-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())  
my_default_monitor.create_monitoring_schedule(      
    monitor_schedule_name=mon_schedule_name,  
    batch_transform_input=BatchTransformInput(  
        destination="opt/ml/processing/input",  
        data_captured_destination_s3_uri=s3_capture_upload_path,  
        dataset_format=MonitoringDatasetFormat.csv(header=False),  
        post_analytics_processor_script=s3_code_postprocessor_uri,  
        output_s3_uri=s3_report_path,  
        statistics=my_default_monitor.baseline_statistics(),  
        constraints=my_default_monitor.suggested_constraints(),  
        schedule_cron_expression=CronExpressionGenerator.hourly(),  
        enable_cloudwatch_metrics=True,  
    )  
)  

Describe and inspect the schedule: After you describe it, observe that the MonitoringScheduleStatus in MonitoringScheduleSummary returned by the ListMonitoringSchedules API changes to Scheduled.

desc_schedule_result = my_default_monitor.describe_schedule()  
print('Schedule status: {}'.format(desc_schedule_result['MonitoringScheduleStatus']))

The cron expression for monitoring schedule

To provide details for the monitoring schedule, use ScheduleConfig, which is a cron expression that describes details about the monitoring schedule.

Amazon SageMaker Model Monitor supports the following cron expressions:

- To set the job to start every hour, use the following:
  
  Hourly: cron(0 * ? * *)

- To run the job daily, use the following:

  cron(0 [00-23] ? * *)

For example, the following are valid cron expressions:

- Daily at 12 PM UTC: cron(0 12 ? * *)
- Daily at 12 AM UTC: cron(0 0 ? * *)

To support running every 6, 12 hours, Model Monitor supports the following expression:

cron(0 [00-23]/[01-24] ? * *)

For example, the following are valid cron expressions:

- Every 12 hours, starting at 5 PM UTC: cron(0 17/12 ? * *)
Amazon SageMaker Developer Guide
Prebuilt container

- Every two hours, starting at 12 AM UTC: `cron(0 0/2 ? * *)`

**Notes**

- Although the `cron` expression is set to start at 5 PM UTC, note that there could be a delay of 0-20 minutes from the actual requested time to run the execution.
- If you want to run on a daily schedule, don't provide this parameter. SageMaker picks a time to run every day.
- Currently, SageMaker only supports hourly integer rates between 1 hour and 24 hours.

**Amazon SageMaker Model Monitor prebuilt container**

SageMaker provides a built-in image called `sagemaker-model-monitor-analyzer` that provides you with a range of model monitoring capabilities, including constraint suggestion, statistics generation, constraint validation against a baseline, and emitting Amazon CloudWatch metrics. This image is based on Spark and is built with Deequ.

**Note**

You can not pull the built-in `sagemaker-model-monitor-analyzer` image directly. You can use the `sagemaker-model-monitor-analyzer` image when you submit a baseline processing or monitoring job using one of the AWS SDKs.

Use the SageMaker Python SDK (see `image_uris.retrieve` in the [SageMaker Python SDK reference guide](https://docs.aws.amazon.com/sagemaker/latest/dg/python-sdk-reference.html)) to generate the ECR image URI for you, or specify the ECR image URI directly. The prebuilt image for SageMaker Model Monitor can be accessed as follows:

```
<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/sagemaker-model-monitor-analyzer
```

For example: `159807026194.dkr.ecr.us-west-2.amazonaws.com/sagemaker-model-monitor-analyzer`

If you are in an AWS region in China, the prebuilt images for SageMaker Model Monitor can be accessed as follows:

```
<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com.cn/sagemaker-model-monitor-analyzer
```

The following table lists the supported values for account IDs and corresponding AWS Region names.

<table>
<thead>
<tr>
<th>ACCOUNT_ID</th>
<th>REGION_NAME</th>
</tr>
</thead>
<tbody>
<tr>
<td>156813124566</td>
<td>us-east-1</td>
</tr>
<tr>
<td>777275614652</td>
<td>us-east-2</td>
</tr>
<tr>
<td>890145073186</td>
<td>us-west-1</td>
</tr>
<tr>
<td>159807026194</td>
<td>us-west-2</td>
</tr>
<tr>
<td>875698925577</td>
<td>af-south-1</td>
</tr>
<tr>
<td>001633400207</td>
<td>ap-east-1</td>
</tr>
<tr>
<td>574779866223</td>
<td>ap-northeast-1</td>
</tr>
</tbody>
</table>
Interpret results

After you run a baseline processing job and obtained statistics and constraint for your dataset, you can execute monitoring jobs that calculate statistics and list any violations encountered relative to the baseline constraints. Amazon CloudWatch metrics are also reported in your account by default. For information on viewing the results of monitoring in Amazon SageMaker Studio, see Visualize results for real-time endpoints in Amazon SageMaker Studio (p. 2902).

List Executions

The schedule starts monitoring jobs at the specified intervals. The following code lists the latest five executions. If you are running this code after creating the hourly schedule, the executions might be empty, and you might have to wait until you cross the hour boundary (in UTC) to see the executions start. The following code includes the logic for waiting.

```python
mon_executions = my_default_monitor.list_executions()
print("We created a hourly schedule above and it will kick off executions ON the hour (plus 0 - 20 min buffer.\nWe will have to wait till we hit the hour...")
```
while len(mon_executions) == 0:
    print("Waiting for the 1st execution to happen...")
    time.sleep(60)
    mon_executions = my_default_monitor.list_executions()

Inspect a Specific Execution

In the previous step, you picked up the latest completed or failed scheduled execution. You can explore what went right or wrong. The terminal states are:

- **Completed** – The monitoring execution completed and no issues were found in the violations report.
- **CompletedWithViolations** – The execution completed, but constraint violations were detected.
- **Failed** – The monitoring execution failed, possibly due to client error (for example, a role issues) or infrastructure issues. To identify the cause, see the `FailureReason` and `ExitMessage`.

```python
latest_execution = mon_executions[-1]  # latest execution's index is -1, previous is -2 and so on..
time.sleep(60)
latest_execution.wait(logs=False)
print("Latest execution status: \{}\".format(latest_execution.describe() ['ProcessingJobStatus']))
print("Latest execution result: \{}\".format(latest_execution.describe() ['ExitMessage']))
```

```python
latest_job = latest_execution.describe()
if (latest_job['ProcessingJobStatus'] != 'Completed'):
    print("====STOP==== 
No completed executions to inspect further. Please wait till an execution completes or investigate previously reported failures.")
```

```python
report_uri=latest_execution.output.destination
print('Report Uri: {}'.format(report_uri))
```

List Generated Reports

List the generated reports

```python
from urllib.parse import urlparse
s3uri = urlparse(report_uri)
report_bucket = s3uri.netloc
report_key = s3uri.path.lstrip('/
print('Report bucket: \{}\".format(report_bucket))
print('Report key: \{}\".format(report_key))
```

```python
s3_client = boto3.Session().client('s3')
result = s3_client.list_objects(Bucket=report_bucket, Prefix=report_key)
report_files = [report_file.get('Key') for report_file in result.get('Contents')]
print("Found Report Files:")
print("\n ".join(report_files))
```

Violations Report

If there are violations compared to the baseline, they are generated in the violations report. Use the following code to list the violations.
```
violations = my_default_monitor.latest_monitoring_constraint_violations()
pd.set_option('display.max_colwidth', -1)
constraints_df = pd.io.json.json_normalize(violations.body_dict['violations'])
constraints_df.head(10)
```

This applies only to datasets that contain tabular data. The following schema files specify the statistics calculated and the violations monitored for.

**Output Files for Tabular Datasets**

<table>
<thead>
<tr>
<th>File Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>statistics.json</strong></td>
<td>Contains columnar statistics for each feature in the dataset that is analyzed. See the schema of this file in the next topic. Note This file is created only for data quality monitoring.</td>
</tr>
<tr>
<td><strong>constraints_violations.json</strong></td>
<td>Contains a list of violations found in this current set of data as compared to the baseline statistics and constraints file specified in the baseline_constraints and baseline_statistics paths.</td>
</tr>
</tbody>
</table>

The Amazon SageMaker Model Monitor prebuilt container (p. 2899) saves a set of Amazon CloudWatch metrics for each feature by default.

The container code can emit CloudWatch metrics in this location: /opt/ml/output/metrics/cloudwatch.

**Visualize results for real-time endpoints in Amazon SageMaker Studio**

If you are monitoring a real-time endpoint, you can also visualize the results in Amazon SageMaker Studio. You can view the details of any monitoring job run, and you can create charts that show the baseline and captured values for any metric that the monitoring job calculates.

**To view the detailed results of a monitoring job**

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the Components and registries icon (🔍).
3. Choose Endpoints in the drop-down menu.
4. On the endpoint tab, choose the monitoring type for which you want to see job details.

5. Choose the name of the monitoring job run for which you want to view details from the list of monitoring jobs.
6. The **MONITORING JOB DETAILS** tab opens with a detailed report of the monitoring job.

You can create a chart that displays the baseline and captured metrics for a time period.
To create a chart in SageMaker Studio to visualize monitoring results

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the Components and registries icon ( ).
3. Choose Endpoints in the drop-down menu.

   ![Components and registries](image)

4. On the Endpoint tab, choose the monitoring type you want to create a chart for. This example shows a chart for the Model quality monitoring type.
5. Choose Add chart.

6. On the CHART PROPERTIES tab, choose the time period, statistic, and metric that you want to chart. This example shows a chart for a Timeline of 1 week, the Average Statistic of, and the F1 Metric.
7. The chart that shows the baseline and current metric statistic you chose in the previous step shows up in the **Endpoint** tab.
Advanced topics

The following sections contain more advanced tasks that explain how to customize monitoring using preprocessing and postprocessing scripts, how to build your own container, and how to use AWS CloudFormation to create a monitoring schedule.

Topics
- Customize monitoring (p. 2908)
- Create a Monitoring Schedule for a Real-time Endpoint with an AWS CloudFormation Custom Resource (p. 2920)

Customize monitoring

In addition to using the built-in monitoring mechanisms, you can create your own custom monitoring schedules and procedures using preprocessing and postprocessing scripts or by using or building your own container.

Topics
- Preprocessing and Postprocessing (p. 2908)
- Bring Your Own Containers (p. 2912)

Preprocessing and Postprocessing

You can use custom preprocessing and postprocessing Python scripts to transform the input to your model monitor or extend the code after a successful monitoring run. Upload these scripts to Amazon S3 and reference them when creating your model monitor.

The following example shows how you can customize monitoring schedules with preprocessing and postprocessing scripts. Replace *user placeholder text* with your own information.

```python
import boto3, os
from sagemaker import get_execution_role, Session
from sagemaker.model_monitor import CronExpressionGenerator, DefaultModelMonitor

# Upload pre and postprocessor scripts
```
session = Session()
bucket = boto3.Session().resource("s3").Bucket(session.default_bucket())
prefix = "demo-sagemaker-model-monitor"
pre_processor_script = bucket.Object(os.path.join(prefix, "preprocessor.py")).upload_file("preprocessor.py")
post_processor_script = bucket.Object(os.path.join(prefix, "postprocessor.py")).upload_file("postprocessor.py")

# Get execution role
role = get_execution_role()  # can be an empty string

# Instance type
instance_type = "instance-type"
# instance_type = "ml.m5.xlarge"  # Example

# Create a monitoring schedule with pre and postprocessing
my_default_monitor = DefaultModelMonitor(
    role=role,
    instance_count=1,
    instance_type=instance_type,
    volume_size_in_gb=20,
    max_runtime_in_seconds=3600,
)
s3_report_path = s3:///reports
monitor_schedule_name = "monitor-schedule-name"
endpoint_name = "endpoint-name"
my_default_monitor.create_monitoring_schedule(
    post_analytics_processor_script=post_processor_script,
    record_preprocessor_script=pre_processor_script,
    monitor_schedule_name=monitor_schedule_name,
    # use endpoint_input for real-time endpoint
    endpoint_input=endpoint_name,
    # or use batch_transform_input for batch transform jobs
    output_s3_uri=s3_report_path,
    statistics=my_default_monitor.baseline_statistics(),
    constraints=my_default_monitor.suggested_constraints(),
    schedule_cron_expression=CronExpressionGenerator.hourly(),
    enable_cloudwatch_metrics=True,
)

Topics

- Preprocessing Script (p. 2909)
- Custom Sampling (p. 2911)
- Postprocessing Script (p. 2912)

Preprocessing Script

Use preprocessing scripts when you need to transform the inputs to your model monitor.

For example, suppose the output of your model is an array [1.0, 2.1]. The Amazon SageMaker Model Monitor container only works with tabular or flattened JSON structures, like {"prediction0": 1.0, "prediction1": 2.1}. You could use a preprocessing script like the following to transform the array into the correct JSON structure.

def preprocess_handler(inference_record):
    input_data = inference_record.endpoint_input.data
    output_data = inference_record.endpoint_output.data.rstrip(\"\n")
    data = output_data + "," + input_data

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In another example, suppose your model has optional features and you use -1 to denote that the optional feature has a missing value. If you have a data quality monitor, you may want to remove the -1 from the input value array so that it isn’t included in the monitor’s metric calculations. You could use a script like the following to remove those values.

```python
def preprocess_handler(inference_record):
    input_data = inference_record.endpoint_input.data
    return {i : None if x == -1 else x for i, x in enumerate(input_data.split(','))}
```

Your preprocessing script receives an `inference_record` as its only input. The following code snippet shows an example of an `inference_record`.

```json
{
    "captureData": {
        "endpointInput": {
            "observedContentType": "text/csv",
            "mode": "INPUT",
            "data": "132,25,113.2,96,269.9,107,,0,0,0,0,0,0,1,0,1,0,0,1",
            "encoding": "CSV"
        },
        "endpointOutput": {
            "observedContentType": "text/csv; charset=utf-8",
            "mode": "OUTPUT",
            "data": "0.01076381653547287",
            "encoding": "CSV"
        }
    },
    "eventMetadata": {
        "eventId": "feca1ab1-8025-47e3-8f6a-99e3fdd7b8d9",
        "inferenceTime": "2019-11-20T23:33:12Z"
    }
}
```

The following code snippet shows the full class structure for an `inference_record`.

```python
KEY_EVENT_METADATA = "eventMetadata"
KEY_EVENT_METADATA_EVENT_ID = "eventId"
KEY_EVENT_METADATA_EVENT_TIME = "inferenceTime"
KEY_EVENT_METADATA_CUSTOM_ATTR = "customAttributes"

KEY_EVENTDATA = "captureData"
KEY_EVENTDATA_INPUT = "endpointInput"
KEY_EVENTDATA_OUTPUT = "endpointOutput"
KEY_EVENTDATA_ENCODING = "encoding"
KEY_EVENTDATA_DATA = "data"
KEY_EVENTDATA_OBSERVED_CONTENT_TYPE = "observedContentType"
KEY_EVENTDATA_MODE = "mode"

KEY_EVENT_VERSION = "eventVersion"

class EventConfig:
    def __init__(self, endpoint, variant, start_time, end_time):
        self.endpoint = endpoint
        self.variant = variant
        self.start_time = start_time
        self.end_time = end_time
```
class EventMetadata:
    def __init__(self, event_metadata_dict):
        self.event_id = event_metadata_dict.get(KEY_EVENT_METADATA_EVENT_ID, None)
        self.event_time = event_metadata_dict.get(KEY_EVENT_METADATA_EVENT_TIME, None)
        self.custom_attribute =
        event_metadata_dict.get(KEY_EVENTDATA_OBSERVED_CONTENT_TYPE, None)

class EventData:
    def __init__(self, data_dict):
        self.encoding = data_dict.get(KEY_EVENTDATA_ENCODING, None)
        self.data = data_dict.get(KEY_EVENTDATA_DATA, None)
        self.observedContentType = data_dict.get(KEY_EVENTDATA_OBSERVED_CONTENT_TYPE, None)
        self.mode = data_dict.get(KEY_EVENTDATA_MODE, None)

    def as_dict(self):
        ret = {
            KEY_EVENTDATA_ENCODING: self.encoding,
            KEY_EVENTDATA_DATA: self.data,
            KEY_EVENTDATA_OBSERVED_CONTENT_TYPE: self.observedContentType,
        }
        return ret

class CapturedData:
    def __init__(self, event_dict):
        self.event_metadata = None
        self.endpoint_input = None
        self.endpoint_output = None
        self.event_version = None
        self.event_dict = event_dict
        self._event_dict_postprocessed = False

        if KEY_EVENT_METADATA in event_dict:
            self.event_metadata = EventMetadata(event_dict[KEY_EVENT_METADATA])
        if KEY_EVENTDATA in event_dict:
            if KEY_EVENTDATA_INPUT in event_dict[KEY_EVENTDATA]:
                self.endpoint_input = EventData(event_dict[KEY_EVENTDATA][KEY_EVENTDATA_INPUT])
            if KEY_EVENTDATA_OUTPUT in event_dict[KEY_EVENTDATA]:
                self.endpoint_output = EventData(event_dict[KEY_EVENTDATA][KEY_EVENTDATA_OUTPUT])

        if KEY_EVENT_VERSION in event_dict:
            self.event_version = event_dict[KEY_EVENT_VERSION]

    def as_dict(self):
        if self._event_dict_postprocessed is True:
            return self.event_dict
        if KEY_EVENTDATA in self.event_dict:
            if KEY_EVENTDATA_INPUT in self.event_dict[KEY_EVENTDATA]:
                self.endpoint_input = self.event_dict[KEY_EVENTDATA][KEY_EVENTDATA_INPUT].as_dict()
            if KEY_EVENTDATA_OUTPUT in self.event_dict[KEY_EVENTDATA]:
                self.endpoint_output = self.event_dict[KEY_EVENTDATA][KEY_EVENTDATA_OUTPUT].as_dict()
        self._event_dict_postprocessed = True
        return self.event_dict

Custom Sampling

You can also apply a custom sampling strategy in your preprocessing script. To do this, configure Model Monitor's first-party, pre-built container to ignore a percentage of the records according to your specified
sampling rate. In the following example, the handler samples 10 percent of the records by returning the record in 10 percent of handler calls and an empty list otherwise.

```python
import random

def preprocess_handler(inference_record):
    # we set up a sampling rate of 0.1
    if random.random() > 0.1:
        # return an empty list
        return []
    return inference_record
```

Postprocessing Script

Use a postprocessing script when you want to extend the code following a successful monitoring run.

```python
def postprocess_handler():
    print("Hello from post-proc script!")
```

Bring Your Own Containers

Amazon SageMaker Model Monitor provides a prebuilt container with ability to analyze the data captured from endpoints or batch transform jobs for tabular datasets. If you would like to bring your own container, Model Monitor provides extension points which you can leverage.

Under the hood, when you create a MonitoringSchedule, Model Monitor ultimately kicks off processing jobs. Hence the container needs to be aware of the processing job contract documented in the Build Your Own Processing Container (Advanced Scenario) (p. 1031) topic. Note that Model Monitor kicks off the processing job on your behalf per the schedule. While invoking, Model Monitor sets up additional environment variables for you so that your container has enough context to process the data for that particular execution of the scheduled monitoring. For additional information on container inputs, see the Container Contract Inputs (p. 2912).

In the container, using the above environment variables/context, you can now analyze the dataset for the current period in your custom code. After this analysis is complete, you can chose to emit your reports to be uploaded to an S3 bucket. The reports that the prebuilt container generates are documented in Container Contract Outputs (p. 2914). If you would like the visualization of the reports to work in SageMaker Studio, you should follow the same format. You can also choose to emit completely custom reports.

You also emit CloudWatch metrics from the container by following the instructions in CloudWatch Metrics for Bring Your Own Containers (p. 2919).

Topics

- Container Contract Inputs (p. 2912)
- Container Contract Outputs (p. 2914)
- CloudWatch Metrics for Bring Your Own Containers (p. 2919)

Container Contract Inputs

The Amazon SageMaker Model Monitor platform invokes your container code according to a specified schedule. If you choose to write your own container code, the following environment variables are available. In this context, you can analyze the current dataset or evaluate the constraints if you choose and emit metrics, if applicable.
The available environment variables are the same for real-time endpoints and batch transform jobs, except for the `dataset_format` variable. If you are using a real-time endpoint, the `dataset_format` variable supports the following options:

```json
{"sagemakerCaptureJson": {"captureIndexNames": ["endpointInput", "endpointOutput"]}}
```

If you are using a batch transform job, the `dataset_format` supports the following options:

```json
{"csv": {"header": ["true", "false"]}}

{"json": {"line": ["true", "false"]}}

{"parquet": {}}
```

The following code sample shows the complete set of environment variables available for your container code (and uses the `dataset_format` format for a real-time endpoint).

```json
"Environment": {
    "dataset_format": "{\"sagemakerCaptureJson\": {\"captureIndexNames\": [\"endpointInput\", \"endpointOutput\"]}}",
    "dataset_source": "/opt/ml/processing/endpointdata",
    "end_time": "2019-12-01T16: 00: 00Z",
    "output_path": "/opt/ml/processing/resultdata",
    "publish_cloudwatch_metrics": "Disabled",
    "sagemaker_endpoint_name": "endpoint-name",
    "sagemaker_monitoring_schedule_name": "schedule-name",
    "start_time": "2019-12-01T15: 00: 00Z"
}
```

### Parameters

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>dataset_format</td>
<td>For a job started from a MonitoringSchedule backed by an Endpoint, this is sagemakerCaptureJson with the capture indices endpointInput, or endpointOutput, or both. For a batch transform job, this specifies the data format, whether CSV, JSON, or Parquet.</td>
</tr>
<tr>
<td>dataset_source</td>
<td>If you are using a real-time endpoint, the local path in which the data corresponding to the monitoring period, as specified by start_time and end_time, are available. At this path, the data is available in <code>/{endpoint-name}/</code>/{variant-name}/yyyy/mm/dd/hh`. We sometimes download more than what is specified by the start and end times. It is up to the container code to parse the data as required.</td>
</tr>
<tr>
<td>output_path</td>
<td>The local path to write output reports and other files. You specify this parameter in the CreateMonitoringSchedule request as MonitoringOutputConfig.MonitoringOutput[0].LocalPath.</td>
</tr>
<tr>
<td>Parameter Name</td>
<td>Description</td>
</tr>
<tr>
<td>----------------</td>
<td>-------------</td>
</tr>
<tr>
<td><strong>publish_cloudwatch_metrics</strong></td>
<td>For a job launched by CreateMonitoringSchedule, this parameter is set to Enabled. The container can choose to write the Amazon CloudWatch output file at [filepath].</td>
</tr>
<tr>
<td><strong>sagemaker_endpoint_name</strong></td>
<td>If you are using a real-time endpoint, the name of the Endpoint that this scheduled job was launched for.</td>
</tr>
<tr>
<td><strong>sagemaker_monitoring_schedule_name</strong></td>
<td>The name of the MonitoringSchedule that launched this job.</td>
</tr>
<tr>
<td><strong>sagemaker_endpoint_datacapture_prefix</strong></td>
<td>If you are using a real-time endpoint, the prefix specified in the DataCaptureConfig parameter of the Endpoint. The container can use this if it needs to directly access more data than already downloaded by SageMaker at the dataset_source path.</td>
</tr>
<tr>
<td><strong>start_time, end_time</strong></td>
<td>The time window for this analysis run. For example, for a job scheduled to run at 05:00 UTC and a job that runs on 20/02/2020, start_time: is 2020-02-19T06:00:00Z and end_time: is 2020-02-20T05:00:00Z</td>
</tr>
<tr>
<td><strong>baseline_constraints:</strong></td>
<td>The local path of the baseline constraint file specified in BaselineConfig.ConstraintResource.S3Uri. This is available only if this parameter was specified in the CreateMonitoringSchedule request.</td>
</tr>
<tr>
<td><strong>baseline_statistics</strong></td>
<td>The local path to the baseline statistics file specified in BaselineConfig.StatisticsResource.S3Uri. This is available only if this parameter was specified in the CreateMonitoringSchedule request.</td>
</tr>
</tbody>
</table>

**Container Contract Outputs**

The container can analyze the data available in the *dataset_source* path and write reports to the path in *output_path*. The container code can write any reports that suit your needs.

If you use the following structure and contract, certain output files are treated specially by SageMaker in the visualization and API. This applies only to tabular datasets.
Output Files for Tabular Datasets

<table>
<thead>
<tr>
<th>File Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>statistics.json</td>
<td>This file is expected to have columnar statistics for each feature in the dataset that is analyzed. The schema for this file is available in the next section.</td>
</tr>
<tr>
<td>constraints.json</td>
<td>This file is expected to have the constraints on the features observed. The schema for this file is available in the next section.</td>
</tr>
<tr>
<td>constraints_violations.json</td>
<td>This file is expected to have the list of violations found in this current set of data as compared to the baseline statistics and constraints file specified in the baseline_constraints and baseline_statistics path.</td>
</tr>
</tbody>
</table>

In addition, if the publish_cloudwatch_metrics value is "Enabled" container code can emit Amazon CloudWatch metrics in this location: /opt/ml/output/metrics/cloudwatch. The schema for these files is described in the following sections.

Topics
- Schema for Statistics (statistics.json file) (p. 2915)
- Schema for Constraints (constraints.json file) (p. 2917)

Schema for Statistics (statistics.json file)

The schema defined in the statistics.json file specifies the statistical parameters to be calculated for the baseline and data that is captured. It also configures the bucket to be used by KLL, a very compact quantiles sketch with lazy compaction scheme.

```json
{
    "version": 0,

    # dataset level stats
    "dataset": {
        "item_count": number
    },

    # feature level stats
    "features": [
        {
            "name": "feature-name",
            "inferred_type": "Fractional" | "Integral",
            "numerical_statistics": {
                "common": {
                    "num_present": number,
                    "num_missing": number
                },
                "mean": number,
                "sum": number,
                "std_dev": number,
                "min": number,
                "max": number,
                "distribution": {
                    "kll": {
                        "buckets": [
                            {
                                "lower_bound": number,
                                "upper_bound": number,
                                "count": number
                            }
                        ]
                    }
                }
            }
        }
    ]
}
```
"count": number
],
"sketch": {
    "parameters": {
        "c": number,
        "k": number
    },
    "data": [
        [num, num, num, num],
        [num, num],
        [num, num]
    ]
}
}
#sketch
}#KLL
}#distribution
}#num_stats
},
{
    "name": "feature-name",
    "inferred_type": "String",
    "string_statistics": {
        "common": {
            "num_present": number,
            "num_missing": number
        },
        "distinct_count": number,
        "distribution": {
            "categorical": {
                "buckets": [
                    {
                        "value": "string",
                        "count": number
                    }
                ]
            }
        }
    },
    #provision for custom stats
}
]

Notes

- The specified metrics are recognized by SageMaker in later visualization changes. The container can emit more metrics if required.
- **KLL sketch** is the recognized sketch. Custom containers can write their own representation, but it won't be recognized by SageMaker in visualizations.
- By default, the distribution is materialized in 10 buckets. You can't change this.
Schema for Constraints (constraints.json file)

A constraints.json file is used to express the constraints that a dataset must satisfy. Amazon SageMaker Model Monitor containers can use the constraints.json file to evaluate datasets against. Prebuilt containers provide the ability to generate the constraints.json file automatically for a baseline dataset. If you bring your own container, you can provide it with similar abilities or you can create the constraints.json file in some other way. Here is the schema for the constraint file that the prebuilt container uses. Bring your own containers can adopt the same format or enhance it as required.

```json
{
  "version" : 0,
  "features": [
    {
      "name": "string",
      "inferred_type": "Integral" | "Fractional" | "String" | "Unknown",
      "completeness": number, # denotes observed non-null value percentage
      "num_constraints": {
        "is_non_negative": boolean,
      },
      "string_constraints": {
        "domains": [list of, "observed values", "for small cardinality"
      ],
      },
      "monitoringConfigOverrides": {
        "monitoringConfigOverrides": {
          "evaluate_constraints": "Enabled",
          "emit_metrics": "Enabled",
          "datatype_check_threshold": 0.1,
          "domain_content_threshold": 0.1,
          "distribution_constraints": {
            "perform_comparison": "Enabled",
            "comparison_threshold": 0.1,
            "comparison_method": "Simple" || "Robust"
          }
        }
      }
    }
  ]
}
```

Monitoring Constraints

<table>
<thead>
<tr>
<th>Constraint</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>evaluate_constraints</td>
<td>When Enabled, evaluates whether the current dataset being analyzed satisfies the constraints specified in the constraints.json file taken as a baseline.</td>
</tr>
<tr>
<td></td>
<td>Valid values: Enabled or Disabled</td>
</tr>
<tr>
<td></td>
<td>Default: Enabled</td>
</tr>
<tr>
<td>Constraint</td>
<td>Description</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td><code>emit_metrics</code></td>
<td>When Enabled, emits CloudWatch metrics for the data contained in the file.</td>
</tr>
<tr>
<td></td>
<td>Valid values: Enabled or Disabled</td>
</tr>
<tr>
<td></td>
<td>Default: Enabled</td>
</tr>
<tr>
<td><code>datatype_check_threshold</code></td>
<td>If the threshold is above the value of the specified <code>datatype_check_threshold</code>, this causes a failure that is treated as a violation in the violation report. If the data types in the current execution are not the same as in the baseline dataset, this threshold is used to evaluate if it needs to be flagged as a violation.</td>
</tr>
<tr>
<td></td>
<td>During the baseline step, the generated constraints suggest the inferred data type for each column. The <code>datatype_check_threshold</code> parameter can be tuned to adjust the threshold on when it is flagged as a violation.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float</td>
</tr>
<tr>
<td></td>
<td>Default: 0.1</td>
</tr>
<tr>
<td><code>domain_content_threshold</code></td>
<td>If there are more unknown values for a String field in the current dataset than in the baseline dataset, this threshold can be used to dictate if it needs to be flagged as a violation.</td>
</tr>
<tr>
<td></td>
<td>Valid values: float</td>
</tr>
<tr>
<td></td>
<td>Default: 0.1</td>
</tr>
<tr>
<td><code>distribution_constraints</code></td>
<td><code>perform_comparison</code></td>
</tr>
<tr>
<td></td>
<td>When Enabled, this flag instructs the code to perform a distribution comparison between the baseline distribution and the distribution observed for the current dataset.</td>
</tr>
<tr>
<td></td>
<td>Valid values: Enabled or Disabled</td>
</tr>
<tr>
<td></td>
<td>Default: Enabled</td>
</tr>
</tbody>
</table>
### Constraint | Description
--- | ---
| comparison_threshold | If the threshold is above the value set for the `comparison_threshold`, this causes a failure that is treated as a violation in the violation report. The distance is calculated by getting the maximum absolute difference between the cumulative distribution functions of two distributions.
Valid values: float  
Default: 0.1 |
| comparison_method | Whether to calculate `linf_simple` or `linf_robust`. The `linf_simple` is based on the maximum absolute difference between the cumulative distribution functions of two distributions. Calculating `linf_robust` is based on `linf_simple`, but is used when there are not enough samples. The `linf_robust` formula is based on the Two-sample Kolmogorov–Smirnov test.
Valid values: `linf_simple` or `linf_robust`. |

**CloudWatch Metrics for Bring Your Own Containers**

If the `publish_cloudwatch_metrics` value is Enabled in the Environment map in the `/opt/ml/processing/processingjobconfig.json` file, the container code emits Amazon CloudWatch metrics in this location: `/opt/ml/output/metrics/cloudwatch`.

The schema for this file is closely based on the CloudWatch PutMetrics API. The namespace is not specified here. It defaults to the following:

- For real-time endpoints: `/aws/sagemaker/Endpoint/data-metrics`
- For batch transform jobs: `/aws/sagemaker/ModelMonitoring/data-metrics`

However, you can specify dimensions. We recommend you add the following dimensions at minimum:

- Endpoint and MonitoringSchedule for real-time endpoints
- MonitoringSchedule for batch transform jobs

The following JSON snippets show how to set your dimensions.

For a real-time endpoint, see the following JSON snippet which includes the Endpoint and MonitoringSchedule dimensions:

```json
{
   "MetricName": "", # Required
   "Timestamp": "2019-11-26T03:00:00Z", # Required
```
For a batch transform job, see the following JSON snippet which includes the MonitoringSchedule dimension:

```
{
  "MetricName": "", # Required
  "Timestamp": "2019-11-26T03:00:00Z", # Required
  "Dimensions": [{"Name":"MonitoringSchedule","Value":"schedule_0"}],
  "Value": Float,
  # Either the Value or the StatisticValues field can be populated and not both.
  "StatisticValues": {
    "SampleCount": Float,
    "Sum": Float,
    "Minimum": Float,
    "Maximum": Float
  },
  "Unit": "Count", # Optional
}
```

Create a Monitoring Schedule for a Real-time Endpoint with an AWS CloudFormation Custom Resource

If you are using a real-time endpoint, you can use an AWS CloudFormation custom resource to create a monitoring schedule. The custom resource is in Python. To deploy it, see Python Lambda deployment.

Custom Resource

Start by adding a custom resource to your AWS CloudFormation template. This points to an AWS Lambda function that you create in the next step.

This resource enables you to customize the parameters for the monitoring schedule. You can add or remove more parameters by modifying the AWS CloudFormation resource and the Lambda function in the following example resource.

```
{
  "AWSTemplateFormatVersion": "2010-09-09",
  "Resources": {
    "MonitoringSchedule": {
      "Type": "Custom::MonitoringSchedule",
      "Version": "1.0",
      "Properties": {
        "ScheduleName": "YourScheduleName",
        "EndpointName": "YourEndpointName",
        "BaselineConstraintsUri": "s3://your-baseline-constraints/constraints.json"
      }
    }
  }
}
```
Lambda Custom Resource Code

This AWS CloudFormation custom resource uses the Custom Resource Helper AWS library, which you can install with pip using `pip install crhelper`.

This Lambda function is invoked by AWS CloudFormation during the creation and deletion of the stack. This Lambda function is responsible for creating and deleting the monitoring schedule and using the parameters defined in the custom resource described in the preceding section.

```python
import boto3
import botocore
import logging
from crhelper import CfnResource
from botocore.exceptions import ClientError

logger = logging.getLogger(__name__)
sm = boto3.client('sagemaker')

# cfnhelper makes it easier to implement a CloudFormation custom resource
helper = CfnResource()

# CFN Handlers

def handler(event, context):
    helper(event, context)

@helper.create
def create_handler(event, context):
    """
    Called when CloudFormation custom resource sends the create event
    """
    create_monitoring_schedule(event)

@helper.delete
def delete_handler(event, context):
    """
    Called when CloudFormation custom resource sends the delete event
    """
    schedule_name = get_schedule_name(event)
    delete_monitoring_schedule(schedule_name)

@helper.poll_create
```
def poll_create(event, context):
    """
    Return true if the resource has been created and false otherwise so
    CloudFormation polls again.
    """
    schedule_name = get_schedule_name(event)
    logger.info('Polling for creation of schedule: %s', schedule_name)
    return is_schedule_ready(schedule_name)

@helper.update
def noop():
    """
    Not currently implemented but crhelper will throw an error if it isn't added
    """
    pass

# Helper Functions
def get_schedule_name(event):
    return event['ResourceProperties']['ScheduleName']

def create_monitoring_schedule(event):
    schedule_name = get_schedule_name(event)
    monitoring_schedule_config = create_monitoring_schedule_config(event)
    logger.info('Creating monitoring schedule with name: %s', schedule_name)
    sm.create_monitoring_schedule(
        MonitoringScheduleName=schedule_name,
        MonitoringScheduleConfig=monitoring_schedule_config)

def is_schedule_ready(schedule_name):
    is_ready = False
    schedule = sm.describe_monitoring_schedule(MonitoringScheduleName=schedule_name)
    status = schedule['MonitoringScheduleStatus']
    if status == 'Scheduled':
        logger.info('Monitoring schedule (%s) is ready', schedule_name)
        is_ready = True
    elif status == 'Pending':
        logger.info('Monitoring schedule (%s) still creating, waiting and polling
        again...', schedule_name)
    else:
        raise Exception('Monitoring schedule ({}) has unexpected status:
        {}').format(schedule_name, status)
    return is_ready

def create_monitoring_schedule_config(event):
    props = event['ResourceProperties']
    return {
        "ScheduleConfig": {
            "ScheduleExpression": props["ScheduleExpression"],
        },
        "MonitoringJobDefinition": {
            "BaselineConfig": {
                "ConstraintsResource": {
                    "S3Uri": props["BaselineConstraintsUri"],
                },
                "StatisticsResource": {
                    "S3Uri": props["BaselineStatisticsUri"],
                }
            },
            "MonitoringInputs": [  
        },
Serverless Inference

Amazon SageMaker Serverless Inference is a purpose-built inference option that makes it easy for you to deploy and scale ML models. Serverless Inference is ideal for workloads which have idle periods between traffic spurts and can tolerate cold starts. Serverless endpoints automatically launch compute resources and scale them in and out depending on traffic, eliminating the need to choose instance types or manage scaling policies. This takes away the undifferentiated heavy lifting of selecting and managing servers. Serverless Inference integrates with AWS Lambda to offer you high availability, built-in fault tolerance and automatic scaling.

With a pay-per-use model, Serverless Inference is a cost-effective option if you have an infrequent or unpredictable traffic pattern. During times when there are no requests, Serverless Inference scales
your endpoint down to 0, helping you to minimize your costs. For more information about pricing for Serverless Inference, see Amazon SageMaker Pricing.

You can integrate Serverless Inference with your MLOps Pipelines to streamline your ML workflow, and you can use a serverless endpoint to host a model registered with Model Registry (p. 2982).

Serverless Inference is generally available in all AWS commercial Regions where SageMaker is available (except the AWS China Regions). For more information about Amazon SageMaker regional availability, see the AWS Regional Services List.

How it works

The following diagram shows the workflow of Serverless Inference and the benefits of using a serverless endpoint.

![Diagram showing the workflow of Serverless Inference](image)

When you create a serverless endpoint, SageMaker provisions and manages the compute resources for you. Then, you can make inference requests to the endpoint and receive model predictions in response. SageMaker scales the compute resources up and down as needed to handle your request traffic, and you only pay for what you use.

The following sections provide additional details about Serverless Inference and how it works.

Topics

- Container support (p. 2924)
- Memory size (p. 2925)
- Concurrent invocations (p. 2925)
- Cold starts (p. 2925)
- Feature exclusions (p. 2926)

Container support

For your endpoint container, you can choose either a SageMaker-provided container or bring your own. SageMaker provides containers for its built-in algorithms and prebuilt Docker images for some of the most common machine learning frameworks, such as Apache MXNet, TensorFlow, PyTorch, and Chainer. For a list of available SageMaker images, see Available Deep Learning Containers Images. If you are bringing your own container, you must modify it to work with SageMaker. For more information about bringing your own container, see Adapting Your Own Inference Container (p. 3177).

The maximum size of the container image you can use is 10 GB. For serverless endpoints, we recommend creating only one worker in the container and only loading one copy of the model. Note that this is unlike real-time endpoints, where some SageMaker containers may create a worker for each vCPU to process inference requests and load the model in each worker.
If you already have a container for a real-time endpoint, you can use the same container for your serverless endpoint, though some capabilities are excluded. To learn more about the container capabilities that are not supported in Serverless Inference, see Feature exclusions (p. 2926). If you choose to use the same container, SageMaker escrows (retains) a copy of your container image until you delete all endpoints that use the image. SageMaker encrypts the copied image at rest with a SageMaker-owned AWS KMS key.

**Memory size**

Your serverless endpoint has a minimum RAM size of 1024 MB (1 GB), and the maximum RAM size you can choose is 6144 MB (6 GB). The memory sizes you can choose are 1024 MB, 2048 MB, 3072 MB, 4096 MB, 5120 MB, or 6144 MB. Serverless Inference auto-assigns compute resources proportional to the memory you select. If you choose a larger memory size, your container has access to more vCPUs. Choose your endpoint's memory size according to your model size. Generally, the memory size should be at least as large as your model size. You may need to benchmark in order to choose the right memory selection for your model based on your latency SLAs. The memory size increments have different pricing; see the Amazon SageMaker pricing page for more information.

Regardless of the memory size you choose, your serverless endpoint has 5 GB of ephemeral disk storage available. For help with container permissions issues when working with storage, see Troubleshooting (p. 2938).

**Concurrent invocations**

Serverless Inference manages predefined scaling policies and quotas for the capacity of your endpoint. Serverless endpoints have a quota for how many concurrent invocations can be processed at the same time. If the endpoint is invoked before it finishes processing the first request, then it handles the second request concurrently. For the US East (Ohio), US East (N. Virginia), US West (Oregon), Asia Pacific (Singapore), Asia Pacific (Sydney), Asia Pacific (Tokyo), Europe (Frankfurt), and Europe (Ireland) Regions, the total concurrency you can share between all serverless endpoints per Region in your account is 1000. For the US West (N. California), Africa (Cape Town), Asia Pacific (Hong Kong), Asia Pacific (Mumbai), Asia Pacific (Osaka), Asia Pacific (Seoul), Canada (Central), Europe (London), Europe (Milan), Europe (Paris), Europe (Stockholm), Middle East (Bahrain), and South America (São Paulo) Regions, the total concurrency per Region is 500. You can set the maximum concurrency for a single endpoint up to 200, and the total number of serverless endpoints you can host in a Region is 50. The maximum concurrency for an individual endpoint prevents that endpoint from taking up all of the invocations allowed for your account, and any endpoint invocations beyond the maximum are throttled.

To learn how to set the maximum concurrency for your endpoint, see Create an endpoint configuration (p. 2930). For more information about quotas and limits, see Amazon SageMaker endpoints and quotas in the AWS General Reference. To request a service limit increase, contact AWS Support. For instructions on how to request a service limit increase, see Supported Regions and Quotas (p. 32).

**Cold starts**

If your endpoint does not receive traffic for a while and then your endpoint suddenly receives new requests, it can take some time for your endpoint to spin up the compute resources to process the requests. This is called a cold start. Since serverless endpoints provision compute resources on demand, your endpoint may experience cold starts. A cold start can also occur if your concurrent requests exceed the current concurrent request usage. The cold start time depends on your model size, how long it takes to download your model, and the start-up time of your container.

To monitor how long your cold start time is, you can use the Amazon CloudWatch metric ModelSetupTime to monitor your serverless endpoint. This metric tracks the time it takes to launch new compute resources for your endpoint. To learn more about using CloudWatch metrics with serverless endpoints, see Monitor a Serverless Endpoint (p. 2938).
Feature exclusions

Some of the features currently available for SageMaker Real-time Inference are not supported for Serverless Inference, including GPUs, AWS marketplace model packages, private Docker registries, Multi-Model Endpoints, VPC configuration, network isolation, data capture, multiple production variants, Model Monitor, and inference pipelines.

You cannot convert your instance-based, real-time endpoint to a serverless endpoint. If you try to update your real-time endpoint to serverless, you receive a `ValidationError` message. You can convert a serverless endpoint to real-time, but once you make the update, you cannot roll it back to serverless.

Getting started

You can create, update, describe, and delete a serverless endpoint using the SageMaker console, the AWS SDKs, the Amazon SageMaker Python SDK, and the AWS CLI. You can invoke your endpoint using the AWS SDKs, the Amazon SageMaker Python SDK, and the AWS CLI. For more information about how to set up and use a serverless endpoint, read the guide Create, Invoke, Update, and Delete an Endpoint (p. 2926).

Example notebooks and blogs

For Jupyter notebook examples that show end-to-end serverless endpoint workflows, see the Serverless Inference example notebooks.

Create, Invoke, Update, and Delete an Endpoint

Unlike other SageMaker real-time endpoints, Serverless Inference manages compute resources and scaling policies for you, reducing complexity so you can focus on your ML model instead of on managing infrastructure. The following guide highlights the key capabilities of serverless endpoints: how to create, invoke, update, describe, or delete an endpoint. You can use the SageMaker console, the AWS SDKs, the Amazon SageMaker Python SDK, or the AWS CLI to manage your serverless endpoints.

Topics

- Prerequisites (p. 2926)
- Create a serverless endpoint (p. 2928)
- Invoke a serverless endpoint (p. 2936)
- Update a serverless endpoint (p. 2936)
- Describe a serverless endpoint (p. 2937)
- Delete a serverless endpoint (p. 2938)

Prerequisites

Before you can create a serverless endpoint, complete the following prerequisites.

1. **Set up an AWS account.** You first need an AWS account and an AWS Identity and Access Management administrator user. For instructions on how to set up an AWS account, see How do I create and activate a new AWS account?. For instructions on how to secure your account with an IAM administrator user, see Creating your first IAM admin user and user group in the IAM User Guide.

2. **Create an Amazon S3 bucket.** You use an Amazon S3 bucket to store your model artifacts. To learn how to create a bucket, see Create your first S3 bucket in the Amazon S3 User Guide.

3. **Upload your model artifacts to your S3 bucket.** For instructions on how to upload your model to your bucket, see Upload an object to your bucket in the Amazon S3 User Guide.
4. **Create an IAM role for Amazon SageMaker.** Amazon SageMaker needs access to the S3 bucket that stores your model. Create an IAM role with a policy that gives SageMaker read access to your bucket. The following procedure shows how to create a role in the console, but you can also use the `CreateRole` API from the IAM User Guide. For information on giving your role more granular permissions based on your use case, see SageMaker Roles (p. 3552).

   a. Sign in to the IAM console.
   b. In the navigation tab, choose Roles.
   c. Choose Create Role.
   d. For Select type of trusted entity, choose AWS service and then choose SageMaker.
   e. Choose Next: Permissions and then choose Next: Tags.
   f. (Optional) Add tags as key-value pairs if you want to have metadata for the role.
   g. Choose Next: Review.
   h. For Role name, enter a name for the new role that is unique within your AWS account. You cannot edit the role name after creating the role.
   i. (Optional) For Role description, enter a description for the new role.
   j. Choose Create role.

5. **Attach S3 bucket permissions to your SageMaker role.** After creating an IAM role, attach a policy that gives SageMaker permission to access the S3 bucket containing your model artifacts.

   a. In the IAM console navigation tab, choose Roles.
   b. From the list of roles, search for the role you created in the previous step by name.
   c. Choose your role, and then choose Attach policies.
   d. For Attach permissions, choose Create policy.
   e. In the Create policy view, select the JSON tab.
   f. Add the following policy statement into the JSON editor. Make sure to replace `<your-bucket-name>` with the name of the S3 bucket that stores your model artifacts. If you want to restrict the access to a specific folder or file in your bucket, you can also specify the Amazon S3 folder path, for example, `<your-bucket-name>/<model-folder>`.

   ```json
   {
     "Version": "2012-10-17",
     "Statement": [
       {
         "Sid": "VisualEditor0",
         "Effect": "Allow",
         "Action": "s3:GetObject",
         "Resource": "arn:aws:s3:::<your-bucket-name>/*"
       }
     ]
   }
   ```
   g. Choose Next: Tags.
   h. (Optional) Add tags in key-value pairs to the policy.
   i. Choose Next: Review.
   j. For Name, enter a name for the new policy.
   k. (Optional) Add a Description for the policy.
   l. Choose Create policy.
   m. After creating the policy, return to Roles in the IAM console and select your SageMaker role.
   n. Choose Attach policies.
   o. For Attach permissions, search for the policy you created by name. Select it and choose Attach policy.
6. **Select a prebuilt Docker container image or bring your own.** The container you choose serves inference on your endpoint. SageMaker provides containers for built-in algorithms and prebuilt Docker images for some of the most common machine learning frameworks, such as Apache MXNet, TensorFlow, PyTorch, and Chainer. For a full list of the available SageMaker images, see Available Deep Learning Containers Images.

    If none of the existing SageMaker containers meet your needs, you may need to create your own Docker container. For information about how to create your Docker image and make it compatible with SageMaker, see Use Your Own Inference Code (p. 3191). To use your container with a serverless endpoint, the container image must reside in an Amazon ECR repository within the same AWS account that creates the endpoint.

7. **(Optional) Register your model with Model Registry.** SageMaker Model Registry (p. 2982) helps you catalog and manage versions of your models for use in ML pipelines. For more information about registering a version of your model, see Create a Model Group (p. 2983) and Register a Model Version (p. 2988). For an example of a Model Registry and Serverless Inference workflow, see the following example notebook.

8. **(Optional) Bring an AWS KMS key.** When setting up a serverless endpoint, you have the option to specify a KMS key that SageMaker uses to encrypt your Amazon ECR image. Note that the key policy for the KMS key must grant access to the IAM role you specify when setting up your endpoint. To learn more about KMS keys, see the AWS Key Management Service Developer Guide.

### Create a serverless endpoint

To create a serverless endpoint, you can use the Amazon SageMaker console, the APIs, or the AWS CLI. You can create a serverless endpoint using a similar process as a real-time endpoint (p. 2744).

#### Topics

- Create a model (p. 2928)
- Create an endpoint configuration (p. 2930)
- Create an endpoint (p. 2933)

### Create a model

To create your model, you must provide the location of your model artifacts and container image. You can also use a model version from SageMaker Model Registry (p. 2982). The examples in the following sections show you how to create a model using the CreateModel API, Model Registry, and the Amazon SageMaker console.

**To create a model (using Model Registry)**

Model Registry (p. 2982) is a feature of SageMaker that helps you catalog and manage versions of your model for use in ML pipelines. To use Model Registry with Serverless Inference, you must first register a model version in a Model Registry model group. To learn how to register a model in Model Registry, follow the procedures in Create a Model Group (p. 2983) and Register a Model Version (p. 2988).

The following example requires you to have the ARN of a registered model version and uses the AWS SDK for Python (Boto3) to call the CreateModel API. For Serverless Inference, Model Registry is currently only supported by the AWS SDK for Python (Boto3). For the example, specify the following values:

- For model_name, enter a name for the model.
- For sagemaker_role, you can use the default SageMaker-created role or a customized SageMaker IAM role from Step 4 of the Prerequisites (p. 2926) section.
- For ModelPackageName, specify the ARN for your model version, which must be registered to a model group in Model Registry.
#Setup
```python
import boto3
import sagemaker
region = boto3.Session().region_name
client = boto3.client("sagemaker", region_name=region)
```

#Role to give SageMaker permission to access AWS services.
```python
sagemaker_role = sagemaker.get_execution_role()
```

#Specify a name for the model
```python
model_name = "<name-for-model>"
```

#Specify a Model Registry model version
```python
container_list = [
    {
        "ModelPackageName": <model-version-arn>
    }
]
```

#Create the model
```python
response = client.create_model(
    ModelName = model_name,
    ExecutionRoleArn = sagemaker_role,
    container_list
)
```

To create a model (using API)

The following example uses the AWS SDK for Python (Boto3) to call the `CreateModel` API. Specify the following values:

- For `sagemaker_role`, you can use the default SageMaker-created role or a customized SageMaker IAM role from Step 4 of the Prerequisites (p. 2926) section.
- For `model_url`, specify the Amazon S3 URI to your model.
- For `container`, retrieve the container you want to use by its Amazon ECR path. This example uses a SageMaker-provided XGBoost container. If you have not selected a SageMaker container or brought your own, see Step 6 of the Prerequisites (p. 2926) section for more information.
- For `model_name`, enter a name for the model.

```python
#Setup
import boto3
import sagemaker
region = boto3.Session().region_name
client = boto3.client("sagemaker", region_name=region)
```

#Role to give SageMaker permission to access AWS services.
```python
sagemaker_role = sagemaker.get_execution_role()
```

#Get model from S3
```python
model_url = "s3://DOC-EXAMPLE-BUCKET/models/model.tar.gz"
```

#Get container image (prebuilt example)
```python
from sagemaker import image_uris
container = image_uris.retrieve("xgboost", region, "0.90-1")
```

#Create model
```python
model_name = "<name-for-model>"
response = client.create_model(
    ModelName = model_name,
    ExecutionRoleArn = sagemaker_role,
    container_list
)
```

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ExecutionRoleArn = sagemaker_role,
Containers = [
    "Image": container,
    "Mode": "SingleModel",
    "ModelDataUrl": model_url,
]

To create a model (using the console)

1. Sign in to the Amazon SageMaker console.
2. In the navigation tab, choose Inference.
3. Next, choose Models.
4. Choose Create model.
5. For Model name, enter a name for the model that is unique to your account and AWS Region.
6. For IAM role, either select an IAM role you have already created (see Prerequisites (p. 2926)) or allow SageMaker to create one for you.
7. In Container definition 1, for Container input options, select Provide model artifacts and input location.
8. For Provide model artifacts and inference image options, select Use a single model.
9. For Location of inference code image, enter an Amazon ECR path to a container. The image must either be a SageMaker-provided first party image (e.g. TensorFlow, XGBoost) or an image that resides in an Amazon ECR repository within the same account in which you are creating the endpoint. If you do not have a container, go back to Step 6 of the Prerequisites (p. 2926) section for more information.
10. For Location of model artifacts, enter the Amazon S3 URI to your ML model. For example, s3://DOC-EXAMPLE-BUCKET/models/model.tar.gz.
11. (Optional) For Tags, add key-value pairs to create metadata for your model.
12. Choose Create model.

Create an endpoint configuration

After you create a model, create an endpoint configuration. You can then deploy your model using the specifications in your endpoint configuration. In the configuration, you specify whether you want a real-time or serverless endpoint. To create a serverless endpoint configuration, you can use the Amazon SageMaker console, the CreateEndpointConfig API, or the AWS CLI. The API and console approaches are outlined in the following sections.

To create an endpoint configuration (using API)

The following example uses the AWS SDK for Python (Boto3) to call the CreateEndpointConfig API. Specify the following values:

- For EndpointConfigName, choose a name for the endpoint configuration. The name should be unique within your account in a Region.
- (Optional) For KmsKeyId, use the key ID, key ARN, alias name, or alias ARN for an AWS KMS key that you want to use. SageMaker uses this key to encrypt your Amazon ECR image.
- For ModelName, use the name of the model you want to deploy. It should be the same model that you used in the Create a model (p. 2928) step.
- For ServerlessConfig:
  - Set MemorySizeInMB to 2048. For this example, we set the memory size to 2048 MB, but you can choose any of the following values for your memory size: 1024 MB, 2048 MB, 3072 MB, 4096 MB, 5120 MB, or 6144 MB.
- Set MaxConcurrency to 20. For this example, we set the maximum concurrency to 20. The maximum number of concurrent invocations you can set for a serverless endpoint is 200, and the minimum value you can choose is 1.

```python
response = client.create_endpoint_config(
    EndpointConfigName="<your-endpoint-configuration>",
    KmsKeyId="arn:aws:kms:us-east-1:123456789012:key/143ef68f-76fd-45e3-abba-ed28fc8d3d5e",
    ProductionVariants=[
        {
            "ModelName": "<your-model-name>",
            "VariantName": "AllTraffic",
            "ServerlessConfig": {
                "MemorySizeInMB": 2048,
                "MaxConcurrency": 20
            }
        }
    ]
)
```

To create an endpoint configuration (using the console)

1. Sign in to the Amazon SageMaker console.
2. In the navigation tab, choose Inference.
3. Next, choose Endpoint configurations.
4. Choose Create endpoint configuration.
5. For Endpoint configuration name, enter a name that is unique within your account in a Region.
6. For Type of endpoint, select Serverless.
7. For Production variants, choose Add model.
8. Under Add model, select the model you want to use from the list of models and then choose Save.
9. After adding your model, under Actions, choose Edit.
10. For Memory size, choose the memory size you want in GB.
11. For **Max Concurrency**, enter your desired maximum concurrent invocations for the endpoint. The maximum value you can enter is 200 and the minimum is 1.

12. Choose **Save**.

13. (Optional) For **Tags**, enter key-value pairs if you want to create metadata for your endpoint configuration.

14. Choose **Create endpoint configuration**.

### Create an endpoint

To create a serverless endpoint, you can use the Amazon SageMaker console, the `CreateEndpoint` API, or the AWS CLI. The API and console approaches are outlined in the following sections. Once you create your endpoint, it can take a few minutes for the endpoint to become available.

#### To create an endpoint (using API)

The following example uses the AWS SDK for Python (Boto3) to call the `CreateEndpoint` API. Specify the following values:

- For **EndpointName**, enter a name for the endpoint that is unique within a Region in your account.
- For **EndpointConfigName**, use the name of the endpoint configuration that you created in the previous section.

```python
response = client.create_endpoint(
    EndpointName="<your-endpoint-name>",
    EndpointConfigName="<your-endpoint-config>"
)```
To create an endpoint (using the console)

1. Sign in to the Amazon SageMaker console.
2. In the navigation tab, choose Inference.
3. Next, choose Endpoints.
4. Choose Create endpoint.
5. For Endpoint name, enter a name than is unique within a Region in your account.
6. For Attach endpoint configuration, select Use an existing endpoint configuration.
7. For Endpoint configuration, select the name of the endpoint configuration you created in the previous section and then choose Select endpoint configuration.
8. (Optional) For Tags, enter key-value pairs if you want to create metadata for your endpoint.
9. Choose Create endpoint.
Create and configure endpoint

To deploy models to Amazon SageMaker, first create an endpoint. Provide an endpoint configuration to specify which models to deploy and the hardware requirements for each. See Deploying a Model on Amazon SageMaker Hosting Services for more information about the API.

### Endpoint

**Endpoint name**
Your application uses this name to access this endpoint.

```plaintext
example-endpoint
```

Maximum of 63 alphanumeric characters. Can include hyphens (-), but not spaces. Must be unique within your account in an AWS Region.

### Attach endpoint configuration

- **Use an existing endpoint configuration**
  Use an existing endpoint configuration or clone an endpoint configuration.

- **Create a new endpoint configuration**
  Add models and configure the instance and initial weight for each model.

### New endpoint configuration

<table>
<thead>
<tr>
<th>Endpoint configuration name</th>
<th>Encryption key</th>
</tr>
</thead>
<tbody>
<tr>
<td>example-epc</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Production variants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model name</td>
</tr>
<tr>
<td>------------</td>
</tr>
<tr>
<td>example-model</td>
</tr>
</tbody>
</table>

### Tags - optional

<table>
<thead>
<tr>
<th>Key</th>
<th>Value</th>
<th>Remove</th>
</tr>
</thead>
</table>

Add tag

Create endpoint
Invoke a serverless endpoint

In order to perform inference using a serverless endpoint, you must send an HTTP request to the endpoint. You can use the `InvokeEndpoint` API or the AWS CLI, which make a POST request to invoke your endpoint. The maximum request and response payload size for serverless invocations is 4 MB. Note that a cold start (or a delay in spinning up compute resources) on the endpoint may delay the response time to up to 4 minutes:

- The model must download and the server must respond successfully to `/ping` within 3 minutes.
- The timeout for the container to respond to inference requests to `/invocations` is 1 minute.

For more information on cold starts for serverless endpoints, see Cold starts (p. 2925).

To invoke an endpoint

The following example uses the AWS SDK for Python (Boto3) to call the `InvokeEndpoint` API. Note that unlike the other API calls in this guide, for `InvokeEndpoint`, you must use SageMaker Runtime as the client. Specify the following values:

- For `endpoint_name`, use the name of the in-service serverless endpoint you want to invoke.
- For `content_type`, specify the MIME type of your input data in the request body (for example, `application/json`).
- For `payload`, use your request payload for inference. Your payload should be in bytes or a file-like object.

```python
runtime = boto3.client("sagemaker-runtime")
endpoint_name = "<your-endpoint-name>"
content_type = "<request-mime-type>"
payload = <your-request-body>
response = client.invoke_endpoint(
    EndpointName=endpoint_name,
    ContentType=content_type,
    Body=payload
)
```

Update a serverless endpoint

Before updating your endpoint, create a new endpoint configuration or use an existing endpoint configuration. The endpoint configuration is where you specify the changes for your update. Then, you can update your endpoint with the SageMaker console, the `UpdateEndpoint` API, or the AWS CLI. The process for updating a serverless endpoint is the same as the process for updating a real-time endpoint (p. 2744). Note that when updating your endpoint, you can experience cold starts when making requests to the endpoint because SageMaker must re-initialize your container and model.

Create a new endpoint configuration

To create a new serverless endpoint configuration, see the previous procedure in Create an endpoint configuration (p. 2930). You can also create a real-time endpoint configuration to switch from serverless to instance-based capacity.

Update the endpoint

Examples of how to update your endpoint using the `UpdateEndpoint` API and the SageMaker console are outlined in the following sections.
To update the endpoint (using API)

The following example uses the AWS SDK for Python (Boto3) to call the UpdateEndpoint API. Specify the following values:

- For EndpointName, use the name of the endpoint you're updating.
- For EndpointConfigName, use the name of the endpoint configuration that you want to use for the update.

```python
response = client.update_endpoint(
    EndpointName="<your-endpoint-name>",
    EndpointConfigName="<new-endpoint-config>",
)
```

To update the endpoint (using the console)

1. Sign in to the Amazon SageMaker console.
2. In the navigation tab, choose Inference.
3. Next, choose Endpoints.
4. From the list of endpoints, select the endpoint you want to update.
5. Choose Update endpoint.
6. For Change the Endpoint configuration, choose Use an existing endpoint configuration.
7. From the list of endpoint configurations, select the one you want to use for your update.
8. Choose Select endpoint configuration.
9. Choose Update endpoint.

Describe a serverless endpoint

You might want to retrieve information about your endpoint, including details such as the endpoint's ARN, current status, deployment configuration, and failure reasons. You can find information about your endpoint using the SageMaker console, the DescribeEndpoint API, or the AWS CLI.

To describe an endpoint (using API)

The following example uses the AWS SDK for Python (Boto3) to call the DescribeEndpoint API. For EndpointName, use the name of the endpoint you want to check.

```python
response = client.describe_endpoint(
    EndpointName="<your-endpoint-name>",
)
```

To describe an endpoint (using the console)

1. Sign in to the Amazon SageMaker console.
2. In the navigation tab, choose Inference.
3. Next, choose Endpoints.
4. From the list of endpoints, choose the endpoint you want to check.

The endpoint page contains the information about your endpoint.
Delete a serverless endpoint

You can delete your serverless endpoint using the SageMaker console, the DeleteEndpoint API, or the AWS CLI. The following examples show you how to delete your endpoint through the API and the SageMaker console.

To delete an endpoint (using API)

The following example uses the AWS SDK for Python (Boto3) to call the DeleteEndpoint API. For EndpointName, use the name of the serverless endpoint you want to delete.

```python
response = client.delete_endpoint(
    EndpointName="<your-endpoint-name>",
)
```

To delete an endpoint (using the console)

1. Sign in to the Amazon SageMaker console.
2. In the navigation tab, choose Inference.
3. Next, choose Endpoints.
4. From the list of endpoints, select the endpoint you want to delete.
5. Choose the Actions drop-down list, and then choose Delete.
6. When prompted again, choose Delete.

Your endpoint should now begin the deletion process.

Monitor a Serverless Endpoint

To monitor your serverless endpoint, you can use Amazon CloudWatch alarms. CloudWatch is a service that collects metrics in real time from your AWS applications and resources. An alarm watches metrics as they are collected and gives you the ability to pre-specify a threshold and the actions to take if that threshold is breached. For example, your CloudWatch alarm can send you a notification if your endpoint breaches an error threshold. By setting up CloudWatch alarms, you gain visibility into the performance and functionality of your endpoint.

To learn more about CloudWatch metrics you can use to monitor your endpoints in SageMaker, see SageMaker Endpoint Invocation Metrics (p. 3664). The ModelSetupTime metric tracks the cold start time for your endpoint, or the time it takes to launch new compute resources for your serverless endpoint. This metric depends on your model size and the container’s start-up time. Serverless endpoints can also use the Invocations4XXErrors, Invocations5XXErrors, and Invocations metrics in the AWS/SageMaker namespace. In the aws/sagemaker/Endpoints namespace, they can use the MemoryUtilization metric. For more information about CloudWatch alarms, see Using Amazon CloudWatch alarms in the Amazon CloudWatch User Guide.

If you want to monitor the logs from your endpoint for debugging or progress analysis, you can use Amazon CloudWatch Logs. The SageMaker-provided log group that you can use for serverless endpoints is /aws/sagemaker/endpoints/[EndpointName]. For more information about using CloudWatch Logs in SageMaker, see Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675). To learn more about CloudWatch Logs, see What is Amazon CloudWatch Logs in the Amazon CloudWatch Logs User Guide.

Troubleshooting

If you are having trouble with Serverless Inference, refer to the following troubleshooting tips.
Container issues

If the container you use for a serverless endpoint is the same one you used on an instance-based endpoint, your container may not have permissions to write files. This can happen for the following reasons:

- Your serverless endpoint fails to create or update due to a ping health check failure.
- The Amazon CloudWatch logs for the endpoint show that the container is failing to write to some file or directory due to a permissions error.

To fix this issue, you can try to add read, write, and execute permissions for other on the file or directory and then rebuild the container. You can perform the following steps to complete this process:

1. In the Dockerfile you used to build your container, add the following command: `RUN chmod o+rwx <file or directory name>`
2. Rebuild the container.
3. Upload the new container image to Amazon ECR.
4. Try to create or update the serverless endpoint again.

Asynchronous inference

Amazon SageMaker Asynchronous Inference is a new capability in SageMaker that queues incoming requests and processes them asynchronously. This option is ideal for requests with large payload sizes (up to 1GB), long processing times (up to 15 minutes), and near real-time latency requirements. Asynchronous Inference enables you to save on costs by autoscaling the instance count to zero when there are no requests to process, so you only pay when your endpoint is processing requests.

How It Works

Creating an asynchronous inference endpoint is similar to creating real-time inference endpoints. You can use your existing SageMaker models and only need to specify the AsyncInferenceConfig object while creating your endpoint configuration with the EndpointConfig field in the CreateEndpointConfig API. The following diagram shows the architecture and workflow of Asynchronous Inference.
To invoke the endpoint, you need to place the request payload in Amazon S3 and provide a pointer to this payload as a part of the `InvokeEndpointAsync` request. Upon invocation, SageMaker queues the request for processing and returns an identifier and output location as a response. Upon processing, SageMaker places the result in the Amazon S3 location. You can optionally choose to receive success or error notifications with Amazon SNS. For more information about how to set up asynchronous notifications, see Check prediction results (p. 2951).

**Note**
The presence of an asynchronous inference configuration (`AsyncInferenceConfig`) object in the endpoint configuration implies that the endpoint can only receive asynchronous invocations.

## How Do I Get Started?

If you are a first-time user of Amazon SageMaker Asynchronous Inference, we recommend that you do the following:

- Read Create, invoke, and update an Asynchronous Endpoint (p. 2940) for information on how to create, invoke, update, and delete an asynchronous endpoint.
- Explore the Asynchronous Inference example notebook in the aws/amazon-sagemaker-examples GitHub repository.

Note that if your endpoint uses any of the features listed in this Exclusions (p. 2980) page, you cannot use Asynchronous Inference.

## Create, invoke, and update an Asynchronous Endpoint

This guide demonstrates the prerequisites you must satisfy to create an asynchronous endpoint, along with how to create, invoke, and delete your asynchronous endpoints. You can create, update, delete, and invoke asynchronous endpoints with the AWS SDKs and the Amazon SageMaker Python SDK.

**Topics**
- Prerequisites (p. 2941)
Prerequisites

To use asynchronous endpoints, first make sure you have met these prerequisites.

1. **Create an IAM role for Amazon SageMaker.**

   Asynchronous Inference needs access to your Amazon S3 bucket URI. To facilitate this, create an IAM role that can run SageMaker and has permission to access Amazon S3 and Amazon SNS. Using this role, SageMaker can run under your account and access your Amazon S3 bucket and Amazon SNS topics.

   You can create an IAM role by using the IAM console, AWS SDK for Python (Boto3), or AWS CLI. The following is an example of how to create an IAM role and attach the necessary policies with the IAM console.

   a. Sign in to the AWS Management Console and open the IAM console at https://console.aws.amazon.com/iam/.
   b. In the navigation pane of the IAM console, choose Roles, and then choose Create role.
   c. For Select type of trusted entity, choose AWS service.
   d. Choose the service that you want to allow to assume this role. In this case, choose SageMaker. Then choose Next: Permissions.
   - This automatically creates an IAM policy that grants access to related services such as Amazon S3, Amazon ECR, and CloudWatch Logs.
   e. Choose Next: Tags.
   f. (Optional) Add metadata to the role by attaching tags as key–value pairs. For more information about using tags in IAM, see Tagging IAM resources.
   g. Choose Next: Review.
   h. Type in a Role name.
   i. If possible, type a role name or role name suffix. Role names must be unique within your AWS account. They are not distinguished by case. For example, you cannot create roles named both PRODROLE and prodrole. Because other AWS resources might reference the role, you cannot edit the name of the role after it has been created.
   j. (Optional) For Role description, type a description for the new role.
   k. Review the role and then choose Create role.

   Note the SageMaker role ARN. To find the role ARN using the console, do the following:
   i. Go to the IAM console: https://console.aws.amazon.com/iam/
   ii. Select Roles.
   iii. Search for the role you just created by typing in the name of the role in the search field.
   iv. Select the role.
   v. The role ARN is at the top of the Summary page.

2. **Add Amazon SageMaker, Amazon S3 and Amazon SNS Permissions to your IAM Role.**

   Once the role is created, grant SageMaker, Amazon S3, and optionally Amazon SNS permissions to your IAM role.
Choose Roles in the IAM console. Search for the role you created by typing in your role name in the Search field.

a. Choose your role.

b. Next, choose Attach Policies.

c. Amazon SageMaker Asynchronous Inference needs permission to perform the following actions: "sagemaker:CreateModel", "sagemaker:CreateEndpointConfig", "sagemaker:CreateEndpoint", and "sagemaker:InvokeEndpointAsync".

These actions are included in the AmazonSageMakerFullAccess policy. Add this policy to your IAM role. Search for AmazonSageMakerFullAccess in the Search field. Select AmazonSageMakerFullAccess.

d. Choose Attach policy.

e. Next, choose Attach Policies to add Amazon S3 permissions.

f. Select Create policy.

g. Select the JSON tab.

h. Add the following policy statement:

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Resource": "arn:aws:s3:::bucket_name/*"
    }
  ]
}
```

i. Choose Next: Tags.

j. Type in a Policy name.

k. Choose Create policy.

l. Repeat the same steps you completed to add Amazon S3 permissions in order to add Amazon SNS permissions. For the policy statement, attach the following:

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Action": ["sns:Publish"],
      "Effect": "Allow",
    }
  ]
}
```

3. Upload your inference data (e.g., machine learning model, sample data) to Amazon S3.

4. Select a prebuilt Docker inference image or create your own Inference Docker Image.
SageMaker provides containers for its built-in algorithms and prebuilt Docker images for some of the most common machine learning frameworks, such as Apache MXNet, TensorFlow, PyTorch, and Chainer. For a full list of the available SageMaker images, see Available Deep Learning Containers Images. If you choose to use a SageMaker provided container, you can increase the endpoint timeout and payload sizes from the default by setting the environment variables in the container. To learn how to set the different environment variables for each framework, see the Create a Model step of creating an asynchronous endpoint.

If none of the existing SageMaker containers meet your needs and you don't have an existing container of your own, you may need to create a new Docker container. See Use Your Own Inference Code (p. 3191) for information on how to create your Docker image.

5. **Create an Amazon SNS topic (optional)**

Create an Amazon Simple Notification Service (Amazon SNS) topic that sends notifications about requests that have completed processing. Amazon SNS is a notification service for messaging-oriented applications, with multiple subscribers requesting and receiving "push" notifications of time-critical messages via a choice of transport protocols, including HTTP, Amazon SQS, and email. You can specify Amazon SNS topics when you create an EndpointConfig object when you specify AsyncInferenceConfig using the EndpointConfig API.

Follow the steps to create and subscribe to an Amazon SNS topic.

a. Using Amazon SNS console, create a topic. For instructions, see Creating an Amazon SNS topic in the Amazon Simple Notification Service Developer Guide.

b. Subscribe to the topic. For instructions, see Subscribing to an Amazon SNS topic in the Amazon Simple Notification Service Developer Guide.

c. When you receive email requesting that you confirm your subscription to the topic, confirm the subscription.

d. Note the topic Amazon Resource Name (ARN). The Amazon SNS topic you created is another resource in your AWS account, and it has a unique ARN. The ARN is in the following format:

```
arn:aws:sns:aws-region:account-id:topic-name
```

For more information about Amazon SNS, see the Amazon SNS Developer Guide.

### Create an Asynchronous Inference Endpoint

Create an asynchronous endpoint the same way you would create an endpoint using SageMaker hosting services:

- Create a model in SageMaker with CreateModel.
- Create an endpoint configuration with CreateEndpointConfig.
- Create an HTTPS endpoint with CreateEndpoint.

To create an endpoint, you first create a model with CreateModel, where you point to the model artifact and a Docker registry path (Image). You then create a configuration using CreateEndpointConfig where you specify one or more models that were created using the CreateModel API to deploy and the resources that you want SageMaker to provision. Create your endpoint with CreateEndpoint using the endpoint configuration specified in the request. You can update an asynchronous endpoint with the UpdateEndpoint API. Send and receive inference requests from the model hosted at the endpoint with InvokeEndpointAsync. You can delete your endpoints with the DeleteEndpoint API.
Create a Model

The following example shows how to create a model using the AWS SDK for Python (Boto3). The first few lines define:

- `sagemaker_client`: A low-level SageMaker client object that makes it easy to send and receive requests to AWS services.
- `sagemaker_role`: A string variable with the SageMaker IAM role Amazon Resource Name (ARN).
- `aws_region`: A string variable with the name of your AWS region.

```python
import boto3
# Specify your AWS Region
aws_region='<aws_region>'

# Create a low-level SageMaker service client.
sagemaker_client = boto3.client('sagemaker', region_name=aws_region)

# Role to give SageMaker permission to access AWS services.
sagemaker_role = "arn:aws:iam::<account>::role/*"
```

Next, specify the location of the pre-trained model stored in Amazon S3. In this example, we use a pre-trained XGBoost model named `demo-xgboost-model.tar.gz`. The full Amazon S3 URI is stored in a string variable `model_url`:

```python
#Create a variable w/ the model S3 URI
s3_bucket = '<your-bucket-name>' # Provide the name of your S3 bucket
bucket_prefix='saved_models'
model_s3_key = f'{bucket_prefix}/demo-xgboost-model.tar.gz'

#Specify S3 bucket w/ model
model_url = f"s3://{s3_bucket}/{model_s3_key}"
```

Specify a primary container. For the primary container, you specify the Docker image that contains inference code, artifacts (from prior training), and a custom environment map that the inference code uses when you deploy the model for predictions.

In this example, we specify an XGBoost built-in algorithm container image:

```python
from sagemaker import image_uris

# Specify an AWS container image.
container = image_uris.retrieve(region=aws_region, framework='xgboost', version='0.90-1')
```

Create a model in Amazon SageMaker with `CreateModel`. Specify the following:

- `ModelName`: A name for your model (in this example it is stored as a string variable called `model_name`).
- `ExecutionRoleArn`: The Amazon Resource Name (ARN) of the IAM role that Amazon SageMaker can assume to access model artifacts and Docker images for deployment on ML compute instances or for batch transform jobs.
- `PrimaryContainer`: The location of the primary Docker image containing inference code, associated artifacts, and custom environment maps that the inference code uses when the model is deployed for predictions.
```python
model_name = '<The_name_of_the_model>'

# Create model
create_model_response = sagemaker_client.create_model(
    ModelName = model_name,
    ExecutionRoleArn = sagemaker_role,
    PrimaryContainer = {
        'Image': container,
        'ModelDataUrl': model_url,
    },
)
```


If you're using a SageMaker provided container, you can increase the model server timeout and payload sizes from the default values to the framework-supported maximums by setting environment variables in this step. You might not be able to leverage the maximum timeout and payload sizes that Asynchronous Inference supports if you don't explicitly set these variables. The following example shows how you can set the environment variables for a PyTorch Inference container based on TorchServe.

```python
model_name = '<The_name_of_the_model>'

# Create model
create_model_response = sagemaker_client.create_model(
    ModelName = model_name,
    ExecutionRoleArn = sagemaker_role,
    PrimaryContainer = {
        'Image': container,
        'ModelDataUrl': model_url,
        'Environment': {
            'TS_MAX_REQUEST_SIZE': '100000000',
            'TS_MAX_RESPONSE_SIZE': '100000000',
            'TS_DEFAULT_RESPONSE_TIMEOUT': '1000',
        },
    },
)
```

After you finish creating your endpoint, you should test that you've set the environment variables correctly by printing them out from your `inference.py` script. The following table lists the environment variables for several frameworks that you can set to change the default values.

<table>
<thead>
<tr>
<th>Framework</th>
<th>Environment variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>PyTorch 1.8 (based on TorchServe)</td>
<td>'TS_MAX_REQUEST_SIZE': '1000000000'</td>
</tr>
<tr>
<td></td>
<td>'TS_MAX_RESPONSE_SIZE': '1000000000'</td>
</tr>
<tr>
<td></td>
<td>'TS_DEFAULT_RESPONSE_TIMEOUT': '1000'</td>
</tr>
<tr>
<td>PyTorch 1.4 (based on MMS)</td>
<td>'MMS_MAX_REQUEST_SIZE': '1000000000000'</td>
</tr>
<tr>
<td></td>
<td>'MMS_MAX_RESPONSE_SIZE': '10000000000000'</td>
</tr>
<tr>
<td></td>
<td>'MMS_DEFAULT_RESPONSE_TIMEOUT': '900'</td>
</tr>
<tr>
<td>HuggingFace Inference Container (based on MMS)</td>
<td>'MMS_MAX_REQUEST_SIZE': '20000000000000'</td>
</tr>
<tr>
<td></td>
<td>'MMS_MAX_RESPONSE_SIZE': '20000000000000'</td>
</tr>
<tr>
<td></td>
<td>'MMS_DEFAULT_RESPONSE_TIMEOUT': '900'</td>
</tr>
</tbody>
</table>
Create an Endpoint Configuration

Once you have a model, create an endpoint configuration with `CreateEndpointConfig`. Amazon SageMaker hosting services uses this configuration to deploy models. In the configuration, you identify one or more models, created using with `CreateModel`, to deploy the resources that you want Amazon SageMaker to provision. Specify the `AsyncInferenceConfig` object and provide an output Amazon S3 location for `OutputConfig`. You can optionally specify Amazon SNS topics on which to send notifications about prediction results. For more information about Amazon SNS topics, see Configuring Amazon SNS.

The following example shows how to create an endpoint configuration using AWS SDK for Python (Boto3):

```python
import datetime
from time import gmtime, strftime

# Create an endpoint config name. Here we create one based on the date
# so it we can search endpoints based on creation time.
endpoint_config_name = f"XGBoostEndpointConfig-{strftime('%Y-%m-%d-%H-%M-%S', gmtime())}"

# The name of the model that you want to host. This is the name that you specified when
creating the model.
model_name="<The_name_of_your_model>"

create_endpoint_config_response = sagemaker_client.create_endpoint_config(
    EndpointConfigName=endpoint_config_name,  # You will specify this name in a
    # CreateEndpoint request.
    # List of ProductionVariant objects, one for each model that you want to host at this
    # endpoint.
    ProductionVariants=[
        {
            "VariantName": "variant1",  # The name of the production variant.
            "ModelName": model_name,
            "InstanceType": "ml.m5.xlarge",  # Specify the compute instance type.
            "InitialInstanceCount": 1  # Number of instances to launch initially.
        }
    ],
    AsyncInferenceConfig={
        "OutputConfig": {
            # Location to upload response outputs when no location is provided in the
            # request.
            "S3OutputPath": f"s3://{s3_bucket}/{bucket_prefix}/output"
            # (Optional) specify Amazon SNS topics
            "NotificationConfig": {
            }
        },
        "ClientConfig": {
            # (Optional) Specify the max number of inflight invocations per instance
            # If no value is provided, Amazon SageMaker will choose an optimal value for
            # you
            "MaxConcurrentInvocationsPerInstance": 4
        }
    }
)

print(f"Created EndpointConfig: {create_endpoint_config_response['EndpointConfigArn']}")
```

In the aforementioned example, you specify the following keys for `OutputConfig` for the `AsyncInferenceConfig` field:

- `S3OutputPath`: Location to upload response outputs when no location is provided in the request.
Create, invoke, and update an Asynchronous Endpoint

- NotificationConfig: (Optional) SNS topics that post notifications to you when an inference request is successful (SuccessTopic) or if it fails (ErrorTopic).

You can also specify the following optional argument for ClientConfig in the AsyncInferenceConfig field:
- MaxConcurrentInvocationsPerInstance: (Optional) The maximum number of concurrent requests sent by the SageMaker client to the model container.

Create Endpoint

Once you have your model and endpoint configuration, use the CreateEndpoint API to create your endpoint. The endpoint name must be unique within an AWS Region in your AWS account.

The following creates an endpoint using the endpoint configuration specified in the request. Amazon SageMaker uses the endpoint to provision resources and deploy models.

```python
# The name of the endpoint. The name must be unique within an AWS Region in your AWS account.
endpoint_name = '<endpoint-name>'

# The name of the endpoint configuration associated with this endpoint.
endpoint_config_name = '<endpoint-config-name>'

create_endpoint_response = sagemaker_client.create_endpoint(
    EndpointName=endpoint_name,
    EndpointConfigName=endpoint_config_name)
```

When you call the CreateEndpoint API, Amazon SageMaker Asynchronous Inference sends a test notification to check that you have configured an Amazon SNS topic. Amazon SageMaker Asynchronous Inference also sends test notifications after calls to UpdateEndpoint and UpdateEndpointWeightsAndCapacities. This lets SageMaker check that you have the required permissions. The notification can simply be ignored. The test notification has the following form:

```json
{
    "eventVersion": "1.0",
    "eventSource": "aws:sagemaker",
    "eventName": "TestNotification"
}
```

Invoke an Asynchronous Endpoint

Get inferences from the model hosted at your asynchronous endpoint with InvokeEndpointAsync.

**Note**
If you have not done so already, upload your inference data (e.g., machine learning model, sample data) to Amazon S3.

Specify the location of your inference data in the InputLocation field and the name of your endpoint for EndpointName:

```python
# Create a low-level client representing Amazon SageMaker Runtime
sagemaker_runtime = boto3.client("sagemaker-runtime", region_name=<aws_region>)

# Specify the location of the input. Here, a single SVM sample
input_location = "s3://bucket-name/test_point_0.libsvm"
```
Create, invoke, and update an Asynchronous Endpoint

# The name of the endpoint. The name must be unique within an AWS Region in your AWS account.
endpoint_name='<endpoint-name>'

# After you deploy a model into production using SageMaker hosting services, your client applications use this API to get inferences from the model hosted at the specified endpoint.
response = sagemaker_runtime.invoke_endpoint_async(  
    EndpointName=endpoint_name,  
    InputLocation=input_location)

You receive a response as a JSON string with your request ID and the name of the Amazon S3 bucket that will have the response to the API call after it is processed.

Update an Asynchronous Endpoint

Update an asynchronous endpoint with the UpdateEndpoint API. When you update an endpoint, SageMaker first provisions and switches to the new endpoint configuration you specify before it deletes the resources that were provisioned in the previous endpoint configuration. Do not delete an EndpointConfig with an endpoint that is live or while the UpdateEndpoint or CreateEndpoint operations are being performed on the endpoint.

# The name of the endpoint. The name must be unique within an AWS Region in your AWS account.
endpoint_name='<endpoint-name>'

# The name of the endpoint configuration associated with this endpoint.
endpoint_config_name='<endpoint-config-name>'

sagemaker_client.update_endpoint(  
    EndpointConfigName=endpoint_config_name,  
    EndpointName=endpoint_name )

When Amazon SageMaker receives the request, it sets the endpoint status to Updating. After updating the asynchronous endpoint, it sets the status to InService. To check the status of an endpoint, use the DescribeEndpoint API. For a full list of parameters you can specify when updating an endpoint, see the UpdateEndpoint API.

Delete an Asynchronous Endpoint

Delete an asynchronous endpoint in a similar manner to how you would delete a SageMaker hosted endpoint with the DeleteEndpoint API. Specify the name of the asynchronous endpoint you want to delete. When you delete an endpoint, SageMaker frees up all of the resources that were deployed when the endpoint was created. Deleting a model does not delete model artifacts, inference code, or the IAM role that you specified when creating the model.

Delete your SageMaker model with the DeleteModel API or with the SageMaker console.

Boto3

import boto3

# Create a low-level SageMaker service client.
sagemaker_client = boto3.client('sagemaker', region_name='<aws_region>')
sagemaker_client.delete_endpoint(EndpointName='<endpoint-name>')

SageMaker console


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Monitor asynchronous endpoint

In addition to deleting the asynchronous endpoint, you might want to clear up other resources that were used to create the endpoint, such as the Amazon ECR repository (if you created a custom inference image), the SageMaker model, and the asynchronous endpoint configuration itself.

### Monitor asynchronous endpoint

You can monitor SageMaker using Amazon CloudWatch, which collects raw data and processes it into readable, near real-time metrics. With Amazon CloudWatch, you can access historical information and gain a better perspective on how your web application or service is performing. For more information about Amazon CloudWatch, see What is Amazon CloudWatch?

### Monitoring with CloudWatch

The metrics below are an exhaustive list of metrics for asynchronous endpoints. Any metric not listed below is not published if the endpoint is enabled for asynchronous inference. Such metrics include (but are not limited to):

- **OverheadLatency**
- **Invocations**
- **InvocationsPerInstance**

### Common Endpoint Metrics

These metrics are the same as the metrics published for real-time endpoints today. For more information about other metrics in Amazon CloudWatch, see Monitor SageMaker with Amazon CloudWatch.

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Unit/Stats</th>
</tr>
</thead>
<tbody>
<tr>
<td>Invocation4XXErrors</td>
<td>The number of requests where the model returned a 4xx HTTP response code. For each 4xx response, 1 is sent; otherwise, 0 is sent.</td>
<td>Units: None Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>Invocation5XXErrors</td>
<td>The number of InvokeEndpoint requests where the model returned a 5xx HTTP response code. For each 5xx response, 1 is sent; otherwise, 0 is sent.</td>
<td>Units: None Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>ModelLatency</td>
<td>The interval of time taken by a model to respond as viewed from SageMaker. This interval includes the local communication times taken to send the request and to fetch the response from the container</td>
<td>Units: Microseconds Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>Metric Name</td>
<td>Description</td>
<td>Unit/Stats</td>
</tr>
<tr>
<td>--------------------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>-------------------------------------</td>
</tr>
<tr>
<td>ApproximateBacklogSize</td>
<td>The number of items in the queue for an endpoint that are currently being processed or yet to be processed.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Max, Min</td>
</tr>
<tr>
<td>ApproximateBacklogSizePerInstance</td>
<td>Number of items in the queue divided by the number of instances behind an endpoint. This metric is primarily used for setting up application autoscaling for an async-enabled endpoint.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Max, Min</td>
</tr>
<tr>
<td>ApproximateAgeOfOldestRequest</td>
<td>Age of the oldest request in the queue.</td>
<td>Units: Seconds</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Max, Min</td>
</tr>
</tbody>
</table>

The following metrics are published with the EndpointName and VariantName dimensions:

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Unit/Stats</th>
</tr>
</thead>
<tbody>
<tr>
<td>RequestDownloadFailures</td>
<td>When an inference failure occurs due to an issue downloading the request from Amazon S3.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>ResponseUploadFailures</td>
<td>When an inference failure occurs due to an issue uploading the response to Amazon S3.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>NotificationFailures</td>
<td>When an issue occurs publishing notifications.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>RequestDownloadLatency</td>
<td>Total time to download the request payload.</td>
<td>Units: Microseconds</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>ResponseUploadLatency</td>
<td>Total time to upload the response payload.</td>
<td>Units: Microseconds</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
</tbody>
</table>

Asynchronous Inference Endpoint Metrics

These metrics are published for endpoints enabled for asynchronous inference. The following metrics are published with the EndpointName dimension:

<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Unit/Stats</th>
</tr>
</thead>
<tbody>
<tr>
<td>ApproximateBacklogSize</td>
<td>The number of items in the queue for an endpoint that are currently being processed or yet to be processed.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Max, Min</td>
</tr>
<tr>
<td>ApproximateBacklogSizePerInstance</td>
<td>Number of items in the queue divided by the number of instances behind an endpoint. This metric is primarily used for setting up application autoscaling for an async-enabled endpoint.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Max, Min</td>
</tr>
<tr>
<td>ApproximateAgeOfOldestRequest</td>
<td>Age of the oldest request in the queue.</td>
<td>Units: Seconds</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Max, Min</td>
</tr>
</tbody>
</table>

The following metrics are published with the EndpointName and VariantName dimensions:
<table>
<thead>
<tr>
<th>Metric Name</th>
<th>Description</th>
<th>Unit/Stats</th>
</tr>
</thead>
<tbody>
<tr>
<td>ExpiredRequests</td>
<td>Number of requests in the queue that fail due to reaching their specified request TTL.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>InvocationFailures</td>
<td>If an invocation fails for any reason.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>InvocationsProcessed</td>
<td>Number of async invocations processed by the endpoint.</td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>TimeInBacklog</td>
<td>Total time the request was queued before being processed. This does not include the actual processing time (i.e. downloading time, uploading time, model latency).</td>
<td>Units: Milliseconds</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>TotalProcessingTime</td>
<td>Time the inference request was received by SageMaker to the time the request finished processing. This includes time in backlog and time to upload and send response notifications, if any.</td>
<td>Units: Milliseconds</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
</tbody>
</table>

Amazon SageMaker Asynchronous Inference also includes host-level metrics. For information on host-level metrics, see [SageMaker Jobs and Endpoint Metrics](#).

**Logs**

In addition to the [Model container logs](#) that are published to Amazon CloudWatch in your account, you also get a new platform log for tracing and debugging inference requests.

The new logs are published under the Endpoint Log Group:

/aws/sagemaker/Endpoints/[EndpointName]

The log stream name consists of:

[production-variant-name]/[instance-id]/data-log.

Log lines contain the request’s inference ID so that errors can be easily mapped to a particular request.

**Check prediction results**

There are several ways you can check predictions results from your asynchronous endpoint. Some options are:

1. Amazon SNS topics.
2. Check for outputs in your Amazon S3 bucket.
Amazon SNS Topics

Amazon SNS is a notification service for messaging-oriented applications, with multiple subscribers requesting and receiving "push" notifications of time-critical messages via a choice of transport protocols, including HTTP, Amazon SQS, and email. Amazon SageMaker Asynchronous Inference posts notifications when you create an endpoint with `CreateEndpointConfig` and specify an Amazon SNS topic.

**Note**
In order to receive Amazon SNS notifications, your IAM role must have `sns:Publish` permissions. See the Prerequisites (p. 2941) for information on requirements you must satisfy to use Asynchronous Inference.

To use Amazon SNS to check prediction results from your asynchronous endpoint, you first need to create a topic, subscribe to the topic, confirm your subscription to the topic, and note the Amazon Resource Name (ARN) of that topic. For detailed information on how to create, subscribe, and find the Amazon ARN of an Amazon SNS topic, see Configuring Amazon SNS.

Provide the Amazon SNS topic ARN(s) in the AsyncInferenceConfig field when you create an endpoint configuration with `CreateEndpointConfig`. You can specify both an Amazon SNS ErrorTopic and a SuccessTopic.

```python
import boto3
sagemaker_client = boto3.client('sagemaker', region_name=<aws_region>)
sagemaker_client.create_endpoint_config(  
    EndpointConfigName=<endpoint_config_name>, # You specify this name in a CreateEndpoint request.  
    ProductionVariants=[  
        {  
            "VariantName": "variant1", # The name of the production variant.  
            "ModelName": "model_name",  
            "InstanceType": "ml.m5.xlarge", # Specify the compute instance type.  
            "InitialInstanceCount": 1 # Number of instances to launch initially.  
        }  
    ],  
    AsyncInferenceConfig={  
        "OutputConfig": {  
            # Location to upload response outputs when no location is provided in the request.  
            "S3OutputPath": "s3://<bucket>/<output_directory>"  
        }  
    })
```

After creating your endpoint and invoking it, you receive a notification from your Amazon SNS topic. For example, if you subscribed to receive email notifications from your topic, you receive an email notification every time you invoke your endpoint. The following example shows the JSON content of a successful invocation email notification.

```json
{
    "awsRegion": "us-east-1",
    "eventTime": "2022-01-25T22:46:00.608Z",
    "receivedTime": "2022-01-25T22:46:00.455Z",
    ...
}
```
Check Your S3 Bucket

When you invoke an endpoint with `InvokeEndpointAsync`, it returns a response object. You can use the response object to get the Amazon S3 URI where your output is stored. With the output location, you can use a SageMaker Python SDK SageMaker session class to programmatically check for on an output.

The following stores the output dictionary of `InvokeEndpointAsync` as a variable named `response`. With the response variable, you then get the Amazon S3 output URI and store it as a string variable called `output_location`.

```python
import uuid
import boto3

sagemaker_runtime = boto3.client("sagemaker-runtime", region_name=<aws_region>)

# Specify the S3 URI of the input. Here, a single SVM sample
input_location = "s3://bucket-name/test_point_0.libsvm"

response = sagemaker_runtime.invoke_endpoint_async(
    EndpointName='<endpoint-name>',
    InputLocation=input_location,
    InferenceId=str(uuid.uuid4()),
    ContentType="text/libsvm"  # Specify the content type of your data
)

output_location = response['OutputLocation']
print(f"OutputLocation: {output_location}"

```

For information about supported content types, see Common Data Formats for Inference (p. 1963).

With the Amazon S3 output location, you can then use a SageMaker Python SDK SageMaker Session Class to read in Amazon S3 files. The following code example shows how to create a function (`get_output`) that repeatedly attempts to read a file from the Amazon S3 output location:

```python
import sagemaker
import urllib, time
from botocore.exceptions import ClientError

sagemaker_session = sagemaker.session.Session()

def get_output(output_location):
    output_url = urllib.parse.urlparse(output_location)
    bucket = output_url.netloc
    key = output_url.path[1:]
    while True:
        try:
            s3 = boto3.resource("s3")
            s3.Bucket(bucket).download_file(key, local_file)
            return
```
Autoscale an asynchronous endpoint

Amazon SageMaker supports automatic scaling (autoscaling) your asynchronous endpoint. Autoscaling dynamically adjusts the number of instances provisioned for a model in response to changes in your workload. Unlike other hosted models Amazon SageMaker supports, with Asynchronous Inference you can also scale down your asynchronous endpoints instances to zero. Requests that are received when there are zero instances are queued for processing once the endpoint scales up.

To autoscale your asynchronous endpoint you must at a minimum:

- Register a deployed model (production variant).
- Define a scaling policy.
- Apply the autoscaling policy.

Before you can use autoscaling, you must have already created a SageMaker model deployment. Deployed models are referred to as a production variant. See Deploy the Model to SageMaker Hosting Services for more information about deploying a model endpoint. To specify the metrics and target values for a scaling policy, you configure a target-tracking scaling policy. For information on how to define a scaling policy, see Define a scaling policy. After registering your model and defining a scaling policy, apply the scaling policy to the registered model. For information on how to apply the scaling policy, see Apply a scaling policy.

For details on other prerequisites and components used with autoscaling, see the Prerequisites section in the SageMaker autoscaling documentation.

Define a Scaling Policy

To specify the metrics and target values for a scaling policy, you configure a target-tracking scaling policy. Define the scaling policy as a JSON block in a text file. You use that text file when invoking the AWS CLI or the Application Auto Scaling API. For more information about policy configuration syntax, see TargetTrackingScalingPolicyConfiguration in the Application Auto Scaling API Reference.

For asynchronous endpoints SageMaker strongly recommends that you create a policy configuration for target-tracking scaling for a variant. In this configuration example, we use a custom metric, CustomizedMetricSpecification, called ApproximateBacklogSizePerInstance.

```python
def get_output(output_location):
    output = sagemaker_session.read_s3_file(
        bucket=output_url.netloc,
        key_prefix=output_url.path[1:])
    except ClientError as e:
        if e.response['Error']['Code'] == 'NoSuchKey':
            print("waiting for output...")
            time.sleep(2)
            continue
        raise
    return sagemaker_session.read_s3_file(
        bucket=output_url.netloc,
        key_prefix=output_url.path[1:])
```

```python
TargetTrackingScalingPolicyConfiguration={
    'TargetValue': 5.0,  # The target value for the metric. Here the metric is:
    'SageMakerVariantInvocationsPerInstance'
    'CustomizedMetricSpecification': {
        'MetricName': 'ApproximateBacklogSizePerInstance',
        'Namespace': 'AWS/SageMaker',
        'Dimensions': [
            {'Name': 'EndpointName', 'Value': '<endpoint_name>'
        }
    },
```
Define a Scaling Policy that Scales to 0

The following shows you how to both define and register your endpoint variant with application autoscaling using the AWS SDK for Python (Boto3). After defining a low-level client object representing application autoscaling with Boto3, we use the `RegisterScalableTarget` method to register the production variant. We set `MinCapacity` to 0 because Asynchronous Inference enables you to autoscale to 0 when there are no requests to process.

```python
# Common class representing application autoscaling for SageMaker
client = boto3.client('application-autoscaling')

# This is the format in which application autoscaling references the endpoint
resource_id='endpoint/' + '<endpoint_name>' + '/variant/' + '<variant1>'

# Define and register your endpoint variant
response = client.register_scalable_target(
    ServiceNamespace='sagemaker',
    ResourceId=resource_id,
    ScalableDimension='sagemaker:variant:DesiredInstanceCount', # The number of EC2 instances for your Amazon SageMaker model endpoint variant.
    MinCapacity=0,
    MaxCapacity=5
)
```

For detailed description about the Application Autoscaling API, see the Application Scaling Boto3 documentation.

Use Batch Transform

Use batch transform when you need to do the following:

- Preprocess datasets to remove noise or bias that interferes with training or inference from your dataset.
- Get inferences from large datasets.
- Run inference when you don’t need a persistent endpoint.
- Associate input records with inferences to assist the interpretation of results.

To filter input data before performing inferences or to associate input records with inferences about those records, see Associate Prediction Results with Input Records (p. 2958). For example, you can filter input data to provide context for creating and interpreting reports about the output data.

Topics

- Use Batch Transform to Get Inferences from Large Datasets (p. 2956)
- Speed up a Batch Transform Job (p. 2957)
- Use Batch Transform to Test Production Variants (p. 2957)
- Batch Transform Errors (p. 2957)
- Batch Transform Sample Notebooks (p. 2958)
- Associate Prediction Results with Input Records (p. 2958)
- Storage in Batch Transform (p. 2963)
Use Batch Transform to Get Inferences from Large Datasets

Batch transform automatically manages the processing of large datasets within the limits of specified parameters. For example, suppose that you have a dataset file, input1.csv, stored in an S3 bucket. The content of the input file might look like the following example.

| Record1-Attribute1, Record1-Attribute2, Record1-Attribute3, ..., Record1-AttributeM |
| Record2-Attribute1, Record2-Attribute2, Record2-Attribute3, ..., Record2-AttributeM |
| Record3-Attribute1, Record3-Attribute2, Record3-Attribute3, ..., Record3-AttributeM |
| ... |
| RecordN-Attribute1, RecordN-Attribute2, RecordN-Attribute3, ..., RecordN-AttributeM |

When a batch transform job starts, SageMaker initializes compute instances and distributes the inference or preprocessing workload between them. Batch Transform partitions the Amazon S3 objects in the input by key and maps Amazon S3 objects to instances. When you have multiples files, one instance might process input1.csv, and another instance might process the file named input2.csv. If you have one input file but initialize multiple compute instances, only one instance processes the input file and the rest of the instances are idle.

You can also split input files into mini-batches. For example, you might create a mini-batch from input1.csv by including only two of the records.

| Record3-Attribute1, Record3-Attribute2, Record3-Attribute3, ..., Record3-AttributeM |
| Record4-Attribute1, Record4-Attribute2, Record4-Attribute3, ..., Record4-AttributeM |

**Note**

SageMaker processes each input file separately. It doesn’t combine mini-batches from different input files to comply with the MaxPayloadInMB limit.

To split input files into mini-batches when you create a batch transform job, set the SplitType parameter value to Line. If SplitType is set to None or if an input file can’t be split into mini-batches, SageMaker uses the entire input file in a single request. Note that Batch Transform doesn’t support CSV-formatted input that contains embedded newline characters. You can control the size of the mini-batches by using the BatchStrategy and MaxPayloadInMB parameters. MaxPayloadInMB must not be greater than 100 MB. If you specify the optional MaxConcurrentTransforms parameter, then the value of (MaxConcurrentTransforms * MaxPayloadInMB) must also not exceed 100 MB.

If the batch transform job successfully processes all of the records in an input file, it creates an output file with the same name and the .out file extension. For multiple input files, such as input1.csv and input2.csv, the output files are named input1.csv.out and input2.csv.out. The batch transform job stores the output files in the specified location in Amazon S3, such as s3://awsexamplebucket/output/.

The predictions in an output file are listed in the same order as the corresponding records in the input file. The output file input1.csv.out, based on the input file shown earlier, would look like the following.

| Inference1-Attribute1, Inference1-Attribute2, Inference1-Attribute3, ..., Inference1-AttributeM |
| Inference2-Attribute1, Inference2-Attribute2, Inference2-Attribute3, ..., Inference2-AttributeM |
| Inference3-Attribute1, Inference3-Attribute2, Inference3-Attribute3, ..., Inference3-AttributeM |
To combine the results of multiple output files into a single output file, set the `AssembleWith` parameter to `Line`.

When the input data is very large and is transmitted using HTTP chunked encoding, to stream the data to the algorithm, set `MaxPayloadInMB` to 0. Amazon SageMaker built-in algorithms don't support this feature.

For information about using the API to create a batch transform job, see the `CreateTransformJob` API. For more information about the correlation between batch transform input and output objects, see `OutputDataConfig`. For an example of how to use batch transform, see (Optional) Make Prediction with Batch Transform (p. 86).

**Speed up a Batch Transform Job**

If you are using the `CreateTransformJob` API, you can reduce the time it takes to complete batch transform jobs by using optimal values for parameters such as `MaxPayloadInMB`, `MaxConcurrentTransforms`, or `BatchStrategy`. The ideal value for `MaxConcurrentTransforms` is equal to the number of compute workers in the batch transform job. If you are using the SageMaker console, you can specify these optimal parameter values in the `Additional configuration` section of the `Batch transform job configuration` page. SageMaker automatically finds the optimal parameter settings for built-in algorithms. For custom algorithms, provide these values through an `execution-parameters` endpoint.

**Use Batch Transform to Test Production Variants**

To test different models or various hyperparameter settings, create a separate transform job for each new model variant and use a validation dataset. For each transform job, specify a unique model name and location in Amazon S3 for the output file. To analyze the results, use Inference Pipeline Logs and Metrics (p. 2796).

**Batch Transform Errors**

SageMaker uses the Amazon S3 Multipart Upload API to upload results from a batch transform job to Amazon S3. If an error occurs, the uploaded results are removed from Amazon S3. In some cases, such as when a network outage occurs, an incomplete multipart upload might remain in Amazon S3. To avoid incurring storage charges, we recommend that you add the S3 bucket policy to the S3 bucket lifecycle rules. This policy deletes incomplete multipart uploads that might be stored in the S3 bucket. For more information, see Object Lifecycle Management.

If a batch transform job fails to process an input file because of a problem with the dataset, SageMaker marks the job as `failed`. If an input file contains a bad record, the transform job doesn't create an output file for that input file because doing so prevents it from maintaining the same order in the transformed data as in the input file. When your dataset has multiple input files, a transform job continues to process input files even if it fails to process one. The processed files still generate useable results.

Exceeding the `MaxPayloadInMB` limit causes an error. This might happen with a large dataset if it can't be split, the `SplitType` parameter is set to `none`, or individual records within the dataset exceed the limit.

If you are using your own algorithms, you can use placeholder text, such as `ERROR`, when the algorithm finds a bad record in an input file. For example, if the last record in a dataset is bad, the algorithm places the placeholder text for that record in the output file.
Batch Transform Sample Notebooks

For a sample notebook that uses batch transform with a principal component analysis (PCA) model to reduce data in a user-item review matrix, followed by the application of a density-based spatial clustering of applications with noise (DBSCAN) algorithm to cluster movies, see Batch Transform with PCA and DBSCAN Movie Clusters. For instructions on creating and accessing Jupyter notebook instances that you can use to run the example in SageMaker, see Use Amazon SageMaker Notebook Instances (p. 291). After creating and opening a notebook instance, choose the SageMaker Examples tab to see a list of all the SageMaker examples. The topic modeling example notebooks that use the NTM algorithms are located in the Advanced functionality section. To open a notebook, choose its Use tab, then choose Create copy.

Associate Prediction Results with Input Records

When making predictions on a large dataset, you can exclude attributes that aren't needed for prediction. After the predictions have been made, you can associate some of the excluded attributes with those predictions or with other input data in your report. By using batch transform to perform these data processing steps, you can often eliminate additional preprocessing or postprocessing. You can use input files in JSON and CSV format only.

Topics
- Workflow for Associating Inferences with Input Records (p. 2958)
- Use Data Processing in Batch Transform Jobs (p. 2959)
- Supported JSONPath Operators (p. 2959)
- Batch Transform Examples (p. 2960)

Workflow for Associating Inferences with Input Records

The following diagram shows the workflow for associating inferences with input records.
To associate inferences with input data, there are three main steps:

1. Filter the input data that is not needed for inference before passing the input data to the batch transform job. Use the `InputFilter` parameter to determine which attributes to use as input for the model.
2. Associate the input data with the inference results. Use the `JoinSource` parameter to combine the input data with the inference.
3. Filter the joined data to retain the inputs that are needed to provide context for interpreting the predictions in the reports. Use `OutputFilter` to store the specified portion of the joined dataset in the output file.

**Use Data Processing in Batch Transform Jobs**

When creating a batch transform job with `CreateTransformJob` to process data:

1. Specify the portion of the input to pass to the model with the `InputFilter` parameter in the `DataProcessing` data structure.
2. Join the raw input data with the transformed data with the `JoinSource` parameter.
3. Specify which portion of the joined input and transformed data from the batch transform job to include in the output file with the `OutputFilter` parameter.
4. Choose either JSON- or CSV-formatted files for input:
   - For JSON- or JSON Lines-formatted input files, SageMaker either adds the `SageMakerOutput` attribute to the input file or creates a new JSON output file with the `SageMakerInput` and `SageMakerOutput` attributes. For more information, see `DataProcessing`.
   - For CSV-formatted input files, the joined input data is followed by the transformed data and the output is a CSV file.

If you use an algorithm with the `DataProcessing` structure, it must support your chosen format for both input and output files. For example, with the `TransformOutput` field of the `CreateTransformJob` API, you must set both the `ContentType` and `Accept` parameters to one of the following values: `text/csv`, `application/json`, or `application/jsonlines`. The syntax for specifying columns in a CSV file and specifying attributes in a JSON file are different. Using the wrong syntax causes an error. For more information, see `Batch Transform Examples` (p. 2960). For more information about input and output file formats for built-in algorithms, see `Use Amazon SageMaker Built-in Algorithms or Pre-trained Models` (p. 1096).

The record delimiters for the input and output must also be consistent with your chosen file input. The `SplitType` parameter indicates how to split the records in the input dataset. The `AssembleWith` parameter indicates how to reassemble the records for the output. If you set input and output formats to `text/csv`, you must also set the `SplitType` and `AssembleWith` parameters to `line`. If you set the input and output formats to `application/jsonlines`, you can set both `SplitType` and `AssembleWith` to `line`.

For CSV files, you cannot use embedded newline characters. For JSON files, the attribute name `SageMakerOutput` is reserved for output. The JSON input file can't have an attribute with this name. If it does, the data in the input file might be overwritten.

**Supported JSONPath Operators**

To filter and join the input data and inference, use a JSONPath subexpression. SageMaker supports only a subset of the defined JSONPath operators. The following table lists the supported JSONPath operators. For CSV data, each row is taken as a JSON array, so only index based JSONPaths can be applied, e.g. `$[0]`, `$[1:]`. CSV data should also follow RFC format.
### JSONPath Operator

<table>
<thead>
<tr>
<th>JSONPath Operator</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>The root element to a query. This operator is required at the beginning of all path expressions.</td>
<td>$</td>
</tr>
<tr>
<td>.&lt;name&gt;</td>
<td>A dot-notated child element.</td>
<td>$.id</td>
</tr>
<tr>
<td>*</td>
<td>A wildcard. Use in place of an attribute name or numeric value.</td>
<td>$.id.*</td>
</tr>
<tr>
<td>['&lt;name&gt;'] (','&lt;name&gt;</td>
<td>A bracket-notated element or multiple child elements.</td>
<td>$['id','SageMakerOutput']</td>
</tr>
<tr>
<td>[&lt;number&gt; (,&lt;number&gt;) ]</td>
<td>An index or array of indexes. Negative index values are also supported. A -1 index refers to the last element in an array.</td>
<td>$[1], $[1,3,5]</td>
</tr>
<tr>
<td>[&lt;start&gt;:&lt;end&gt;]</td>
<td>An array slice operator. The array slice() method extracts a section of an array and returns a new array. If you omit &lt;start&gt;, SageMaker uses the first element of the array. If you omit &lt;end&gt;, SageMaker uses the last element of the array.</td>
<td>$[2:5], $[:5], $[2:]</td>
</tr>
</tbody>
</table>

When using the bracket-notation to specify multiple child elements of a given field, additional nesting of children within brackets is not supported. For example, $.field1.['child1', 'child2'] is supported while $.field1.['child1', 'child2.grandchild'] is not.

For more information about JSONPath operators, see [JsonPath](https://github.com/json-path/jsonpath) on GitHub.

### Batch Transform Examples

The following examples show some common ways to join input data with prediction results.

#### Topics

- Example: Output Only Inferences (p. 2960)
- Example: Output Inferences Joined with Input Data (p. 2961)
- Example: Output Inferences Joined with Input Data and Exclude the ID Column from the Input (CSV) (p. 2962)
- Example: Output Inferences Joined with an ID Column and Exclude the ID Column from the Input (CSV) (p. 2962)

### Example: Output Only Inferences

By default, the DataProcessing parameter doesn't join inference results with input. It outputs only the inference results.

If you want to explicitly specify to not join results with input, use the Amazon SageMaker Python SDK and specify the following settings in a transformer call.

```python
sm_transformer = sagemaker.transformer.Transformer(...)  
sm_transformer.transform(..., input_filter="$", join_source= "None", output_filter="$")
```
To output inferences using the AWS SDK for Python, add the following code to your CreateTransformJob request. The following code mimics the default behavior.

```json
{
    "DataProcessing": {
        "InputFilter": "$",
        "JoinSource": "None",
        "OutputFilter": "$
    }
}
```

### Example: Output Inferences Joined with Input Data

If you're using the Amazon SageMaker Python SDK to combine the input data with the inferences in the output file, specify the `assemble_with` and `accept` parameters when initializing the transformer object. When you use the transform call, specify `Input` for the `join_source` parameter, and specify the `split_type` and `content_type` parameters as well. The `split_type` parameter must have the same value as `assemble_with`, and the `content_type` parameter must have the same value as `accept`.

For more information about the parameters and their accepted values, see the Transformer page in the Amazon SageMaker Python SDK.

```python
sm_transformer = sagemaker.transformer.Transformer(…, assemble_with="Line", accept="text/csv")
sm_transformer.transform(…, join_source="Input", split_type="Line", content_type="text/csv")
```

If you're using the AWS SDK for Python (Boto 3), join all input data with the inference by adding the following code to your CreateTransformJob request. The values for `Accept` and `ContentType` must match, and the values for `AssembleWith` and `SplitType` must also match.

```json
{
    "DataProcessing": {
        "JoinSource": "Input"
    },
    "TransformOutput": {
        "Accept": "text/csv",
        "AssembleWith": "Line"
    },
    "TransformInput": {
        "ContentType": "text/csv",
        "SplitType": "Line"
    }
}
```

For JSON or JSON Lines input files, the results are in the `SageMakerOutput` key in the input JSON file. For example, if the input is a JSON file that contains the key-value pair {"key":1}, the data transform result might be {"label":1}.

SageMaker stores both in the input file in the `SageMakerInput` key.

```json
{
    "key":1,
    "SageMakerOutput": {"label":1}
}
```

**Note**

The joined result for JSON must be a key-value pair object. If the input isn't a key-value pair object, SageMaker creates a new JSON file. In the new JSON file, the input data is stored in the `SageMakerInput` key and the results are stored as the `SageMakerOutput` value.
For a CSV file, for example, if the record is \([1, 2, 3]\), and the label result is \([1]\), then the output file would contain \([1, 2, 3, 1]\).

**Example: Output Inferences Joined with Input Data and Exclude the ID Column from the Input (CSV)**

If you are using the Amazon SageMaker Python SDK to join your input data with the inference output while excluding an ID column from the transformer input, specify the same parameters from the preceding example as well as a JSONPath subexpression for the input_filter in your transformer call. For example, if your input data includes five columns and the first one is the ID column, use the following transform request to select all columns except the ID column as features. The transformer still outputs all of the input columns joined with the inferences. For more information about the parameters and their accepted values, see the Transformer page in the Amazon SageMaker Python SDK.

```python
sm_transformer = sagemaker.transformer.Transformer(…, assemble_with="Line", accept="text/csv")
sm_transformer.transform(…, split_type="Line", content_type="text/csv",
input_filter="$[1:]", join_source="Input")
```

If you are using the AWS SDK for Python (Boto 3), add the following code to your `CreateTransformJob` request.

```json
{
  "DataProcessing": {
    "InputFilter": "$[1:]",
    "JoinSource": "Input"
  },
  "TransformOutput": {
    "Accept": "text/csv",
    "AssembleWith": "Line"
  },
  "TransformInput": {
    "ContentType": "text/csv",
    "SplitType": "Line"
  }
}
```

To specify columns in SageMaker, use the index of the array elements. The first column is index 0, the second column is index 1, and the sixth column is index 5.

To exclude the first column from the input, set `InputFilter` to "$[1:]". The colon (:) tells SageMaker to include all of the elements between two values, inclusive. For example, $[1:4]$ specifies the second through fifth columns.

If you omit the number after the colon, for example, $[5:]$, the subset includes all columns from the 6th column through the last column. If you omit the number before the colon, for example, $[:5]$, the subset includes all columns from the first column (index 0) through the sixth column.

**Example: Output Inferences Joined with an ID Column and Exclude the ID Column from the Input (CSV)**

If you are using the Amazon SageMaker Python SDK, you can specify the output to join only specific input columns (such as the ID column) with the inferences by specifying the output_filter in the transformer call. The output_filter uses a JSONPath subexpression to specify which columns to return as output after joining the input data with the inference results. The following request shows how you can make predictions while excluding an ID column and then join the ID column with the inferences.

Note that in the following example, the last column (-1) of the output contains the inferences. If you are using JSON files, SageMaker stores the inference results in the attribute `SageMakerOutput`. For more
information about the parameters and their accepted values, see the Transformer page in the Amazon SageMaker Python SDK.

```python
sm_transformer = sagemaker.transformer.Transformer(…, assemble_with="Line", accept="text/csv")
sm_transformer.transform(…, split_type="Line", content_type="text/csv",
input_filter="[$1:]", join_source="Input", output_filter="[$0,-1]")
```

If you are using the AWS SDK for Python (Boto 3), join only the ID column with the inferences by adding the following code to your `CreateTransformJob` request.

```json
{
    "DataProcessing": {
        "InputFilter": "[$1:]",
        "JoinSource": "Input",
        "OutputFilter": "[$0,-1]"
    },
    "TransformOutput": {
        "Accept": "text/csv",
        "AssembleWith": "Line"
    },
    "TransformInput": {
        "ContentType": "text/csv",
        "SplitType": "Line"
    }
}
```

**Warning**

If you are using a JSON-formatted input file, the file can't contain the attribute name `SageMakerOutput`. This attribute name is reserved for the inferences in the output file. If your JSON-formatted input file contains an attribute with this name, values in the input file might be overwritten with the inference.

**Storage in Batch Transform**

When you run a batch transform job, Amazon SageMaker attaches an Amazon Elastic Block Store storage volume to Amazon EC2 instances that process your job. The volume stores your model, and the size of the storage volume is fixed at 30 GB. You have the option to encrypt your model at rest in the storage volume.

**Note**

If you have a large model, you may encounter an `InternalServerError`.

For more information about Amazon EBS storage and features, see the following pages:

- Amazon EBS in the Amazon EC2 User Guide for Linux Instances
- Amazon EBS volumes in the Amazon EC2 User Guide for Linux Instances

**Note**

G4dn instances come with their own local SSD storage. To learn more about G4dn instances, see the Amazon EC2 G4 Instances page.

**Deployment guardrails**

Deployment guardrails are a set of model deployment options in Amazon SageMaker Inference to update your machine learning models in production. Using the fully managed deployment options, you can control the switch from the current model in production to a new one. Traffic shifting modes, such
as canary and linear, give you granular control over the traffic shifting process from your current model to the new one during the course of the update. There are also built-in safeguards such as auto-rollbacks that help you catch issues early and automatically take corrective action before they significantly impact production.

Deployment guardrails provide the following benefits:

- **Deployment safety while updating production environments.** A regressive update to a production environment can cause unplanned downtime and business impact, such as increased model latency and high error rates. Deployment guardrails help you mitigate those risks by providing best practices and built-in operational safety guardrails.

- **Fully managed deployment.** SageMaker takes care of setting up and orchestrating these deployments and integrates them with endpoint update mechanisms. You do not need to build and maintain orchestration, monitoring, or rollback mechanisms. You can leverage SageMaker to set up and orchestrate these deployments and focus on leveraging ML for your applications.

- **Visibility.** You can track the progress of your deployment through the DescribeEndpoint API or through Amazon CloudWatch Events (for supported endpoints (p. 2980)). To learn more about events in SageMaker, see the Endpoint deployment state change section in Automating Amazon SageMaker with Amazon EventBridge (p. 3681). Note that if your endpoint uses any of the features in the Exclusions (p. 2980) page, you cannot use CloudWatch Events.

**Note**

Deployment guardrails only apply to Asynchronous inference (p. 2939) and Real-time inference (p. 2744) endpoint types.

### How to Get Started

We support **blue/green deployments with multiple traffic shifting modes (p. 2967).** A traffic shifting mode is a configuration that specifies how SageMaker routes endpoint traffic to a new fleet containing your updates. The following traffic shifting modes provide you with different levels of control over the endpoint update process:

- **Blue/Green: All At Once (p. 2968)** shifts all of your endpoint traffic from the blue fleet to the green fleet. Once the traffic shifts to the green fleet, your pre-specified Amazon CloudWatch alarms begin monitoring the green fleet for a set amount of time (the **baking period**). If no alarms trip during the baking period, then SageMaker terminates the blue fleet.

- **Blue/Green: Canary (p. 2971)** lets you shift one small portion of your traffic (a **canary**) to the green fleet and monitor it for a baking period. If the canary succeeds on the green fleet, then SageMaker shifts the rest of the traffic from the blue fleet to the green fleet before terminating the blue fleet.

- **Blue/Green: Linear (p. 2976)** provides even more customization over the number of traffic-shifting steps and the percentage of traffic to shift for each step. While canary shifting lets you shift traffic in two steps, linear shifting extends this to \( n \) linearly spaced steps.

You can create and manage your deployment through the UpdateEndpoint and CreateEndpoint SageMaker API and AWS Command Line Interface commands. See the individual deployment pages for more details on how to set up your deployment. Note that if your endpoint uses any of the features listed in the Exclusions (p. 2980) page, you cannot use deployment guardrails.

To follow guided examples that shows how to use deployment guardrails, see our example Jupyter notebooks for the canary and linear traffic shifting modes.

### Auto-Rollback Configuration and Monitoring

Amazon CloudWatch alarms are a prerequisite for using baking periods in deployment guardrails. You can only use the auto-rollback functionality in deployment guardrails if you set up CloudWatch
alarms that can monitor an endpoint. If any of your alarms trip during the specified monitoring period, SageMaker initiates a complete rollback to the old endpoint to protect your application. If you do not have any CloudWatch alarms set up to monitor your endpoint, then the auto-rollback functionality does not work during your deployment.

To learn more about Amazon CloudWatch, see What is Amazon CloudWatch? in the Amazon CloudWatch User Guide.

### Alarm Examples

To help you get started, we provide the following examples to demonstrate the capabilities of CloudWatch alarms. In addition to using or modifying the following examples, you can create your own alarms and configure the alarms to monitor various metrics on the specified fleets for a certain period of time. To see more SageMaker metrics and dimensions you can add to your alarms, see Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663).

#### Topics

- Monitor invocation errors on both old and new fleets (p. 2965)
- Monitor model latency on the new fleet (p. 2966)

### Monitor invocation errors on both old and new fleets

The following CloudWatch alarm monitors an endpoint's average error rate. You can use this alarm with any deployment guardrails traffic shifting type to provide overall monitoring on both the old and new fleets. If the alarm trips, then SageMaker initiates a rollback to the old fleet.

Invocation errors coming from both the old fleet and new fleet contribute to the average error rate. If the average error rate exceeds the specified threshold, then the alarm trips. This particular example monitors the 4xx errors (client errors) on both the old and new fleets for the duration of a deployment. You can also monitor the 5xx errors (server errors) by using the metric Invocation5XXErrors.

**Note**

For this alarm type, if your old fleet trips the alarm during the deployment, SageMaker terminates your deployment. Therefore, if your current production fleet already causes errors, consider using or modifying one of the following examples that only monitors the new fleet for errors.

```json
#Applied deployment type: all types
{
    "AlarmName": "EndToEndDeploymentHighErrorRateAlarm",
    "AlarmDescription": "Monitors the error rate of 4xx errors",
    "MetricName": "Invocation4XXErrors",
    "Namespace": "AWS/SageMaker",
    "Statistic": "Average",
    "Dimensions": [
        {
            "Name": "EndpointName",
            "Value": <your-endpoint-name>
        },
        {
            "Name": "VariantName",
            "Value": "AllTraffic"
        }
    ],
    "Period": 600,
    "EvaluationPeriods": 2,
    "Threshold": 1,
    "ComparisonOperator": "GreaterThanThreshold",
    "TreatMissingData": "notBreaching"
}
```

2965
In the previous example, note the values for the following fields:

- For **AlarmName** and **AlarmDescription**, enter a name and description you choose for the alarm.
- For **MetricName**, use the value `Invocation4XXErrors` to monitor for 4xx errors on the endpoint.
- For **Namespace**, use the value `AWS/SageMaker`. You can also specify your own custom metric, if applicable.
- For **Statistic**, use Average. This means that the alarm takes the average error rate over the evaluation periods when calculating whether the error rate has exceeded the threshold.
- For the dimension **EndpointName**, use the name of the endpoint you are updating as the value.
- For the dimension **VariantName**, use the value `AllTraffic` to specify all endpoint traffic.
- For **Period**, use 600. This sets the alarm's evaluation periods to 10 minutes long.
- For **EvaluationPeriods**, use 2. This value tells the alarm to consider the two most recent evaluation periods when determining the alarm status.

**Monitor model latency on the new fleet**

The following CloudWatch alarm example monitors the new fleet's model latency during your deployment. You can use this alarm to monitor only the new fleet and exclude the old fleet. The alarm lasts for the entire deployment. This example gives you comprehensive, end-to-end monitoring of the new fleet and initiates a rollback to the old fleet if the new fleet has any response time issues.

CloudWatch publishes the metrics with the dimension `EndpointConfigName:{New-Ep-Config}` after the new fleet starts receiving traffic, and these metrics last even after the deployment is complete.

You can use the following alarm example with any deployment type.

```json
#Applied deployment type: all types
{
    "AlarmName": "NewEndpointConfigVersionHighModelLatencyAlarm",
    "AlarmDescription": "Monitors the model latency on new fleet",
    "MetricName": "ModelLatency",
    "Namespace": "AWS/SageMaker",
    "Statistic": "Average",
    "Dimensions": [ 
        { 
            "Name": "EndpointName",
            "Value": "<your-endpoint-name>"
        },
        { 
            "Name": "VariantName",
            "Value": "AllTraffic"
        },
        { 
            "Name": "EndpointConfigName",
            "Value": "<your-config-name>"
        }
    ],
    "Period": 300,
    "EvaluationPeriods": 2,
    "Threshold": 100000, # 100ms
    "ComparisonOperator": "GreaterThanThreshold",
    "TreatMissingData": "notBreaching"
}
```

In the previous example, note the values for the following fields:
For MetricName, use the value ModelLatency to monitor the model's response time.

- For Namespace, use the value AWS/SageMaker. You can also specify your own custom metric, if applicable.
- For the dimension EndpointName, use the name of the endpoint you are updating as the value.
- For the dimension VariantName, use the value AllTraffic to specify all endpoint traffic.
- For the dimension EndpointConfigName, the value should refer to the endpoint configuration name for your new or updated endpoint.

**Note**

If you want to monitor your old fleet instead of the new fleet, you can change the dimension EndpointConfigName to specify the name of your old fleet's configuration.

**Blue/Green Deployments**

When you update your endpoint, Amazon SageMaker automatically uses a blue/green deployment to maximize the availability of your endpoints. In a blue/green deployment, SageMaker provisions a new fleet with the updates (the green fleet). Then, SageMaker shifts traffic from the old fleet (the blue fleet) to the green fleet. Once the green fleet operates smoothly for a set evaluation period (called the baking period), SageMaker terminates the blue fleet. With the additional capabilities in blue/green deployments, you can utilize traffic shifting modes and auto-rollback monitoring to protect your endpoint from significant production impact.

The following list describes the key features of blue/green deployments in SageMaker:

- **Traffic shifting modes.** The traffic shifting modes for deployment guardrails let you control the volume of traffic and number of traffic-shifting steps between the blue fleet and the green fleet. This capability gives you the ability to progressively evaluate the performance of the green fleet without fully committing to a 100% traffic shift.

- **Baking period.** The baking period is a set amount of time to monitor the green fleet before proceeding to the next deployment stage. If any of the pre-specified alarms trip during any baking period, then all endpoint traffic rolls back to the blue fleet. The baking period helps you to build confidence in your update before making the traffic shift permanent.

- **Auto-rollback.** You can specify Amazon CloudWatch alarms that SageMaker uses to monitor the green fleet. If an issue with the updated code trips any of the alarms, SageMaker initiates an auto-rollback to the blue fleet in order to maintain availability thereby minimizing risk.

**Traffic Shifting Modes**

The various traffic shifting modes in blue/green deployments give you more granular control over traffic shifting between the blue fleet and the green fleet. The available traffic shifting modes for blue/green deployments are all at once, canary, and linear. The following table shows a comparison of the options.

**Important**

For blue/green deployments that involve multiple stage traffic shifting or baking periods, you are billed for both the fleets for the duration of the update, irrespective of the traffic to the fleet. This is in contrast to blue/green deployments with all at once traffic shifting and no baking periods, where you are only billed for one fleet during the course of the update.

<table>
<thead>
<tr>
<th>Name</th>
<th>What is it?</th>
<th>Pros</th>
<th>Cons</th>
<th>Recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>All at once</td>
<td>Shifts all of the traffic to the new</td>
<td>Minimizes the overall update duration.</td>
<td>Regressive updates affect</td>
<td>Use this option to minimize update time and cost.</td>
</tr>
</tbody>
</table>
### Get Started

Once you specify your desired deployment configuration, SageMaker handles provisioning new instances, terminating old instances, and shifting traffic for you. You can create and manage your deployment through the existing `UpdateEndpoint` and `CreateEndpoint` SageMaker API and AWS Command Line Interface commands. Note that if your endpoint uses any of the features listed in the [Exclusions](p. 2980) page, you cannot use deployment guardrails. See the individual deployment pages for more details on how to set up your deployment:

- Blue/Green Update with All At Once Traffic Shifting (p. 2968)
- Blue/Green Update with Canary Traffic Shifting (p. 2971)
- Blue/Green Update with Linear Traffic Shifting (p. 2971)

To follow guided examples that show how to use deployment guardrails, see our example Jupyter notebooks for the canary and linear traffic shifting modes.

### All At Once Traffic Shifting

With all at once traffic shifting, you can quickly roll out an endpoint update using the safety guardrails of a blue/green deployment. You can use this traffic shifting option to minimize the update duration while still taking advantage of the availability guarantees of blue/green deployments. The baking period feature helps you to monitor the performance and functionality of your new instances before terminating your old instances, ensuring that your new fleet is fully operational.

The following diagram shows how all at once traffic shifting manages the old and new fleets.

<table>
<thead>
<tr>
<th>Name</th>
<th>What is it?</th>
<th>Pros</th>
<th>Cons</th>
<th>Recommendation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canary</td>
<td>Traffic shifts in two steps. The first (canary) step shifts a small portion of the traffic followed by the second step, which shifts the remainder of the traffic.</td>
<td>Confines the blast radius of regressive updates to only the canary fleet.</td>
<td>Both fleets are operational in parallel for entire deployment.</td>
<td>Use this option to balance between minimizing the blast radius of regressive updates and minimizing the time that two fleets are operational.</td>
</tr>
<tr>
<td>Linear</td>
<td>A fixed portion of the traffic shifts in a pre-specified number of equally spaced steps.</td>
<td>Minimizes the risk of regressive updates by shifting traffic over several steps.</td>
<td>The update duration and cost are proportional to the number of steps.</td>
<td>Use this option to minimize risk by spreading out deployment across multiple steps.</td>
</tr>
</tbody>
</table>
When you use all at once traffic shifting, SageMaker routes 100% of the traffic to the new fleet (green fleet). Once the green fleet starts receiving traffic, the baking period begins. The baking period is a set amount of time in which pre-specified Amazon CloudWatch alarms monitor the performance of the green fleet. If no alarms trip during the baking period, SageMaker terminates the old fleet (blue fleet). If any alarms trip during the baking period, then an auto-rollback initiates and 100% of the traffic shifts back to the blue fleet.

**Prerequisites**

Before setting up a deployment with all at once traffic shifting, you must create Amazon CloudWatch alarms to watch metrics from your endpoint. If any of the alarms trip during the baking period, then the traffic rolls back to your blue fleet. To learn how to set up CloudWatch alarms on an endpoint, see
the prerequisite page Auto-Rollback Configuration and Monitoring (p. 2964). To learn more about CloudWatch alarms, see Using Amazon CloudWatch alarms in the Amazon CloudWatch User Guide.

**Configure All At Once Traffic Shifting**

Once you are ready for your deployment and have set up CloudWatch alarms for your endpoint, you can use either the SageMaker UpdateEndpoint API or the update-endpoint command in the AWS Command Line Interface to initiate the deployment.

**Topics**
- How to update an endpoint (API) (p. 2970)
- How to update an endpoint with an existing blue/green update policy (API) (p. 2971)
- How to update an endpoint (CLI) (p. 2971)

**How to update an endpoint (API)**

The following example shows how you can update your endpoint with all at once traffic shifting using UpdateEndpoint in the Amazon SageMaker API.

```python
import boto3
client = boto3.client("sagemaker")
response = client.update_endpoint(
    EndpointName="<your-endpoint-name>",
    EndpointConfigName="<your-config-name>",
    DeploymentConfig={
        "BlueGreenUpdatePolicy": {
            "TrafficRoutingConfiguration": {
                "Type": "ALL_AT_ONCE",
            },
            "TerminationWaitInSeconds": 600,
            "MaximumExecutionTimeoutInSeconds": 1800
        },
        "AutoRollbackConfiguration": {
            "Alarms": [
                {"AlarmName": "<your-cw-alarm>"}
            ]
        }
    }
)
```

To configure the all at once traffic shifting option, do the following:

- For EndpointName, use the name of the existing endpoint you want to update.
- For EndpointConfigName, use the name of the endpoint configuration you want to use.
- Under DeploymentConfig and BlueGreenUpdatePolicy, in TrafficRoutingConfiguration, set the Type parameter to ALL_AT_ONCE. This specifies that the deployment uses the all at once traffic shifting mode.
- For TerminationWaitInSeconds, use 600. This parameter tells SageMaker to wait for the specified amount of time (in seconds) after your green fleet is fully active before terminating the instances in the blue fleet. In this example, SageMaker waits for 10 minutes after the final baking period before terminating the blue fleet.
- For MaximumExecutionTimeoutInSeconds, use 1800. This parameter sets the maximum amount of time that the deployment can run before it times out. In the preceding example, your deployment has a limit of 30 minutes to finish.
• In AutoRollbackConfiguration, within the Alarms field, you can add your CloudWatch alarms by name. Create one AlarmName: `<your-cw-alarm>` entry for each alarm you want to use.

How to update an endpoint with an existing blue/green update policy (API)

When you use the CreateEndpoint API to create an endpoint, you can optionally specify a deployment configuration to reuse for future endpoint updates. You can use the same DeploymentConfig options as the previous UpdateEndpoint API example. There are no changes to the CreateEndpoint API behavior. Specifying the deployment configuration does not automatically perform a blue/green update on your endpoint.

The option to use a previous deployment configuration happens when using the UpdateEndpoint API to update your endpoint. When updating your endpoint, you can use the RetainDeploymentConfig option to keep the deployment configuration you specified when you created the endpoint.

When calling the UpdateEndpoint API, set RetainDeploymentConfig to True to keep the DeploymentConfig options from your original endpoint configuration.

```python
response = client.update_endpoint(
    EndpointName="<your-endpoint-name>",
    EndpointConfigName="<your-config-name>",
    RetainDeploymentConfig=True
)
```

How to update an endpoint (CLI)

If you are using the AWS CLI, the following example shows how to start a blue/green all at once deployment using the update-endpoint command.

```bash
update-endpoint
--endpoint-name <your-endpoint-name>
--endpoint-config-name <your-config-name>
--deployment-config '{"BlueGreenUpdatePolicy": {"TrafficRoutingConfiguration": {"Type": "ALL_AT_ONCE"},
  "TerminationWaitInSeconds": 600,
  "MaximumExecutionTimeoutInSeconds": 1800},
  "AutoRollbackConfiguration": {"Alarms": [["AlarmName": "<your-alarm>" ]]}'}
```

To configure the all at once traffic shifting option, do the following:

• For endpoint-name, use the name of the endpoint you want to update.
• For endpoint-config-name, use the name of the endpoint configuration you want to use.
• For deployment-config, use a BlueGreenUpdatePolicy JSON object.

Note
If you would rather save your JSON object in a file, see Generating AWS CLI skeleton and input parameters in the AWS CLI User Guide.

Canary Traffic Shifting

With canary traffic shifting, you can test a portion of your endpoint traffic on the new fleet while the old fleet serves the remainder of the traffic. This testing step is a safety guardrail that validates the new fleet’s functionality before shifting all of your traffic to the new fleet. You still have the benefits of a blue/green deployment, and the added canary feature lets you ensure that your new (green) fleet can serve inference before letting it handle 100% of the traffic.
The portion of your green fleet that turns on to receive traffic is called the canary, and you can choose the size of this canary. Note that the canary size should be less than or equal to 50% of the new fleet's capacity. Once the baking period finishes and no pre-specified Amazon CloudWatch alarms trip, the rest of the traffic shifts from the old (blue) fleet to the green fleet. Canary traffic shifting provides you with more safety during your deployment since any issues with the updated model only impact the canary.

The following diagram shows how canary traffic shifting manages the distribution of traffic between the blue and green fleets.
Once SageMaker provisions the green fleet, SageMaker routes a portion of the incoming traffic (for example, 25%) to the canary. Then the baking period begins, during which your CloudWatch alarms monitor the performance of the green fleet. During this time, both the blue fleet and green fleet are partially active and receiving traffic. If any of the alarms trip during the baking period, then SageMaker initiates a rollback and all traffic returns to the blue fleet. If none of the alarms trip, then all of the traffic shifts to the green fleet and there is a final baking period. If the final baking period finishes without tripping any alarms, then the green fleet serves all traffic and SageMaker terminates the blue fleet.

**Prerequisites**

Before setting up a deployment with canary traffic shifting, you must create Amazon CloudWatch alarms to monitor metrics from your endpoint. The alarms are active during the baking period, and if any alarms trip, then all endpoint traffic rolls back to the blue fleet. To learn how to set up CloudWatch alarms on an endpoint, see the prerequisite page Auto-Rollback Configuration and Monitoring (p. 2964). To learn more about CloudWatch alarms, see Using Amazon CloudWatch alarms in the Amazon CloudWatch User Guide.

**Configure Canary Traffic Shifting**

Once you are ready for your deployment and have set up Amazon CloudWatch alarms for your endpoint, you can use either the Amazon SageMaker UpdateEndpoint API or the update-endpoint command in the AWS CLI to initiate the deployment.

**Topics**

- How to update an endpoint (API) (p. 2974)
- How to update an endpoint with an existing blue/green update policy (API) (p. 2975)
- How to update an endpoint (CLI) (p. 2975)

**How to update an endpoint (API)**

The following example of the UpdateEndpoint API shows how you can update an endpoint with canary traffic shifting.

```python
import boto3
client = boto3.client("sagemaker")

response = client.update_endpoint(
    EndpointName="<your-endpoint-name>",
    EndpointConfigName="<your-config-name>",
    DeploymentConfig={
        "BlueGreenUpdatePolicy": {
            "TrafficRoutingConfiguration": {
                "Type": "CANARY",
                "CanarySize": {
                    "Type": "CAPACITY_PERCENT",
                    "Value": 30
                },
                "WaitIntervalInSeconds": 600
            },
            "TerminationWaitInSeconds": 600,
            "MaximumExecutionTimeoutInSeconds": 1800
        },
        "AutoRollbackConfiguration": {
            "Alarms": [
                "AlarmName": "<your-cw-alarm>"
            ]
        }
    }
)
```
To configure the canary traffic shifting option, do the following:

- For **EndpointName**, use the name of the existing endpoint you want to update.
- For **EndpointConfigName**, use the name of the endpoint configuration you want to use.
- Under **DeploymentConfig** and **BlueGreenUpdatePolicy**, in **TrafficRoutingConfiguration**, set the **Type** parameter to **CANARY**. This specifies that the deployment uses canary traffic shifting.
- In the **CanarySize** field, you can change the size of the canary by modifying the **Type** and **Value** parameters. For **Type**, use **CAPACITY_PERCENT**, meaning the percentage of your green fleet you want to use as the canary, and then set **Value** to 30. In this example, you use 30% of the green fleet's capacity as the canary. Note that the canary size should be equal to or less than 50% of the green fleet's capacity.
- For **WaitIntervalInSeconds**, use 600. The parameter tells SageMaker to wait for the specified amount of time (in seconds) between each interval shift. This interval is the duration of the canary baking period. In the preceding example, SageMaker waits for 10 minutes after the canary shift and then completes the second and final traffic shift.
- For **TerminationWaitInSeconds**, use 600. This parameter tells SageMaker to wait for the specified amount of time (in seconds) after your green fleet is fully active before terminating the instances in the blue fleet. In this example, SageMaker waits for 10 minutes after the final baking period before terminating the blue fleet.
- For **MaximumExecutionTimeoutInSeconds**, use 1800. This parameter sets the maximum amount of time that the deployment can run before it times out. In the preceding example, your deployment has a limit of 30 minutes to finish.
- In **AutoRollbackConfiguration**, within the **Alarms** field, you can add your CloudWatch alarms by name. Create one **AlarmName**: `<your-cw-alarm>` entry for each alarm you want to use.

### How to update an endpoint with an existing blue/green update policy (API)

When you use the **CreateEndpoint** API to create an endpoint, you can optionally specify a deployment configuration to reuse for future endpoint updates. You can use the same **DeploymentConfig** options as the previous **UpdateEndpoint** API example. There are no changes to the **CreateEndpoint** API behavior. Specifying the deployment configuration does not automatically perform a blue/green update on your endpoint.

The option to use a previous deployment configuration happens when using the **UpdateEndpoint** API to update your endpoint. When updating your endpoint, you can use the **RetainDeploymentConfig** option to keep the deployment configuration you specified when you created the endpoint.

When calling the **UpdateEndpoint** API, set **RetainDeploymentConfig** to `True` to keep the **DeploymentConfig** options from your original endpoint configuration.

```python
response = client.update_endpoint(
    EndpointName="<your-endpoint-name>",
    EndpointConfigName="<your-config-name>",
    RetainDeploymentConfig=True
)
```

### How to update an endpoint (CLI)

If you are using the AWS CLI, the following example shows how to start a blue/green canary deployment using the **update-endpoint** command.
To configure the canary traffic shifting option, do the following:

- For `endpoint-name`, use the name of the endpoint you want to update.
- For `endpoint-config-name`, use the name of the endpoint configuration you want to use.
- For `deployment-config`, use a `BlueGreenUpdatePolicy` JSON object.

**Note**
If you would rather save your JSON object in a file, see *Generating AWS CLI skeleton and input parameters* in the *AWS CLI User Guide*.

### Linear Traffic Shifting

Linear traffic shifting enables you to gradually shift traffic from your old fleet (blue fleet) to your new fleet (green fleet). With linear traffic shifting, you can shift traffic in multiple steps, minimizing the chance of a disruption to your endpoint. This blue/green deployment option gives you the most granular control over traffic shifting.

You can choose either the number of instances or the percentage of the green fleet’s capacity to activate during each step. Each linear step should only be between 10-50% of the green fleet’s capacity. For each step, there is a baking period during which your pre-specified Amazon CloudWatch alarms monitor metrics on the green fleet. Once the baking period finishes and no alarms trip, the active portion of your green fleet continues receiving traffic and a new step begins. If alarms trip during any of the baking periods, 100% of the endpoint traffic rolls back to the blue fleet.

The following diagram shows how linear traffic shifting routes traffic to the blue and green fleets.
Once SageMaker provisions the new fleet, the first portion of the green fleet turns on and receives traffic. SageMaker deactivates the same size portion of the blue fleet, and the baking period begins. If any alarms trip, all of the endpoint traffic rolls back to the blue fleet. If the baking period finishes, then the next step begins. Another portion of the green fleet activates and receives traffic, part of the blue fleet deactivates, and another baking period begins. The same process repeats until the blue fleet is fully deactivated and the green fleet is fully active and receiving all traffic. If an alarm goes off at any point, SageMaker terminates the shifting process and 100% of the traffic rolls back to the blue fleet.

Prerequisites

Before setting up a deployment with linear traffic shifting, you must create CloudWatch alarms to monitor metrics from your endpoint. The alarms are active during the baking period, and if any alarms trip, then all endpoint traffic rolls back to the blue fleet. To learn how to set up CloudWatch alarms on an endpoint, see the prerequisite page Auto-Rollback Configuration and Monitoring (p. 2964). To learn more about CloudWatch alarms, see Using Amazon CloudWatch alarms in the Amazon CloudWatch User Guide.

Configure Linear Traffic Shifting

Once you are ready for your deployment and have set up CloudWatch alarms for your endpoint, you can use either the Amazon SageMaker UpdateEndpoint API or the update-endpoint command in the AWS CLI to initiate the deployment.

Topics

- How to update an endpoint (API) (p. 2978)
- How to update an endpoint with an existing blue/green update policy (API) (p. 2979)
- How to update an endpoint (CLI) (p. 2975)

How to update an endpoint (API)

The following example of the UpdateEndpoint API shows how you can update an endpoint with linear traffic shifting.

```python
import boto3
client = boto3.client("sagemaker")
response = client.update_endpoint(
    EndpointName="<your-endpoint-name>",
    EndpointConfigName="<your-config-name>",
    DeploymentConfig={
        "BlueGreenUpdatePolicy": {
            "TrafficRoutingConfiguration": {
                "Type": "LINEAR",
                "LinearStepSize": {
                    "Type": "CAPACITY_PERCENT",
                    "Value": 20
                },
                "WaitIntervalInSeconds": 300
            },
            "TerminationWaitInSeconds": 300,
            "MaximumExecutionTimeoutInSeconds": 3600
        },
        "AutoRollbackConfiguration": {
            "Alarms": [
                {"AlarmName": "<your-cw-alarm>"}
            ]
        }
    }
)
```
To configure the linear traffic shifting option, do the following:

- For `EndpointName`, use the name of the existing endpoint you want to update.
- For `EndpointConfigName`, use the name of the endpoint configuration you want to use.
- Under `DeploymentConfig` and `BlueGreenUpdatePolicy`, in `TrafficRoutingConfiguration`, set the `Type` parameter to `LINEAR`. This specifies that the deployment uses linear traffic shifting.
- In the `LinearStepSize` field, you can change the size of the steps by modifying the `Type` and `Value` parameters. For `Type`, use `CAPACITY_PERCENT`, meaning the percentage of your green fleet you want to use as the step size, and then set `Value` to 20. In this example, you turn on 20% of the green fleet's capacity for each traffic shifting step. Note that when customizing your linear step size, you should only use steps that are 10-50% of the green fleet's capacity.
- For `WaitIntervalInSeconds`, use 300. The parameter tells SageMaker to wait for the specified amount of time (in seconds) between each traffic shift. This interval is the duration of the baking period between each linear step. In the preceding example, SageMaker waits for 5 minutes between each traffic shift.
- For `TerminationWaitInSeconds`, use 300. This parameter tells SageMaker to wait for the specified amount of time (in seconds) after your green fleet is fully active before terminating the instances in the blue fleet. In this example, SageMaker waits for 5 minutes after the final baking period before terminating the blue fleet.
- For `MaximumExecutionTimeoutInSeconds`, use 3600. This parameter sets the maximum amount of time that the deployment can run before it times out. In the preceding example, your deployment has a limit of 1 hour to finish.
- In `AutoRollbackConfiguration`, within the `Alarms` field, you can add your CloudWatch alarms by name. Create one `AlarmName`: `<your-cw-alarm>` entry for each alarm you want to use.

**How to update an endpoint with an existing blue/green update policy (API)**

When you use the `CreateEndpoint` API to create an endpoint, you can optionally specify a deployment configuration to reuse for future endpoint updates. You can use the same `DeploymentConfig` options as the previous `UpdateEndpoint` API example. There are no changes to the `CreateEndpoint` API behavior. Specifying the deployment configuration does not automatically perform a blue/green update on your endpoint.

The option to use a previous deployment configuration happens when using the `UpdateEndpoint` API to update your endpoint. When updating your endpoint, you can use the `RetainDeploymentConfig` option to keep the deployment configuration you specified when you created the endpoint.

When calling the `UpdateEndpoint` API, set `RetainDeploymentConfig` to `True` to keep the `DeploymentConfig` options from your original endpoint configuration.

```python
response = client.update_endpoint(
    EndpointName="<your-endpoint-name>",
    EndpointConfigName="<your-config-name>",
    RetainDeploymentConfig=True
)
```

**How to update an endpoint (CLI)**

If you are using the AWS CLI, the following example shows how to start a blue/green linear deployment using the `update-endpoint` command.

```bash
update-endpoint
```
To configure the linear traffic shifting option, do the following:

- For `endpoint-name`, use the name of the endpoint you want to update.
- For `endpoint-config-name`, use the name of the endpoint configuration you want to use.
- For `deployment-config`, use a `BlueGreenUpdatePolicy` JSON object.

**Note**
If you would rather save your JSON object in a file, see Generating AWS CLI skeleton and input parameters in the AWS CLI User Guide.

---

### Exclusions

You can only use deployment guardrails with newly created endpoints. There are also feature-based exclusions that make your endpoint incompatible with deployment guardrails at this time. If your endpoint uses any of the following features, you cannot use deployment guardrails on your endpoint, and your endpoint will fall back to using a blue/green deployment with all at once traffic shifting and no final baking period.

- Marketplace containers
- Multi-container endpoints
- Multi-model endpoints
- Multi-variant endpoints
- Endpoints that use Inf1 (Inferentia-based) instances
- Endpoints that use Amazon SageMaker Model Monitor (with data capture enabled)
- Amazon Elastic Inference endpoints

---

### Inference cost optimization best practices

The following content provides techniques and considerations for optimizing the cost of endpoints. You can use these recommendations to optimize the cost for both new and existing endpoints.

#### Best practices

To optimize your SageMaker Inference costs, follow these best practices.

**Pick the best inference option for the job.**

SageMaker offers 4 different inference options to provide the best inference option for the job. You may be able to save on costs by picking the inference option that best matches your workload.

- Use **real-time inference** for low latency workloads with predictable traffic patterns that need to have consistent latency characteristics and are always available. You pay for using the instance.
• Use serverless inference for synchronous workloads that have a spiky traffic pattern and can accept variations in the p99 latency. Serverless inference automatically scales to meet your workload traffic so you don't pay for any idle resources. You only pay for the duration of the inference request. The same model and containers can be used with both real-time and serverless inference so you can switch between these two modes if your needs change.

• Use asynchronous inference for asynchronous workloads that process up to 1 GB of data (such as text corpus, image, video, and audio) that are latency insensitive and cost sensitive. With asynchronous inference, you can control costs by specifying a fixed number of instances for the optimal processing rate instead of provisioning for the peak. You can also scale down to zero to save additional costs.

• Use batch inference for workloads for which you need inference for a large set of data for processes that happen offline (that is, you don’t need a persistent endpoint). You pay for the instance for the duration of the batch inference job.

Opt in to a SageMaker Savings Plan.

• If you have a consistent usage level across all SageMaker services, you can opt in to a SageMaker Savings Plan to help reduce your costs by up to 64%.

• Amazon SageMaker Savings Plans provide a flexible pricing model for Amazon SageMaker, in exchange for a commitment to a consistent amount of usage (measured in $/hour) for a one-year or three-year term. These plans automatically apply to eligible SageMaker ML instance usages including SageMaker Studio Notebook, SageMaker On-Demand Notebook, SageMaker Processing, SageMaker Data Wrangler, SageMaker Training, SageMaker Real-Time Inference, and SageMaker Batch Transform regardless of instance family, size, or Region. For example, you can change usage from a CPU ml.c5.xlarge instance running in US East (Ohio) to a ml.Inf1 instance in US West (Oregon) for inference workloads at any time and automatically continue to pay the Savings Plans price.

Optimize your model to run better.

• Unoptimized models can lead to longer run times and use more resources. You may choose to use more or bigger instances to improve performance; however, this leads to higher costs.

• By optimizing your models to be more performant, you may be able to lower costs by using fewer or smaller instances while keeping the same or better performance characteristics. You can use SageMaker Neo with SageMaker Inference to automatically optimize models. For more details and samples, see Optimize model performance using Neo (p. 3063).

Use the most optimal instance type and size for real-time inference.

• SageMaker Inference has over 70 instance types and sizes that can be used to deploy ML models including AWS Inferentia and Graviton chipsets that are optimized for ML. Choosing the right instance for your model helps ensure you have the most performant instance at the lowest cost for your models.

• By using Inference Recommender, you can quickly compare different instances to understand the performance of the model and the costs. With these results, you can choose the instance to deploy with the best return on investment.

Improve efficiency and costs by combining multiple endpoints into a single endpoint for real-time inference.

• Costs can quickly add up when you deploy multiple endpoints, especially if the endpoints don’t fully utilize the underlying instances. To understand if the instance is under-utilized, check the utilization metrics (CPU, GPU, etc) in Amazon CloudWatch for your instances. If you have more than one of
these endpoints, you can combine the models or containers on these multiple endpoints into a single endpoint.

- Using **Multi-model endpoints** (MME) or **Multi-container endpoints** (MCE), you can deploy multiple ML models or containers in a single endpoint to share the instance across multiple models or containers and improve your return on investment. To learn more, see this [Save on inference costs by using Amazon SageMaker multi-model endpoints](https://aws.amazon.com/blogs/machine-learning/save-on-inference-costs-by-using-amazon-sagemaker-multi-model-endpoints/) or [Deploy multiple serving containers on a single instance using Amazon SageMaker multi-container endpoints](https://aws.amazon.com/blogs/machine-learning/deploy-multiple-serving-containers-on-a-single-instance-using-amazon-sagemaker-multi-container-endpoints/) on the AWS Machine Learning blog.

**Set up autoscaling to match your workload requirements for real-time and asynchronous inference.**

- Without autoscaling, you need to provision for peak traffic or risk model unavailability. Unless the traffic to your model is steady throughout the day, there will be excess unused capacity. This leads to low utilization and wasted resources.
- **Autoscaling** is an out-of-the-box feature that monitors your workloads and dynamically adjusts the capacity to maintain steady and predictable performance at the possible lowest cost. When the workload increases, autoscaling brings more instances online. When the workload decreases, autoscaling removes unnecessary instances, helping you reduce your compute cost. To learn more, see [Configuring autoscaling inference endpoints in Amazon SageMaker](https://aws.amazon.com/blogs/machine-learning/configuring-autoscaling-inference-endpoints-in-amazon-sagemaker/) on the AWS Machine Learning blog.

**Register and Deploy Models with Model Registry**

With the SageMaker model registry you can do the following:

- Catalog models for production.
- Manage model versions.
- Associate metadata, such as training metrics, with a model.
- Manage the approval status of a model.
- Deploy models to production.
- Automate model deployment with CI/CD.

Catalog models by creating model package groups that contain different versions of a model. You can create a model group that tracks all of the models that you train to solve a particular problem. You can then register each model you train and the model registry adds it to the model group as a new model version. A typical workflow might look like the following:

- Create a model group.
- Create an ML pipeline that trains a model. For information about SageMaker pipelines, see [Create and Manage SageMaker Pipelines](https://docs.aws.amazon.com/sagemaker/latest/dg/pipelines.html). (p. 3250).
- For each run of the ML pipeline, create a model version that you register in the model group you created in the first step.

**Model Registry Structure**

The SageMaker Model Registry is structured as several model groups with model packages in each group. Each model package in a model group corresponds to a trained model. The version of each model package is a numerical value that starts at 1 and is incremented with each new model package added to a model group. For example, if 5 model packages are added to a model group, the model package versions will be 1, 2, 3, 4, and 5. The example Model Registry shown in the following image contains 3 model groups, where each group contains the model packages related to a particular ML problem.
There are two types of model packages in SageMaker. One type is used in the AWS Marketplace, and the other is used in the Model Registry. Model packages used in the AWS Marketplace are not versionable entities and are not associated with model groups in the Model Registry. For more information about model packages used in the AWS Marketplace, see Buy and Sell Amazon SageMaker Algorithms and Models in AWS Marketplace (p. 3475).

The model packages used in the Model Registry are versioned, and must be associated with a model group. The ARN of this model package type has the structure: `arn:aws:sagemaker:region:account:model-group/version`

The following topics show you how to use the Model Registry.

**Topics**
- Create a Model Group (p. 2983)
- Delete a Model Group (p. 2987)
- Register a Model Version (p. 2988)
- View Model Groups and Versions (p. 2995)
- View the Details of a Model Version (p. 2997)
- Delete a Model Version (p. 2999)
- Update the Approval Status of a Model (p. 3001)
- Deploy a Model from the Registry (p. 3005)
- View the Deployment History of a Model (p. 3008)
- Amazon SageMaker Model Registry FAQ (p. 3011)

## Create a Model Group

A model group contains a group of versioned models. Create a model group by using either the AWS SDK for Python (Boto3) or Amazon SageMaker Studio.

### Create a Model Package Group (Boto3)

To create a model group by using Boto3, call the `create_model_package_group` method and specify a name and description as parameters. The following example shows how to create a model group.

```python
model_package_group_name = 'my-model-package-group'
model_package_group_description = 'This is a model package group for my experiment.'
create_model_package_group(ModelGroupName=model_package_group_name, ModelGroupDescription=model_package_group_description)
```
response from the `create_model_package_group` call is the Amazon Resource Name (ARN) of the new model package group.

First, import the required packages and set up the SageMaker Boto3 client.

```python
import time
import os
from sagemaker import get_execution_role, session
import boto3

region = boto3.Session().region_name
role = get_execution_role()
sm_client = boto3.client('sagemaker', region_name=region)

Now create the model group.

```python
model_package_group_name = "scikit-iris-detector-" + str(round(time.time()))
model_package_group_input_dict = {
    "ModelPackageGroupName" : model_package_group_name,
    "ModelPackageGroupDescription" : "Sample model package group"
}

create_model_package_group_response = sm_client.create_model_package_group(**model_package_group_input_dict)
print('ModelPackageGroup Arn : {}'.format(create_model_package_group_response["ModelPackageGroupArn"]))
```

Create a Model Package Group (Amazon SageMaker Studio)

To create a model group in Amazon SageMaker Studio, complete the following steps.

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the SageMaker Resources icon (🔍).
3. Choose Model registry.
4. Choose Create model group.
5. In the **Create new model group** dialog box, enter the following information:

   - Enter the name of the new model group in the **Name** field.
   - (Optional) Enter a description for the model group in the **Description** field.
   - (Optional) Enter any key-value pairs you want to associate with the model group in the **Tags** field. For information about using tags, see *Tagging AWS resources* in the *AWS General Reference*.
   - (Optional) Choose a project with which to associate the model group in the **Project** field. For information about projects, see *Automate MLOps with SageMaker Projects* (p. 3281).

6. Choose **Create model group**.
Delete a Model Group

This procedure demonstrates how to delete a model group in Amazon SageMaker Studio.

Delete a Model Package Group (Amazon SageMaker Studio)

To delete a model group in Amazon SageMaker Studio, complete the following steps.

1. Sign in to Amazon SageMaker Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the SageMaker Resources icon (🔗).
3. Choose Model registry in the dropdown menu at the top of the SageMaker resources panel.
   A list of your model groups appears.
4. From the model groups list, double-click the model group you want to delete.
   The model details tab opens to the right.
5. In the Actions dropdown menu in the top right corner of the model details tab, choose Delete.
6. In the confirmation dialog box, choose Delete.

**Register a Model Version**

You can register an Amazon SageMaker model by creating a model version that specifies the model group to which it belongs. A model version must include both the model artifacts (the trained weights of a model) and the inference code for the model.

An *inference pipeline* is a SageMaker model composed of a linear sequence of two to fifteen containers that process inference requests. You register an inference pipeline by specifying the containers and the associated environment variables. For more information on inference pipelines, see Host models along with pre-processing logic as serial inference pipeline behind one endpoint (p. 2789).

You can register a model with an inference pipeline, by specifying the containers and the associated environment variables. To create a model version with an inference pipeline by using either the AWS SDK for Python (Boto3) or by creating a step in a SageMaker model building pipeline, use the following steps.

**Topics**
- Register a Model Version (SageMaker Pipelines) (p. 2989)
Register a Model Version (SageMaker Pipelines)

To register a model version by using a SageMaker model building pipeline, create a RegisterModel step in your pipeline. For information about creating a RegisterModel step as part of a pipeline, see Step 8: Define a RegisterModel Step to Create a Model Package (p. 3261).

Register a Model Version (Boto3)

To register a model version by using Boto3, call the create_model_package method.

First, you set up the parameter dictionary to pass to the create_model_package method.

```python
# Specify the model source
model_url = "s3://your-bucket-name/model.tar.gz"

modelpackage_inference_specification = {
    "InferenceSpecification": {
        "Containers": [
            {
                "Image": '257758044811.dkr.ecr.us-east-2.amazonaws.com/sagemaker-xgboost:1.2-1',
                "ModelDataUrl": model_url
            }
        ],
        "SupportedContentTypes": [ "text/csv" ],
        "SupportedResponseMIMETypes": [ "text/csv" ],
    }
}

create_model_package_input_dict = {
    "ModelPackageGroupName": model_package_group_name,
    "ModelPackageDescription": "Model to detect 3 different types of irises (Setosa, Versicolour, and Virginica)",
    "ModelApprovalStatus": "PendingManualApproval"

create_model_package_input_dict.update(modelpackage_inference_specification)

create_model_package_response = sm_client.create_model_package(**create_model_package_input_dict)
model_package_arn = create_model_package_response["ModelPackageArn"]
print('ModelPackage Version ARN : {}'.format(model_package_arn))
```

Register a Model Version from a Different Account

To register model versions with a model package group created by a different AWS account, you must add a cross-account AWS Identity and Access Management resource policy to enable that account. For example, one AWS account in your organization is responsible for training models, and a different
account is responsible for managing, deploying, and updating models. You create IAM resource policies and apply the policies to the specific account resource to which you want to grant access for this case. For more information about cross-account resource policies in AWS, see Cross-account policy evaluation logic in the AWS Identity and Access Management User Guide.

Note
You must also use a KMS key to encrypt the output data config action during training for cross-account model deployment.

To enable cross-account model registry in SageMaker, you have to provide a cross-account resource policy for the model group that contains the model versions. The following is an example that creates cross-account policies for the model package group and applies these policies to that specific resource.

The following configuration must be set in the source account which registers models cross-account in a model package group. In this example, the source account is the model training account which will train and then register the model cross-account into the Model Registry of the model registry account.

The example assumes that you previously defined the following variables:

- **sm_client** - A SageMaker Boto3 client.
- **model_package_group_name** - The model group to which you want to grant access.
- **model_package_group_arn** - The model group arn to which you want to grant cross-account access.
- **bucket** - The S3 bucket where the model training artifacts are stored.

To be able to deploy a model created in a different account, the user must have a role that has access to SageMaker actions, such as a role with the AmazonSageMakerFullAccess managed policy. For information about SageMaker managed policies, see AWS Managed Policies for Amazon SageMaker (p. 3571).

**Required IAM resource policies**

The following diagram captures the policies required to allow cross-account model registration. As shown, these policies need to be active during model training to properly register the model into the model registry account.
Amazon ECR, Amazon S3, and AWS KMS policies are demonstrated in the following code samples.

**Sample Amazon ECR policy**

```json
{
  'Version': '2012-10-17',
  'Statement': [
    {
      'Sid': 'AddPerm',
      'Effect': 'Allow',
```
Sample Amazon S3 policy

```json
{
  'Version': '2012-10-17',
  'Statement': [
    {
      'Sid': 'AddPerm',
      'Effect': 'Allow',
      'Principal': {
        'AWS': 'arn:aws:iam::{model_registry_account}:root'
      },
      'Action': ['s3:GetObject', 's3:GetBucketAcl', 's3:GetObjectAcl'],
      'Resource': 'arn:aws:s3:::{bucket}/*'
    }
  ]
}
```

Sample AWS KMS policy

```json
{
  'Version': '2012-10-17',
  'Statement': [
    {
      'Sid': 'AddPerm',
      'Effect': 'Allow',
      'Principal': {
        'AWS': 'arn:aws:iam::{model_registry_account}:root'
      },
      'Action': ['kms:Decrypt', 'kms:GenerateDataKey*'],
      'Resource': '*'
    }
  ]
}
```

Apply resource policies to accounts

The following policy configuration applies the policies discussed in the previous section and must be put in the model training account.

```python
import json

# The model registry account id of the model package group
model_registry_account = '111111111111'
```
# The model training account id where training happens
model_training_account = '222222222222'

# 1. Create a policy for access to the ECR repository
# in the model training account for the model registry account model package group
ecr_repo_policy = {'Version': '2012-10-17',
                   'Statement': [{'Sid': 'AddPerm',
                                  'Effect': 'Allow',
                                  'Principal': {'AWS': f'arn:aws:iam::{model_registry_account}:root'},
                                  'Action': ['ecr:BatchGetImage',
                                             'ecr:Describe*']
                     ]}

# Convert the ECR policy from JSON dict to string
ecr_repo_policy = json.dumps(ecr_repo_policy)

# Set the new ECR policy
ecr = boto3.client('ecr')
response = ecr.set_repository_policy(registryId=model_training_account,
                                        repositoryName='decision-trees-sample',
                                        policyText=ecr_repo_policy)

# 2. Create a policy in the model training account for access to the S3 bucket
# where the model is present in the model registry account model package group
bucket_policy = {'Version': '2012-10-17',
                 'Statement': [{'Sid': 'AddPerm',
                                'Effect': 'Allow',
                                'Principal': {'AWS': f'arn:aws:iam::{model_registry_account}:root'},
                                'Action': ['s3:GetObject',
                                           's3:GetBucketAcl',
                                           's3:GetObjectAcl']
                   },
                   'Resource': f'arn:aws:s3::{bucket}/**'
                 ]}

# Convert the S3 policy from JSON dict to string
bucket_policy = json.dumps(bucket_policy)

# Set the new bucket policy
s3 = boto3.client('s3')
response = s3.put_bucket_policy(Bucket=bucket,
                                Policy=bucket_policy)

# 3. Create the KMS grant for the key used during training for encryption
# in the model training account to the model registry account model package group
client = boto3.client('kms')
response = client.create_grant(GranteePrincipal=model_registry_account,
                               KeyId=kms_key_id,
                               Operations=[
                                             'Decrypt',
                                             'GenerateDataKey'
                                             ],
                               CiphertextBlob=ciphertext_blob)
The following configuration needs to be put in the model registry account where the model package group exists.

```python
# The model registry account id of the model package group
model_registry_account = '111111111111'

# 1. Create policy to allow the model training account to access the ModelPackageGroup
model_package_group_policy = {'Version': '2012-10-17',
   'Statement': [
      {
         'Sid': 'AddPermModelPackageVersion',
         'Effect': 'Allow',
         'Principal': {'AWS': f'arn:aws:iam::{model_training_account}:root'},
         'Action': ['sagemaker:CreateModelPackage'],
         'Resource': f'arn:aws:sagemaker:{region}:{model_registry_account}:model-package/{model_package_group_name}/*'
      }
   ]
}

# Convert the policy from JSON dict to string
model_package_group_policy = json.dumps(model_package_group_policy)

# Set the new policy
response = sm_client.put_model_package_group_policy(
    ModelPackageGroupName = model_package_group_name,
    ResourcePolicy = model_package_group_policy)

Finally, use the create_model_package action from the model training account to register the model package in the cross-account.

```python
# Specify the model source
model_url = "s3://(bucket)/model.tar.gz"

# Set up the parameter dictionary to pass to the create_model_package method
modelpackage_inference_specification = {
   "InferenceSpecification": {
      "Containers": [
         {
            "Image": f'${model_training_account}.dkr.ecr.us-east-2.amazonaws.com/decision-trees-sample:latest',
            "ModelDataUrl": model_url
         }
      ],
      "SupportedContentTypes": [ "text/csv" ],
      "SupportedResponseMIMETypes": [ "text/csv" ],
   }
}

# Alternatively, you can specify the model source like this:
# modelpackage_inference_specification["InferenceSpecification"]["Containers"][0]["ModelDataUrl"] = model_url

create_model_package_input_dict = {
   "ModelPackageGroupName" : model_package_group_arn,
   "ModelPackageDescription" : "Model to detect 3 different types of irises (Setosa, Versicolour, and Virginica)",
   "ModelApprovalStatus" : "PendingManualApproval"
}
} create_model_package_input_dict.update(modelpackage_inference_specification)

# Create the model package in the model registry account
create_model_package_response =
    sm_client.create_model_package(**create_model_package_input_dict)
model_package_arn = create_model_package_response['ModelPackageArn']
print('ModelPackage Version ARN : {}'.format(model_package_arn))

View Model Groups and Versions

Model groups and versions help you organize your models. You can view a list of the model versions in a model group.

View a List of Model Versions in a Group

You can view all of the model versions that are associated with a model group. If a model group represents all models that you train to address a specific ML problem, you can view all of those related models.

View a List of Model Versions in a Group (Boto3)

To view model versions associated with a model group by using Boto3, call the list_model_packages method, and pass the name of the model group as the value of the ModelPackageGroupName parameter. The following code lists the model versions associated with the model group you created in Create a Model Package Group (Boto3) (p. 2983).

```
sm_client.list_model_packages(ModelPackageGroupName=model_package_group_name)
```

View a List of Model Versions in a Group (Amazon SageMaker Studio)

To view a list of the model versions in a model group, complete the following steps.

1. Sign in to Amazon SageMaker Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the SageMaker Resources icon (🔍).
3. Choose Model registry.
4. From the model groups list, choose the model group you want to view.
5. A new tab appears with a list of the model versions in the model group, as shown in the following image.
View the Details of a Model Version

You can view details of a specific model version by using either the AWS SDK for Python (Boto3) or by using Amazon SageMaker Studio.

View the Details of a Model Version (Boto3)

To view the details of a model version by using Boto3, complete the following steps.

1. Call the `list_model_packages` method to view the model versions in a model group.

   ```python
   sm_client.list_model_packages(ModelPackageGroupName="ModelGroup1")
   ```

   The response is a list of model package summaries. You can get the Amazon Resource Name (ARN) of the model versions from this list.

   ```json
   {'ModelPackageSummaryList': 

   2. Call `describe_model_package` to see the details of the model version. You pass in the ARN of a model version that you got in the output of the call to `list_model_packages`.

   ```python
   sm_client.describe_model_package(ModelPackageName="arn:aws:sagemaker:us-east-2:123456789012:model-package/ModelGroup1/1")
   ```

   The output of this call is a JSON object with the model version details.

   ```json
   {'ModelPackageName': 'ModelGroup1', 'ModelPackageVersion': 1, 'ModelPackageArn': 'arn:aws:sagemaker:us-east-2:123456789012:model-package/ModelGroup1/1', 'ModelPackageDescription': 'Test Model', 'CreationTime': datetime.datetime(2020, 10, 29, 1, 27, 46, 46000, tzinfo=tzlocal()), 'InferenceSpecification': {'Containers': [{'Image': '257758044811.dkr.ecr.us-east-2.amazonaws.com/sagemaker-xgboost:1.0-1-cpu-py3', 'ImageDigest': 'sha256:99fa682cfff19ae33297a5926f8497ca7bcd2a391b7d600300204efb03bca66', 'ModelDataUrl': 's3://sagemaker-us-east-2-123456789012/ModelGroup1/pipelines-0gdoncek7o9-AbaloneTrain-stmlyht1R/output/model.tar.gz'}], 'SupportedTransformInstanceTypes': ['ml.m5.xlarge'], 'SupportedRealtimeInferenceInstanceTypes': ['ml.t2.medium', 'ml.m5.xlarge'], 'SupportedContentTypes': ['text/csv'], 'SupportedResponseMIMETypes': ['text/csv'], 'ModelPackageStatus': 'Completed', 'ModelPackageStatusDetails': {'ValidationStatuses': [], 'ImageScanStatuses': []}}

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View the Details of a Model Version (Amazon SageMaker Studio)

To view the details of a model version in Amazon SageMaker Studio, complete the following steps.

1. Sign in to Amazon SageMaker Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the SageMaker Resources icon (licas).
3. Choose Model registry.
4. From the model groups list, double-click the model group you want to view.
5. A new tab appears with a list of the model versions in the model group, as shown in the following image.

6. In the list of model versions, double-click the model version for which you want to view details.

7. On the model version tab that opens, choose one of the following to see details about the model version:

   - **Activity**: Shows events for the model version, such as approval status updates.
   - **Metrics**: Shows quality metrics for the model. For metrics to appear, you must enable data capture for your model by using SageMaker Model Monitor. For information about capturing data, see [Capture data](p. 2855).
   - **Settings**: Shows information such as the project with which the model version is associated, the pipeline that generated the model, the model group, and the model's location in Amazon S3.

---

**Delete a Model Version**

This procedure demonstrates how to delete a model version in Amazon SageMaker Studio.
Delete a Model Version (Amazon SageMaker Studio)

To delete a model version in Amazon SageMaker Studio, complete the following steps.

1. Sign in to Amazon SageMaker Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the SageMaker Resources icon ().
3. Choose Model registry in the dropdown menu at the top of the SageMaker resources panel.

A list of your model groups appears.
4. From the model groups list, double-click the model group of the model version you want to delete.

The model details tab opens to the right.
5. From the list of model versions in the model details tab, double-click the model version you want to delete.

6. Choose the Settings tab.
7. Choose Delete Version in the Settings tab.
8. In the confirmation dialog box, choose **Delete**.

## Update the Approval Status of a Model

After you create a model version, you typically want to evaluate its performance before you deploy it to a production endpoint. If it performs to your requirements, you can update the approval status of the model version to **Approved**. Setting the status to **Approved** can initiate CI/CD deployment for the model. If the model version does not perform to your requirements, you can update the approval status to **Rejected**.

You can manually update the approval status of a model version after you register it, or you can create a condition step to evaluate the model when you create a SageMaker pipeline. For information about creating a condition step in a SageMaker pipeline, see **Pipeline Steps** (p. 3211).

When you use one of the SageMaker provided project templates and the approval status of a model version changes, the following action occurs. Only valid transitions are shown.

- **PendingManualApproval** to **Approved** – initiates CI/CD deployment for the approved model version
- **PendingManualApproval** to **Rejected** – No action
• Rejected to Approved – initiates CI/CD deployment for the approved model version
• Approved to Rejected – initiates CI/CD to deploy the latest model version with an Approved status

You can update the approval status of a model version by using the AWS SDK for Python (Boto3) or by using Amazon SageMaker Studio. You can also update the approval status of a model version as part of a condition step in a SageMaker pipeline. For information about using a model approval step in a SageMaker pipeline, see SageMaker Pipelines Overview (p. 3204).

Update the Approval Status of a Model (Boto3)

When you created the model version in Register a Model Version (p. 2988), you set the ModelApprovalStatus to PendingManualApproval. You update the approval status for the model by calling update_model_package. Note that you can automate this process by writing code that, for example, sets the approval status of a model depending on the result of an evaluation of some measure of the model's performance. You can also create a step in a pipeline that automatically deploys a new model version when it is approved. The following code snippet shows how to manually change the approval status to Approved.

```python
model_package_update_input_dict = {
    "ModelPackageArn" : model_package_arn,
    "ModelApprovalStatus" : "Approved"
}
model_package_update_response = sm_client.update_model_package(**model_package_update_input_dict)
```

Update the Approval Status of a Model (Amazon SageMaker Studio)

The following procedure shows how to manually change the approval status from Approved to Rejected.

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the SageMaker Resources icon (🔍).
3. Choose Model registry.
4. From the model groups list, choose the model group you want to view. A new tab opens with a list of the model versions in the group.

5. In the list of model versions, right-click the model version you want to update and choose **Update model version status**.
6. In the **Update model version status** dialog box, for **Status** choose **Rejected**, and then choose **Update status**.

![Update model version status dialog box](image)
Deploy a Model from the Registry

After you register a model version and approve it for deployment, deploy it to a SageMaker endpoint for real-time inference.

When you create an MLOps project and choose an MLOps project template that includes model deployment, approved model versions in the model registry are automatically deployed to production. For information about using SageMaker MLOps projects, see Automate MLOps with SageMaker Projects (p. 3281).

You can also enable an AWS account to deploy model versions that were created in a different account by adding a cross-account resource policy. For example, one team in your organization might be responsible for training models, and a different team is responsible for deploying and updating models.

Topics

- Deploy a Model from the Registry (SageMaker SDK) (p. 3005)
- Deploy a Model from the Registry (Boto3) (p. 3005)
- Deploy a Model Version from a Different Account (p. 3006)

Deploy a Model from the Registry (SageMaker SDK)

To deploy a model version using the Amazon SageMaker Python SDK use the following code snippet:

```python
from sagemaker import ModelPackage
from time import gmtime, strftime

model_package_arn = 'arn:aws:sagemaker:us-east-2:12345678901:model-package/modeltest/1'
model = ModelPackage(role=role,
                     model_package_arn=model_package_arn,
                     sagemaker_session=sagemaker_session)
model.deploy(initial_instance_count=1, instance_type='ml.m5.xlarge')
```

Deploy a Model from the Registry (Boto3)

To deploy a model version using the AWS SDK for Python (Boto3), complete the following steps:

1. Create a model object from the model version by calling the create_model method. Pass the Amazon Resource Name (ARN) of the model version as part of the Containers for the model object.

   The following code snippet assumes you have already created the SageMaker Boto3 client `sm_client`, and that you have already created a model version with an ARN that you have stored in a variable named `model_version_arn`.

   ```python
   model_name = 'DEMO-modelregistry-model-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
   print("Model name : {}".format(model_name))
   container_list = ["ModelPackageName": model_version_arn]

   create_model_response = sm_client.create_model(
       ModelName = model_name,
       ExecutionRoleArn = role,
       Containers = container_list
   )
   print("Model arn : {}".format(create_model_response["ModelArn"]))
   ```

2. Create an endpoint configuration by calling create_endpoint_config. The endpoint configuration specifies the number and type of Amazon EC2 instances to use for the endpoint.
endpoint_config_name = 'DEMO-modelregistry-EndpointConfig-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
p
print(endpoint_config_name)
create_endpoint_config_response = sm_client.create_endpoint_config(
    EndpointConfigName = endpoint_config_name,
    ProductionVariants=[{
        'InstanceType':'ml.m4.xlarge',
        'InitialVariantWeight':1,
        'InitialInstanceCount':1,
        'ModelName':model_name,
        'VariantName':'AllTraffic'}])

3. Create the endpoint by calling create_endpoint.

endpoint_name = 'DEMO-modelregistry-endpoint-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
p
print("EndpointName=", endpoint_name)
create_endpoint_response = sm_client.create_endpoint(
    EndpointName=endpoint_name,
    EndpointConfigName=endpoint_config_name)
p

Deploy a Model Version from a Different Account

You can permit an AWS account to deploy model versions that were created in a different account by adding a cross-account resource policy. For example, one team in your organization might be responsible for training models, and a different team is responsible for deploying and updating models. When you create these resource policies, you apply the policy to the specific resource to which you want to grant access. For more information about cross-account resource policies in AWS, see Cross-account policy evaluation logic in the AWS Identity and Access Management User Guide.

Note
You must use a KMS key to encrypt the output data config action during training for cross-account model deployment.

To enable cross-account model deployment in SageMaker, you have to provide a cross-account resource policy for the model group that contains the model versions you want to deploy, the Amazon ECR repository where the inference image for the model group resides, and the Amazon S3 bucket where the model versions are stored.

To be able to deploy a model that was created in a different account, you must have a role that has access to SageMaker actions, such as a role with the AmazonSageMakerFullAccess managed policy. For information about SageMaker managed policies, see AWS Managed Policies for Amazon SageMaker (p. 3571).

The following example creates cross-account policies for all three of these resources, and applies the policies to the resources.

The example assumes that you previously defined the following variables:

- bucket - The Amazon S3 bucket where the model versions are stored.
- kms_key_id - The KMS key used to encrypt the training output.
- model_package_group_name - The model group to which you want to grant cross-account access.
- model_package_group_arn - The model group arn to which you want to grant cross-account access.
import json

# The cross-account id to grant access to
cross_account_id = "123456789012"

# Create the policy for access to the ECR repository
ecr_repository_policy = {
    'Version': '2012-10-17',
    'Statement': [{
        'Sid': 'AddPerm',
        'Effect': 'Allow',
        'Principal': {
            'AWS': f'arn:aws:iam::{cross_account_id}:root'
        },
        'Action': ['ecr:*']
    }]
}

# Convert the ECR policy from JSON dict to string
ecr_repository_policy = json.dumps(ecr_repository_policy)

# Set the new ECR policy
ecr = boto3.client('ecr')
response = ecr.set_repository_policy(
    registryId = account,
    repositoryName = 'decision-trees-sample',
    policyText = ecr_repository_policy
)

# Create a policy for accessing the S3 bucket
bucket_policy = {
    'Version': '2012-10-17',
    'Statement': [{
        'Sid': 'AddPerm',
        'Effect': 'Allow',
        'Principal': {
            'AWS': f'arn:aws:iam::{cross_account_id}:root'
        },
        'Action': 's3:*',
        'Resource': f'arn:aws:s3:::{bucket}/*'
    }]
}

# Convert the policy from JSON dict to string
bucket_policy = json.dumps(bucket_policy)

# Set the new policy
s3 = boto3.client('s3')
response = s3.put_bucket_policy(
    Bucket = bucket,
    Policy = bucket_policy
)

# Create the KMS grant for encryption in the source account to the
# model registry account model package group
client = boto3.client('kms')
response = client.create_grant(
    GranteePrincipal=cross_account_id,
    KeyId=kms_key_id
    Operations=[
        'Decrypt',
        'GenerateDataKey',
    ],
)
# 3. Create a policy for access to the model package group.

```python
model_package_group_policy = {
    'Version': '2012-10-17',
    'Statement': [
        {'Sid': 'AddPermModelPackageGroup',
         'Effect': 'Allow',
         'Principal': {
             'AWS': f'arn:aws:iam::{cross_account_id}:root' },
         'Action': ['sagemaker:DescribeModelPackageGroup'],
         'Resource': f'arn:aws:sagemaker:{region}:{account}:model-package-group/
{model_package_group_name}'
    ],
    {'Sid': 'AddPermModelPackageVersion',
     'Effect': 'Allow',
     'Principal': {
         'AWS': f'arn:aws:iam::{cross_account_id}:root'
     },
     'Action': ['sagemaker:DescribeModelPackage',
                'sagemaker:ListModelPackages',
                'sagemaker:UpdateModelPackage',
                'sagemaker:CreateModel'],
     'Resource': f'arn:aws:sagemaker:{region}:{account}:model-package/
{model_package_group_name}/*' ]
}
```

# Convert the policy from JSON dict to string

```python
model_package_group_policy = json.dumps(model_package_group_policy)
```

# Set the policy to the model package group

```python
response = sm_client.put_model_package_group_policy(
    ModelPackageGroupName = model_package_group_name,
    ResourcePolicy = model_package_group_policy)
```

print('ModelPackageGroupArn : ' + create_model_package_group_response['ModelPackageGroupArn'])
print("First Versioned ModelPackageArn: " + model_package_arn)
print("Second Versioned ModelPackageArn: " + model_package_arn2)

print("Success! You are all set to proceed for cross-account deployment.")
```

### View the Deployment History of a Model

View the deployments for a model version Amazon SageMaker Studio by opening the tab for that model version.

**View the deployment history for a model version**

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the left navigation pane, choose the **SageMaker Resources** icon (🔗).
3. Choose **Model registry**.
4. From the model groups list, choose the model group you want to view.
5. A new tab appears with a list of the model versions in the model group.
6. In the list of model versions, double-click the model version for which you want to view details.
7. On the model version tab that opens, choose Activity. Deployments for the model version appear as events in the activity list with an Event type of ModelDeployment.
Amazon SageMaker Model Registry FAQ

Use the following FAQ items to find answers to commonly asked questions about SageMaker Model Registry.

Q. How should I organize my models into model groups and model packages in the SageMaker Model Registry?

A model package is the actual model that is registered into the model registry as a versioned entity. Please note there are two ways you can use model packages in SageMaker. One is with SageMaker Marketplace — these model packages are not versioned. The other is with the SageMaker Model Registry, in which the model package must be versioned. The model registry receives every new model that you retrain, gives it a version, and assigns it to a model group inside the model registry. The following image shows an example of a model group with 25 consecutively-versioned models.
### sagemaker-e2e-<unfilled>-p-<unfilled>

<table>
<thead>
<tr>
<th>Version</th>
<th>Stage</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>24</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>23</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>22</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>21</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>20</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>19</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>18</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>17</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>16</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>15</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>14</td>
<td>staging</td>
<td>Approved</td>
</tr>
<tr>
<td>13</td>
<td>staging</td>
<td>Approved</td>
</tr>
<tr>
<td>12</td>
<td>None</td>
<td>Pending</td>
</tr>
<tr>
<td>11</td>
<td>None</td>
<td>Pending</td>
</tr>
</tbody>
</table>
Q. How does a model registry differ from Amazon Elastic Container Registry (Amazon ECR)?

SageMaker’s Model Registry is a metadata store for your machine learning models. Amazon Elastic Container Registry is a repository that stores all of your containers. Within the model registry, models are versioned and registered as model packages within model groups. Each model package contains an Amazon S3 URI to the model files associated with the trained model and an Amazon ECR URI that points to the container used while serving the model.

Deploy models at the edge with SageMaker Edge Manager

Amazon SageMaker Edge Manager provides model management for edge devices so you can optimize, secure, monitor, and maintain machine learning models on fleets of edge devices such as smart cameras, robots, personal computers, and mobile devices.

Why Use Edge Manager?

Many machine learning (ML) use cases require running ML models on a fleet of edge devices, which allows you to get predictions in real-time, preserves the privacy of the end users, and lowers the cost of network connectivity. With the increasing availability of low-power edge hardware designed for ML, it is now possible to run multiple complex neural network models on edge devices.

However, operating ML models on edge devices is challenging, because devices, unlike cloud instances, have limited compute, memory, and connectivity. After the model is deployed, you need to continuously monitor the models, because model drift can cause the quality of model to decay overtime. Monitoring models across your device fleets is difficult because you need to write custom code to collect data samples from your device and recognize skew in predictions. In addition, models are often hard-coded into the application. To update the model, you must rebuild and update the entire application or device firmware, which can disrupt your operations.

With SageMaker Edge Manager, you can optimize, run, monitor, and update machine learning models across fleets of devices at the edge.

How Does it Work?

At a high level, there are five main components in the SageMaker Edge Manager workflow: compiling models with SageMaker Neo, packaging Neo-compiled models, deploying models to your devices, running models on the SageMaker inference engine (Edge Manager agent), and maintaining models on the devices.
SageMaker Edge Manager uses SageMaker Neo to optimize your models for the target hardware in one click, then to cryptographically sign your models before deployment. Using SageMaker Edge Manager, you can sample model input and output data from edge devices and send it to the cloud for monitoring and analysis, and view a dashboard that tracks and visually reports on the operation of the deployed models within the SageMaker console.

SageMaker Edge Manager extends capabilities that were previously only available in the cloud to the edge, so developers can continuously improve model quality by using Amazon SageMaker Model Monitor for drift detection, then relabel the data with SageMaker Ground Truth and retrain the models in SageMaker.

**How Do I Use SageMaker Edge Manager?**

If you are a first time user of SageMaker Edge Manager, we recommend that you do the following:

1. **Read the Getting Started section** - This section walks you through setting up your first edge packaging job and creating your first fleet.
2. **Explore Edge Manager Jupyter notebook examples** - Example notebooks are stored in the [amazon-sagemaker-examples](https://github.com/aws-samples/sagemaker-examples) GitHub repository in the `sagemaker_edge_manager` folder.

**Getting Started**

This guide demonstrates how to complete the necessary steps to register, deploy, and manage a fleet of devices, and how to satisfy Amazon SageMaker Edge Manager prerequisites.

**Topics**

- Setting Up (p. 3015)
- Train, Compile, and Package Your Model (p. 3017)
- Create and Register Fleets and Authenticate Devices (p. 3020)
- Download and Set Up Edge Manager (p. 3023)
- Run Agent (p. 3026)
Setting Up

Before you begin using SageMaker Edge Manager to manage models on your device fleets, you must first create IAM Roles for both SageMaker and AWS IoT. You will also want to create at least one Amazon S3 bucket where you will store your pre-trained model, the output of your SageMaker Neo compilation job, as well as input data from your edge devices.

1. **Set up an AWS account.**

   Create an AWS account and an IAM administrator user. For instructions on how to set up your AWS account, see [How do I create and activate a new AWS account?](#) For instructions on how to create an administrator user in your AWS account, see [Creating your first IAM admin user and group](#).

2. **Create an IAM role for Amazon SageMaker.**

   SageMaker Edge Manager needs access to your Amazon S3 bucket URI. To facilitate this, create an IAM role that can run SageMaker and has permission to access Amazon S3. Using this role, SageMaker can run under your account and access to your Amazon S3 bucket.

   You can create an IAM role by using the IAM console, AWS SDK for Python (Boto3), or AWS CLI. The following is an example of how to create an IAM role and attach the necessary policies with the IAM console.

   a. Sign in to the AWS Management Console and open the IAM console at [https://console.aws.amazon.com/iam/](https://console.aws.amazon.com/iam/).
   b. In the navigation pane of the IAM console, choose **Roles**, and then choose **Create role**.
   c. For **Select type of trusted entity**, choose **AWS service**.
   d. Choose the service that you want to allow to assume this role. In this case, choose **SageMaker**. Then choose **Next: Permissions**.
      - This automatically creates an IAM policy that grants access to related services such as Amazon S3, Amazon ECR, and CloudWatch Logs.
   e. Choose **Next: Tags**.
   f. (Optional) Add metadata to the role by attaching tags as key–value pairs. For more information about using tags in IAM, see [Tagging IAM resources](#).
   g. Choose **Next: Review**.
   h. Type in a **Role name**.
   i. If possible, type a role name or role name suffix. Role names must be unique within your AWS account. They are not distinguished by case. For example, you cannot create roles named both PR0DROLE and prodrole. Because other AWS resources might reference the role, you cannot edit the name of the role after it has been created.
   j. (Optional) For **Role description**, type a description for the new role.
   k. Review the role and then choose **Create role**.

   Note the SageMaker Role ARN, which you use to create a compilation job with SageMaker Neo and a packaging job with Edge Manager. To find out the role ARN using the console, do the following:

   i. Go to the IAM console: [https://console.aws.amazon.com/iam/](https://console.aws.amazon.com/iam/)
   ii. Select **Roles**.
   iii. Search for the role you just created by typing in the name of the role in the search field.
   iv. Select the role.
   v. The role ARN is at the top of the **Summary** page.

3. **Create an IAM role for AWS IoT.**
The AWS IoT IAM role you create is used to authorize your thing objects. You also use the IAM role ARN to create and register device fleets with a SageMaker client object.

Configure an IAM role in your AWS account for the credentials provider to assume on behalf of the devices in your device fleet. Then, attach a policy to authorize your devices to interact with AWS IoT services.

Create a role for AWS IoT either programmatically or with the IAM console, similar to what you did when you created a role for SageMaker.

a. Sign in to the AWS Management Console and open the IAM console at https://console.aws.amazon.com/iam/.
b. In the navigation pane of the IAM console, choose Roles, and then choose Create role.
c. For Select type of trusted entity, choose AWS service.
d. Choose the service that you want to allow to assume this role. In this case, choose IoT. Select IoT as the Use Case.
e. Choose Next: Permissions.
f. Choose Next: Tags.
g. (Optional) Add metadata to the role by attaching tags as key–value pairs. For more information about using tags in IAM, see Tagging IAM resources.
h. Choose Next: Review.
i. Type in a Role name. The role name must start with SageMaker.
j. (Optional) For Role description, type a description for the new role.
k. Review the role and then choose Create role.
l. Once the role is created, choose Roles in the IAM console. Search for the role you created by typing in role name in the Search field.
m. Choose your role.
n. Next, choose Attach Policies.
o. Search for AmazonSageMakerEdgeDeviceFleetPolicy in the Search field. Select AmazonSageMakerEdgeDeviceFleetPolicy.
p. Choose Attach policy.
q. Add the following policy statement to the trust relationship:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {"Service": "credentials.iot.amazonaws.com"},
            "Action": "sts:AssumeRole"
        },
        {
            "Effect": "Allow",
            "Principal": {"Service": "sagemaker.amazonaws.com"},
            "Action": "sts:AssumeRole"
        }
    ]
}
```

A trust policy is a JSON policy document in which you define the principals that you trust to assume the role. For more information about trust policies, see Roles terms and concepts.

r. Note the AWS IoT role ARN. You use the AWS IoT Role ARN to create and register the device fleet. To find the IAM role ARN with the console:
i. Go to the IAM console: https://console.aws.amazon.com/iam/
ii. Choose Roles.
iii. Search for the role you created by typing in the name of the role in the Search field.
iv. Select the role.
v. The role ARN is on the Summary page.

4. Create an Amazon S3 bucket.

SageMaker Neo and Edge Manager access your pre-compiled model and compiled model from an Amazon S3 bucket. Edge Manager also stores sample data from your device fleet in Amazon S3.

a. Open the Amazon S3 console at https://console.aws.amazon.com/s3/.
b. Choose Create bucket.
c. In Bucket name, enter a name for your bucket.
d. In Region, choose the AWS Region where you want the bucket to reside.
e. In Bucket settings for Block Public Access, choose the settings that you want to apply to the bucket.
f. Choose Create bucket.

For more information about creating Amazon S3 buckets, see Getting started with Amazon S3.

Train, Compile, and Package Your Model

In this section you will create SageMaker and AWS IoT client objects, download a pre-trained machine learning model, upload your model to your Amazon S3 bucket, compile your model for your target device with SageMaker Neo, and package your model so that it can be deployed with the Edge Manager agent.

1. Import libraries and create client objects.

This tutorial uses the AWS SDK for Python (Boto3) to create clients to interact with SageMaker, Amazon S3, and AWS IoT.

Import Boto3, specify your Region, and initialize the client objects you need as shown in the following example:

```python
import boto3
import json
import time

AWS_REGION = 'us-west-2'  # Specify your Region
bucket = 'bucket-name'
sagemaker_client = boto3.client('sagemaker', region_name=AWS_REGION)
iot_client = boto3.client('iot', region_name=AWS_REGION)
```

Define variables and assign them the role ARN you created for SageMaker and AWS IoT as strings:

```python
# Replace with the role ARN you created for SageMaker
sagemaker_role_arn = "arn:aws:iam::<account>:role/*"

# Replace with the role ARN you created for AWS IoT.
# Note: The name must start with 'SageMaker'
iot_role_arn = "arn:aws:iam::<account>:role/SageMaker*
```
2. **Train a machine learning model.**

   See [*Train a Model with Amazon SageMaker*](#) for more information on how to train a machine learning model using SageMaker. You can optionally upload your locally trained model directly into an Amazon S3 URI bucket.

   If you do not have a model yet, you can use a pre-trained model for the next steps in this tutorial. For example, you can save the MobileNet V2 models from the TensorFlow framework. MobileNet V2 is an image classification model optimized for mobile applications. For more information about MobileNet V2, see the [*MobileNet GitHub README*](#).

   Type the following into your Jupyter Notebook to save the pre-trained MobileNet V2 model:

   ```python
   # Save the MobileNet V2 model to local storage
   import tensorflow as tf
   model = tf.keras.applications.MobileNetV2()
   model.save("mobilenet_v2.h5")
   ```

   **Note**
   - If you do not have TensorFlow installed, you can do so by running `pip install tensorflow=2.4`
   - Use TensorFlow version 2.4 or lower for this tutorial.

   The model will be saved into the `mobilenet_v2.h5` file. Before packaging the model, you will need to first compile your model using SageMaker Neo. See [*Supported Frameworks, Devices, Systems, and Architectures*](#) to check if your version of TensorFlow (or other framework of choice) is currently supported by SageMaker Neo.

   SageMaker Neo requires models to be stored as a compressed TAR file. Repackage it as a compressed TAR file (*.tar.gz):

   ```python
   # Package MobileNet V2 model into a TAR file
   import tarfile
   tarfile_name='mobilenet-v2.tar.gz'
   with tarfile.open(tarfile_name, mode='w:gz') as archive:
       archive.add('mobilenet-v2.h5')
   ```

3. **Upload your model to Amazon S3.**

   Once you have a machine learning model, store it in an Amazon S3 bucket. The following example uses an AWS CLI command to upload the model to the Amazon S3 bucket you created earlier in a directory called `models`. Type in the following into your Jupyter Notebook:

   ```bash
   !aws s3 cp mobilenet-v2.tar.gz s3://{bucket}/models/
   ```

4. **Compile your model with SageMaker Neo.**

   Compile your machine learning model with SageMaker Neo for an edge device. You need to know your Amazon S3 bucket URI where you stored the trained model, the machine learning framework you used to train your model, the shape of your model's input, and your target device.

   For the MobileNet V2 model, use the following:

   ```python
   framework = 'tensorflow'
   target_device = 'jetson_nano'
   ```
SageMaker Neo requires a specific model input shape and model format based on the deep learning framework you use. For more information about how to save your model, see What input data shapes does SageMaker Neo expect? (p. 3065). For more information about devices and frameworks supported by Neo, see Supported Frameworks, Devices, Systems, and Architectures (p. 3105).

Use the CreateCompilationJob API to create a compilation job with SageMaker Neo. Provide a name to the compilation job, the SageMaker Role ARN, the Amazon S3 URI where your model is stored, the input shape of the model, the name of the framework, the Amazon S3 URI where you want SageMaker to store your compiled model, and your edge device target.

```python
# Specify the path where your model is stored
model_directory = 'models'
s3_model_uri = 's3://{}/models.tar'.format(bucket, model_directory, tarfile_name)

# Store compiled model in S3 within the 'compiled-models' directory
compilation_output_dir = 'compiled-models'
s3_output_location = 's3://{}/{}'.format(bucket, compilation_output_dir)

# Give your compilation job a name
compilation_job_name = 'getting-started-demo'
sagemaker_client.create_compilation_job(CompilationJobName=compilation_job_name,
    RoleArn=sagemaker_role_arn,
    InputConfig={'S3Uri': s3_model_uri,
                 'DataInputConfig': data_shape,
                 'Framework': framework.upper()},
    OutputConfig={'S3OutputLocation': s3_output_location,
                  'TargetDevice': target_device},
    StoppingCondition={'MaxRuntimeInSeconds': 900})
```

5. **Package your compiled model.**

Packaging jobs take SageMaker Neo–compiled models and make any changes necessary to deploy the model with the inference engine, Edge Manager agent. To package your model, create an edge packaging job with the create_edge_packaging API or the SageMaker console.

You need to provide the name that you used for your Neo compilation job, a name for the packaging job, a role ARN (see Setting Up (p. 3015) section), a name for the model, a model version, and the Amazon S3 bucket URI for the output of the packaging job. Note that Edge Manager packaging job names are case-sensitive. The following is an example of how to create a packaging job using the API.

```python
edge_packaging_name='edge-packaging-demo'
model_name='sample-model'
model_version='1.1'

define the Amazon S3 URI where you want to store the packaged model.

# Output directory where you want to store the output of the packaging job
packaging_output_dir = 'packaged_models'
packaging_s3_output = 's3://{}/'.format(bucket, packaging_output_dir)

Use CreateEdgePackagingJob to package your Neo-compiled model. Provide a name for your edge packaging job and the name you provided for your compilation job (in this example, it was
stored in the variable compilation_job_name). Also provide a name for your model, a version for your model (this is used to help you keep track of what model version you are using), and the S3 URI where you want SageMaker to store the packaged model.

```python
sagemaker_client.create_edge_packaging_job(
    EdgePackagingJobName=edge_packaging_name,
    CompilationJobName=compilation_job_name,
    RoleArn=sagemaker_role_arn,
    ModelName=model_name,
    ModelVersion=model_version,
    OutputConfig={
        "S3OutputLocation": packaging_s3_output
    }
)
```

Create and Register Fleets and Authenticate Devices

In this section you will create your AWS IoT thing object, create a device fleet, register your device fleet so it can interact with the cloud, create X.509 certificates to authenticate your devices to AWS IoT Core, associate the role alias with AWS IoT that was generated when you created your fleet, get your AWS account-specific endpoint for the credentials provider, get an official Amazon Root CA file, and upload the Amazon CA file to Amazon S3.

1. **Create AWS IoT things.**

   SageMaker Edge Manager takes advantage of the AWS IoT Core services to facilitate the connection between the edge devices and endpoints in the AWS cloud. You can take advantage of existing AWS IoT functionality after you set up your devices to work with Edge Manager.

   To connect your device to AWS IoT, you need to create AWS IoT thing objects, create and register a client certificate with AWS IoT, and create and configure the IAM role for your devices.

   First, create AWS IoT thing objects with the AWS IoT client (iot_client) you created earlier with Boto3. The following example shows how to create two thing objects:

   ```python
   iot_thing_name = 'sample-device'
   iot_thing_type = 'getting-started-demo'

   iot_client.create_thing_type(
       thingTypeName=iot_thing_type
   )

   # Create an AWS IoT thing objects
   iot_client.create_thing(
       thingName=iot_thing_name,
       thingTypeName=iot_thing_type
   )
   ```

2. **Create your device fleet.**

   Create a device fleet with the SageMaker client object defined in a previous step. You can also use the SageMaker console to create a device fleet.

   ```python
   import time
   device_fleet_name="demo-device-fleet" + str(time.time()).split('.')[0]
device_name="sagemaker-edge-demo-device" + str(time.time()).split('.')[0]
   ```

   Specify your IoT role ARN. This lets AWS IoT grant temporary credentials to devices.
device_model_directory='device_output'
s3_device_fleet_output = 's3://{}'.format(bucket, device_model_directory)

sagemaker_client.create_device_fleet(
    DeviceFleetName=device_fleet_name,
    RoleArn=iot_role_arn, # IoT Role ARN specified in previous step
    OutputConfig={'S3OutputLocation': s3_device_fleet_output}
)

An AWS IoT role alias is created when you create a device fleet. This role alias is associated with AWS IoT using the `iot_client` object in a later step.

3. **Register your device fleet.**

To interact with the cloud, you need to register your device with SageMaker Edge Manager. In this example, you register a single device with the fleet you created. To register the device, you need to provide a device name and the AWS IoT thing name as shown in the following example:

```python
# Device name should be 36 characters
device_name = "sagemaker-edge-demo-device" + str(time.time()).split('.')[0]

sagemaker_client.register_devices(
    DeviceFleetName=device_fleet_name,
    Devices=[
        {
            "DeviceName": device_name,
            "IotThingName": iot_thing_name
        }
    ]
)
```

4. **Create X.509 certificates.**

After creating the AWS IoT thing object, you must create a X.509 device certificate for your thing object. This certificate authenticates your device to AWS IoT Core.

Use the following to create a private key, public key, and a X.509 certificate file using the AWS IoT client defined (`iot_client`) earlier.

```python
# Creates a 2048-bit RSA key pair and issues an X.509 # certificate # using the issued public key.
create_cert = iot_client.create_keys_and_certificate(setAsActive=True)

# Get certificate from dictionary object and save in its own
with open('./device.pem.crt', 'w') as f:
    for line in create_cert['certificatePem'].split('
'):
        f.write(line)
        f.write('
')

# Get private key from dictionary object and save in its own
with open('./private.pem.key', 'w') as f:
    for line in create_cert['keyPair']['PrivateKey'].split('
'):
        f.write(line)
        f.write('
')

# Get a private key from dictionary object and save in its own
with open('./public.pem.key', 'w') as f:
    for line in create_cert['keyPair']['PublicKey'].split('
'):
        f.write(line)
```
5. **Associate the role alias with AWS IoT.**

When you create a device fleet with SageMaker (sagemaker_client.create_device_fleet()), a role alias is generated for you. An AWS IoT role alias provides a mechanism for connected devices to authenticate to AWS IoT using X.509 certificates, and then obtain short-lived AWS credentials from an IAM role that is associated with an AWS IoT role alias. The role alias allows you to change the role of the device without having to update the device. Use DescribeDeviceFleet to get the role alias name and ARN.

```python
# Print Amazon Resource Name (ARN) and alias that has access
# to AWS Internet of Things (IoT).
sagemaker_client.describe_device_fleet(DeviceFleetName=device_fleet_name)

# Store iot role alias string in a variable
# Grabs role ARN
full_role_alias_name =
sagemaker_client.describe_device_fleet(DeviceFleetName=device_fleet_name)['IotRoleAlias']
start_index = full_role_alias_name.find('SageMaker')  # Find beginning of role name
role_alias_name = full_role_alias_name[start_index:]
```

Use the iot_client to facilitate associating the role alias generated from creating the device fleet with AWS IoT:

```python
role_alias = iot_client.describe_role_alias(
    roleAlias=role_alias_name)
```

For more information about IAM role alias, see [Role alias allows access to unused services](#).

You created and registered a certificate with AWS IoT earlier for successful authentication of your device. Now, you need to create and attach a policy to the certificate to authorize the request for the security token.

```python
alias_policy = {
    "Version": "2012-10-17",
    "Statement": {
        "Effect": "Allow",
        "Action": "iot:AssumeRoleWithCertificate",
        "Resource": role_alias['roleAliasDescription']['roleAliasArn']
    }
}

policy_name = 'aliaspolicy-\' + str(time.time()).split('.')[0]
aliaspolicy = iot_client.create_policy(policyName=policy_name,
    policyDocument=json.dumps(alias_policy))

# Attach policy
iot_client.attach_policy(policyName=policy_name,
    target=create_cert['certificateArn'])
```

6. **Get your AWS account-specific endpoint for the credentials provider.**

Edge devices need an endpoint in order to assume credentials. Obtain your AWS account-specific endpoint for the credentials provider.

```python
# Get the unique endpoint specific to your AWS account that is making the call.
s3_endpoint = s3_client.describe_endpoint(    endpointType='s3:CredentialProvider'
```
7. **Get the official Amazon root CA file and upload it to the Amazon S3 bucket.**

Use the following in your Jupyter Notebook or AWS CLI (if you use your terminal, remove the `!` magic function):

```bash
!wget https://www.amazontrust.com/repository/AmazonRootCA1.pem
```

Use the endpoint to make an HTTPS request to the credentials provider to return a security token. The following example command uses `curl`, but you can use any HTTP client.

```bash
!curl --cert device.pem.crt --key private.pem.key --cacert AmazonRootCA1.pem $endpoint
```

If the certificate is verified, upload the keys and certificate to your Amazon S3 bucket URI:

```bash
!aws s3 cp private.pem.key s3://{bucket}/authorization-files/
!aws s3 cp device.pem.crt s3://{bucket}/authorization-files/
!aws s3 cp AmazonRootCA1.pem s3://{bucket}/authorization-files/
```

Clean your working directory by moving your keys and certificate to a different directory:

```bash
# Optional - Clean up working directory
!mkdir authorization-files
!mv private.pem.key device.pem.crt AmazonRootCA1.pem authorization-files/
```

---

**Download and Set Up Edge Manager**

The Edge Manager agent is an inference engine for your edge devices. Use the agent to make predictions with models loaded onto your edge devices. The agent also collects model metrics and captures data at specific intervals.

In this section you will set up your device with the agent. To do so, first copy a release artifact and signing root certificate from the release bucket locally to your machine. After you unzip the release artifact, upload it to Amazon S3. Next, define and save a configuration file for the agent. A template is provided for you to copy and paste. Finally, copy the release artifacts, configuration file, and credentials to your device.

1. **Download the SageMaker Edge Manager agent.**

   The agent is released in binary format for supported operating systems. This example runs inference on a Jetson Nano which uses a Linux operating system and has an ARM64 architecture. For more information about what operating system and architecture supported devices use, see [Supported Devices, Chip Architectures, and Systems](p. 3107).

   Fetch the latest version of binaries from the SageMaker Edge Manager release bucket from the us-west-2 Region.

   ```bash
   !aws s3 ls s3://sagemaker-edge-release-store-us-west-2-linux-armv8/Releases/ | sort -r
   ```

   This returns release artifacts sorted by their version.
The version has the following format: `<MAJOR_VERSION>.<YYYY-MM-DD>.<SHA-7>`. It consists of three components:

- `<MAJOR_VERSION>`: The release version. The release version is currently set to 1.
- `<YYYY-MM-DD>`: The time stamp of the artifact release.
- `<SHA-7>`: The repository commit ID from which the release is built.

Copy the zipped TAR file locally or to your device directly. The following example shows how to copy the latest release artifact at the time this document was released.

```bash
!aws s3 cp s3://sagemaker-edge-release-store-us-west-2-linux-x64/Releases/1.20201218.81f481f/1.20201218.81f481f.tgz ./
```

Once you have the artifact, unzip the zipped TAR file. The following unzips the TAR file and stores it in a directory called `agent_demo`:

```bash
!mkdir agent_demo
!tar -xvzf 1.20201218.81f481f.tgz -C ./agent_demo
```

Upload the agent release artifacts to your Amazon S3 bucket. The following code example copies the content within `agent_demo` and uploads it to a directory within your Amazon S3 bucket called `agent_demo`:

```bash
!aws s3 cp --recursive ./agent_demo s3://{bucket}/agent_demo
```

You also need the signing root certificates from the release bucket:

```bash
!aws s3 cp s3://sagemaker-edge-release-store-us-west-2-linux-x64/Certificates/us-west-2/us-west-2.pem ./
```

Upload the signing root certificate to your Amazon S3 bucket:

```bash
!aws s3 cp us-west-2.pem s3://{bucket}/authorization-files/
```

2. **Define a SageMaker Edge Manager agent configuration file.**

First, define the agent configuration file as follows:

```python
sagemaker_edge_config = {
    "sagemaker_edge_core_device_name": "device_name",
    "sagemaker_edge_core_device_fleet_name": "device_fleet_name",
    "sagemaker_edge_core_capture_data_buffer_size": 30,
    "sagemaker_edge_core_capture_data_push_period_seconds": 4,
    "sagemaker_edge_core_folder_prefix": "demo_capture",
    "sagemaker_edge_core_region": "us-west-2",
    "sagemaker_edge_core_root_certs_path": "/agent_demo/certificates",
    "sagemaker_edge_provider_aws_ca_cert_file": "/agent_demo/iot-credentials/AmazonRootCA1.pem",
}
```
Replace the following:

- "device_name" with the name of your device (this string was stored in an earlier step in a variable named device_name).
- "device_fleet_name" with the name of your device fleet (this string was stored in an earlier step in a variable named device_fleet_name)
- "endpoint" with your AWS account-specific endpoint for the credentials provider (this string was stored in an earlier step in a variable named endpoint).

Next, save it as a JSON file:

```python
edge_config_file = open("sagemaker_edge_config.json", "w")
json.dump(sagemaker_edge_config, edge_config_file, indent = 6)
edge_config_file.close()
```

Upload the configuration file to your Amazon S3 bucket:

```
!aws s3 cp sagemaker_edge_config.json s3://{bucket}/
```

3. **Copy the release artifacts, configuration file, and credentials to your device.**

The following instructions are performed on the edge device itself.

**Note**

You must first install Python, the AWS SDK for Python (Boto3), and the AWS CLI on your edge device.

Open a terminal on your device. Create a folder to store the release artifacts, your credentials, and the configuration file.

```bash
mkdir agent_demo
cd agent_demo
```

Copy the contents of the release artifacts that you stored in your Amazon S3 bucket to your device:

```bash
# Copy release artifacts
aws s3 cp s3://<bucket-name>/agent_demo/ ./ --recursive
```

(The contents of the release artifact was stored in a directory called agent_demo in a previous step. Replace <bucket-name> and agent_demo with the name of your Amazon S3 bucket and the file path to your release artifacts, respectively.

Go the /bin directory and make the binary files executable:

```bash
cd bin
```
chmod +x sagemaker_edge_agent_binary
chmod +x sagemaker_edge_agent_client_example

cd agent_demo

Make a directory to store your AWS IoT credentials and copy your credentials from your Amazon S3 bucket to your edge device (use the same on you define in the variable bucket):

```bash
mkdir iot-credentials
cd iot-credentials
aws s3 cp s3://<bucket-name>/authorization-files/AmazonRootCA1.pem ./
aws s3 cp s3://<bucket-name>/authorization-files/device.pem.crt ./
aws s3 cp s3://<bucket-name>/authorization-files/private.pem.key ./
cd ../
```

Make a directory to store your model signing root certificates:

```bash
mkdir certificates
cd certificates
aws s3 cp s3://<bucket-name>/authorization-files/us-west-2.pem ./
cd agent_demo
```

Copy your configuration file to your device:

```bash
#Download config file from S3
aws s3 cp s3://<bucket-name>/sagemaker_edge_config.json ./
cd agent_demo
```

Your `agent_demo` directory on your edge device should look similar to the following:

```
###agent_demo
 |    ### bin
 |        ### sagemaker_edge_agent_binary
 |        ### sagemaker_edge_agent_client_example
 |    ### sagemaker_edge_config.json
 |    ### certificates
 |        ###us-west-2.pem
 |    ### iot-credentials
 |        ###AmazonRootCA1.pem
 |        ### device.pem.crt
 |        ### private.pem.key
 |    ### docs
 |        ### api
 |        ### examples
 |        ### ATTRIBUTIONS.txt
 |        ### LICENSE.txt
 |    ### RELEASE_NOTES.md
```

**Run Agent**

In this section you will run the agent as a binary using gRPC, and check that both your device and fleet are working and collecting sample data.
1. **Launch the agent.**

The SageMaker Edge Manager agent can be run as a standalone process in the form of an Executable and Linkable Format (ELF) executable binary or can be linked against as a Dynamic Shared Object (.dll). Running as a standalone executable binary is the preferred mode and is supported on Linux.

This example uses gRPC to run the agent. gRPC is an open source high-performance Remote Procedure Call (RPC) framework that can run in any environment. For more information about gRPC, see the [gRPC documentation](#).

To use gRPC, perform the following steps:

- b. Generate server and client code using the protocol buffer compiler.
- c. Use the Python (or other languages supported by gRPC) gRPC API to write the server for your service.
- d. Use the Python (or other languages supported by gRPC) gRPC API to write a client for your service.

The release artifact you downloaded contains a gRPC application ready for you to run the agent. The example is located within the /bin directory of your release artifact. The `sagemaker_edge_agent_binary` binary executable is in this directory.

To run the agent with this example, provide the path to your socket file (.sock) and JSON .config file:

```bash
./bin/sagemaker_edge_agent_binary -a /tmp/sagemaker_edge_agent_example.sock -c sagemaker_edge_config.json
```

2. **Check your device.**

Check that your device is connected and sampling data. Making periodic checks, manually or automatically, allows you to check that your device or fleet is working properly.

Provide the name of the fleet to which the device belongs and the unique device identifier. From your local machine, run the following:

```python
sagemaker_client.describe_device(
    DeviceName=device_name,
    DeviceFleetName=device_fleet_name
)
```

For the given model, you can see the name, model version, latest sample time, and when the last inference was made.

```json
{
    "DeviceName": "sample-device",
    "DeviceFleetName": "demo-device-fleet",
    "IoTThingName": "sample-thing-name-1",
    "RegistrationTime": 1600977370,
    "LatestHeartbeat": 1600977370,
    "Models": [
        {
            "ModelName": "mobilenet_v2.tar.gz",
            "ModelVersion": "1.1",
            "LatestSampleTime": 1600977370,
            "LatestInference": 1600977370
        }
    ]
}
```
The timestamp provided by LastetHeartbeat indicates the last signal that was received from the device. LatestSampleTime and LatestInference describe the time stamp of the last data sample and inference, respectively.

3. **Check your fleet.**

Check that your fleet is working with `GetDeviceFleetReport`. Provide the name of the fleet the device belongs to.

```python
sagemaker_client.get_device_fleet_report(
    DeviceFleetName=device_fleet_name
)
```

For a given model, you can see the name, model version, latest sample time, and when the last inference was made, along with the Amazon S3 bucket URI where the data samples are stored.

```python
# Sample output
{
    "DeviceFleetName": "sample-device-fleet",
    "OutputConfig": {
        "S3OutputLocation": "s3://fleet-bucket/package_output",
    },
    "AgentVersions": [{"Version": "1.1", "AgentCount": 2}]
    "DeviceStats": {"Connected": 2, "Registered": 2},
    "Models": [{
        "ModelName": "sample-model",
        "ModelVersion": "1.1",
        "OfflineDeviceCount": 0,
        "ConnectedDeviceCount": 2,
        "ActiveDeviceCount": 2,
        "SamplingDeviceCount": 100
    }]
}
```

## Set Up Devices and Fleets

Fleets are collections of logically grouped devices you can use to collect and analyze data. You can use SageMaker Edge Manager to operate machine learning models on a fleet of smart cameras, smart speakers, robots, and other edge devices.

Create a fleet and register your devices either programmatically with the AWS SDK for Python (Boto3) or through the SageMaker console.

**Topics**
- Create a Fleet (p. 3028)
- Register a Device (p. 3032)
- Check Status (p. 3034)

### Create a Fleet

You can create a fleet programmatically with the AWS SDK for Python (Boto3) or through the SageMaker console [https://console.aws.amazon.com/sagemaker].
Create a Fleet (Boto3)

Use the CreateDeviceFleet API to create a fleet. Specify a name for the fleet, your AWS IoT Role ARN for the RoleArn field, as well as an Amazon S3 URI where you want the device to store sampled data.

You can optionally include a description of the fleet, tags, and an AWS KMS Key ID.

```python
import boto3

# Create SageMaker client so you can interact and manage SageMaker resources
sagemaker_client = boto3.client("sagemaker", region_name="aws-region")

sagemaker_client.create_device_fleet(
    DeviceFleetName="sample-fleet-name",
    RoleArn="arn:aws:iam::999999999:role/rolename", # IoT Role ARN
    Description="fleet description",
    OutputConfig={
        S3OutputLocation="s3://bucket/",
        KMSKeyId: "1234abcd-12ab-34cd-56ef-1234567890ab",
    },
    Tags=[
        {"Key": "string",
         "Value": "string"
        }
    ],
)

An AWS IoT Role Alias is created for you when you create a device fleet. The AWS IoT role alias provides a mechanism for connected devices to authenticate to AWS IoT using X.509 certificates and then obtain short-lived AWS credentials from an IAM role that is associated with the AWS IoT role alias.

Use DescribeDeviceFleet to get the role alias name and ARN.

```python
# Print Amazon Resource Name (ARN) and alias that has access
# to AWS Internet of Things (IoT).
sagemaker_client.describe_device_fleet(DeviceFleetName=device_fleet_name)['IotRoleAlias']
```

Use DescribeDeviceFleet API to get a description of fleets you created.

```python
sagemaker_client.describe_device_fleet(
    DeviceFleetName="sample-fleet-name"
)
```

By default, it returns the name of the fleet, the device fleet ARN, the Amazon S3 bucket URI, the IAM role, the role alias created in AWS IoT, a timestamp of when the fleet was created, and a timestamp of when the fleet was last modified.

```
{
    "DeviceFleetName": "sample-fleet-name",
    "IAMRole": "arn:aws:iam::999999999:role/rolename",
    "Description": "this is a sample fleet",
    "OutputConfig": {
        "S3OutputLocation": "s3://bucket/folder",
        "KMSKeyId": "1234abcd-12ab-34cd-56ef-1234567890ab"
    },
```
Create a Fleet (Console)

You can create a Edge Manager packaging job using the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker.

1. In the SageMaker console, choose Edge Manager and then choose Edge device fleets.
2. Choose Create device fleet.
3. Enter a name for the device fleet in the Device fleet name field. Choose Next.
4. On the **Output configuration** page, specify the Amazon S3 bucket URI where you want to store sample data from your device fleet. You can optionally add an encryption key as well by electing an existing AWS KMS key from the dropdown list or by entering a key’s ARN. Choose **Submit**.
5. Choose the name of your device fleet to be redirected to the device fleet details. This page displays the name of the device fleet, ARN, description (if you provided one), date the fleet was created, last time the fleet was modified, Amazon S3 bucket URI, AWS KMS key ID (if provided), AWS IoT alias (if provided), and IAM role. If you added tags, they appear in the **Device fleet tags** section.

## Register a Device

**Important**
Device registration is required to use any part of SageMaker Edge Manager.

You can create a fleet programmatically with the AWS SDK for Python (Boto3) or through the SageMaker console at [https://console.aws.amazon.com/sagemaker](https://console.aws.amazon.com/sagemaker).

### Register a Device (Boto3)

To register your device, first create and register an AWS IoT thing object and configure an IAM role. SageMaker Edge Manager takes advantage of the AWS IoT Core services to facilitate the connection between the edge devices and the cloud. You can take advantage of existing AWS IoT functionality after you set up your devices to work with Edge Manager.

To connect your device to AWS IoT you need to create AWS IoT thing objects, create and register a client certificate with AWS IoT, and create and configure IAM role for your devices.

See the [Getting Started Guide](https://console.aws.amazon.com/sagemaker) for an in-depth example or the [Explore AWS IoT Core services in hands-on tutorial](https://console.aws.amazon.com/sagemaker).

Use the `register_devices` API to register your device. Provide the name of the fleet of which you want the devices to be a part, as well as a name for the device. You can optionally add a description to the device, tags, and AWS IoT thing name associated with the device.

```python
sagemaker_client.register_devices(
    DeviceFleetName="sample-fleet-name",
    # Other parameters...
)```

---

**Output configuration**

Use the fields below to specify the S3 bucket URI where you want devices to store sample data. You can also (optional) specify a KMS key.

- **S3 bucket URI**
  Enter your S3 bucket URI where you want devices to store sample data.

  ```
  s3://bucket-example/sagmaker-edge/device-output
  ```

  To find a path, [go to Amazon S3](https://console.aws.amazon.com/s3).

- **Encryption key - optional**
  Encrypt your data. Choose an existing KMS key or enter a key’s ARN.

  ```
  No Custom Encryption
  ```
Register a Device (Console)

You can register your device using the SageMaker console at https://console.aws.amazon.com/sagemaker.

1. In the SageMaker console, choose Edge Inference and then choose Edge devices.
2. Choose Register devices.
3. In the Device properties section, enter the name of the fleet the device belongs to under the Device fleet name field. Choose Next.
4. In the Device source section, add your devices one by one. You must include a Device Name for each device in your fleet. You can optionally provide a description (in the Description field) and an
Internet of Things (IoT) object name (in the IoT name field). Choose Submit once you have added all your devices.

### Device source

#### Add devices one by one

<table>
<thead>
<tr>
<th>Device Name</th>
<th>Description - optional</th>
<th>IoT name - optional</th>
</tr>
</thead>
<tbody>
<tr>
<td>Enter device name</td>
<td>Enter description</td>
<td>Enter IoT name</td>
</tr>
</tbody>
</table>

Add another device

You can add up to 50 devices

The Devices page displays the name of the device you have added, the fleet to which it belongs, when it was registered, the last heartbeat, and the description and AWS IoT name, if you provided one.

Choose a device to view the device's details, including the device name, fleet, ARN, description, IoT Thing name, when the device was registered, and the last heartbeat.

### Check Status

Check that your device or fleet is connected and sampling data. Making periodic checks, manually or automatically, allows you to check that your device or fleet is working properly.

Use the Amazon S3 console at https://console.aws.amazon.com/s3/ to interactively choose a fleet for a status check. You can also use the AWS SDK for Python (Boto3). The following describes different APIs from Boto3 you can use to check the status of your device or fleet. Use the API that best fits your use case.

- **Check an individual device.**

  To check the status of an individual device, use DescribeDevice API. A list containing one or more models is provided if a models have been deployed to the device.

  ```python
  sagemaker_client.describe_device(
      DeviceName="sample-device-1",
      DeviceFleetName="sample-fleet-name"
  )
  ```

  Running DescribeDevice returns:

  ```json
  { "DeviceName": "sample-device",
    "Description": "this is a sample device",
    "DeviceFleetName": "sample-device-fleet",
    "IoTThingName": "SampleThing",
  ```
"RegistrationTime": 1600977370,
"LatestHeartbeat": 1600977370,
"Models": [
  {
    "ModelName": "sample-model",
    "ModelVersion": "1.1",
    "LatestSampleTime": 1600977370,
    "LatestInference": 1600977370
  }
]

• **Check a fleet of devices.**

To check the status of the fleet, use the `GetDeviceFleetReport` API. Provide the name of the device fleet to get a summary of the fleet.

```python
sagemaker_client.get_device_fleet_report(
    DeviceFleetName="sample-fleet-name"
)
```

• **Check for a heartbeat.**

Each device within a fleet periodically generates a signal, or "heartbeat". The heartbeat can be used to check that the device is communicating with Edge Manager. If the timestamp of the last heartbeat is not being updated, the device may be failing.

Check the last heartbeat with made by a device with the `DescribeDevice` API. Specify the name of the device and the fleet to which the edge device belongs.

```python
sagemaker_client.describe_device(
    DeviceName="sample-device-1",
    DeviceFleetName="sample-fleet-name"
)
```

---

**Package Model**

SageMaker Edge Manager packaging jobs take Amazon SageMaker Neo–compiled models and make any changes necessary to deploy the model with the inference engine, Edge Manager agent.

**Topics**

- Prerequisites (p. 3035)
- Package a Model (Amazon SageMaker Console) (p. 3037)
- Package a Model (Boto3) (p. 3040)

**Prerequisites**

To package a model, you must do the following:

1. **Compile your machine learning model with SageMaker Neo.**

   If you have not already done so, compile your model with SageMaker Neo. For more information on how to compile your model, see Compile and Deploy Models with Neo. If you are first-time user of SageMaker Neo, go through Getting Started with Neo Edge Devices.

2. **Get the name of your compilation job.**
Provide the name of the compilation job name you used when you compiled your model with SageMaker Neo. Open the SageMaker console at https://console.aws.amazon.com/sagemaker/ and choose Compilation jobs to find a list of compilations that have been submitted to your AWS account. The names of submitted compilation jobs are in the Name column.

3. **Get your IAM ARN.**

You need an Amazon Resource Name (ARN) of an IAM role that you can use to download and upload the model and contact SageMaker Neo.

Use one of the following methods to get your IAM ARN:

- **Programmatically with the SageMaker Python SDK**

  ```python
  import sagemaker
  # Initialize SageMaker Session object so you can interact with AWS resources
  sess = sagemaker.Session()
  # Get the role ARN
  role = sagemaker.get_execution_role()
  print(role)
  >> arn:aws:iam::<your-aws-account-id>:role/<your-role-name>
  
  For more information about using the SageMaker Python SDK, see the SageMaker Python SDK API.

- **Using the AWS Identity and Access Management (IAM) console**

  Navigate to the IAM console at https://console.aws.amazon.com/iam/. In the IAM Resources section, choose Roles to view a list of roles in your AWS account. Select or create a role that has AmazonSageMakerFullAccess, AWSSoTFullAccess, and AmazonS3FullAccess.

  For more information on IAM, see What is IAM?

4. **Have an S3 bucket URI.**

You need to have at least one Amazon Simple Storage Service (Amazon S3) bucket URI to store your Neo-compiled model, the output of the Edge Manager packaging job, and sample data from your device fleet.

Use one of the following methods to create an Amazon S3 bucket:

- **Programmatically with the SageMaker Python SDK**

  You can use the default Amazon S3 bucket during a session. A default bucket is created based on the following format: sagemaker-{region}-{aws-account-id}. To create a default bucket with the SageMaker Python SDK, use the following:

  ```python
  import sagemaker
  session=sagemaker.create_session()
  bucket=session.default_bucket()
  
  On AWS Identity and Access Management (IAM) console
  
  Navigate to the IAM console at https://console.aws.amazon.com/iam/ and choose Roles to view a list of roles in your AWS account. Select or create a role that has AmazonSageMakerFullAccess, AWSSoTFullAccess, and AmazonS3FullAccess.

  For more information on IAM, see What is IAM?

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Use one of the following methods to create an Amazon S3 bucket:

- **Programmatically with the SageMaker Python SDK**

  You can use the default Amazon S3 bucket during a session. A default bucket is created based on the following format: sagemaker-{region}-{aws-account-id}. To create a default bucket with the SageMaker Python SDK, use the following:

  ```python
  import sagemaker
  session=sagemaker.create_session()
  bucket=session.default_bucket()
  
  On AWS Identity and Access Management (IAM) console
  
  Navigate to the IAM console at https://console.aws.amazon.com/iam/ and choose Roles to view a list of roles in your AWS account. Select or create a role that has AmazonSageMakerFullAccess, AWSSoTFullAccess, and AmazonS3FullAccess.

  For more information on IAM, see What is IAM?

4. **Have an S3 bucket URI.**

You need to have at least one Amazon Simple Storage Service (Amazon S3) bucket URI to store your Neo-compiled model, the output of the Edge Manager packaging job, and sample data from your device fleet.

Use one of the following methods to create an Amazon S3 bucket:

- **Programmatically with the SageMaker Python SDK**

  You can use the default Amazon S3 bucket during a session. A default bucket is created based on the following format: sagemaker-{region}-{aws-account-id}. To create a default bucket with the SageMaker Python SDK, use the following:

  ```python
  import sagemaker
  session=sagemaker.create_session()
  bucket=session.default_bucket()
  
  On AWS Identity and Access Management (IAM) console
  
  Navigate to the IAM console at https://console.aws.amazon.com/iam/ and choose Roles to view a list of roles in your AWS account. Select or create a role that has AmazonSageMakerFullAccess, AWSSoTFullAccess, and AmazonS3FullAccess.

  For more information on IAM, see What is IAM?

4. **Have an S3 bucket URI.**

You need to have at least one Amazon Simple Storage Service (Amazon S3) bucket URI to store your Neo-compiled model, the output of the Edge Manager packaging job, and sample data from your device fleet.

Use one of the following methods to create an Amazon S3 bucket:

- **Programmatically with the SageMaker Python SDK**

  You can use the default Amazon S3 bucket during a session. A default bucket is created based on the following format: sagemaker-{region}-{aws-account-id}. To create a default bucket with the SageMaker Python SDK, use the following:

  ```python
  import sagemaker
  session=sagemaker.create_session()
  bucket=session.default_bucket()
  
  On AWS Identity and Access Management (IAM) console
  
  Navigate to the IAM console at https://console.aws.amazon.com/iam/ and choose Roles to view a list of roles in your AWS account. Select or create a role that has AmazonSageMakerFullAccess, AWSSoTFullAccess, and AmazonS3FullAccess.

  For more information on IAM, see What is IAM?
Package a Model (Amazon SageMaker Console)

You can create a SageMaker Edge Manager packaging job using the SageMaker console at https://console.aws.amazon.com/sagemaker/. Before continuing, make sure you have satisfied the Prerequisites (p. 3035).

1. In the SageMaker console, choose **Edge Inference** and then choose **Edge packaging jobs**, as shown in the following image.

![Image of SageMaker console showing Edge packaging jobs](https://console.aws.amazon.com/sagemaker/

2. On the **Job properties** page, enter a name for your packaging job under **Edge packaging job name**. Note that Edge Manager packaging job names are case-sensitive. Name your model and give it a version: enter this under **Model name** and **Model version**, respectively.

3. Next, select an **IAM role**. You can chose a role or let AWS create a role for you. You can optionally specify a **resource key ARN** and **job tags**.

4. Choose **Next**.
5. Specify the name of the compilation job you used when compiling your model with SageMaker Neo in the **Compilation job name** field. Choose **Next**.
On the **Output configuration** page, enter the Amazon S3 bucket URI in which you want to store the output of the packaging job.

The **Status** column on the **Edge packaging** jobs page should read **IN PROGRESS**. Once the packaging job is complete, the status updates to **COMPLETED**.

Selecting a packaging job directs you to that job's settings. The **Job settings** section displays the job name, ARN, status, creation time, last modified time, duration of the packaging job, and role ARN.

The **Input configuration** section displays the location of the model artifacts, the data input configuration, and the machine learning framework of the model.
The **Output configuration** section displays the output location of the packaging job, the target device for which the model was compiled, and any tags you created.

7. Choose the name of your device fleet to be redirected to the device fleet details. This page displays the name of the device fleet, ARN, description (if you provided one), date the fleet was created, last time the fleet was modified, Amazon S3 bucket URI, AWS KMS key ID (if provided), AWS IoT alias (if provided), and IAM role. If you added tags, they appear in the **Device fleet tags** section.

---

## Package a Model (Boto3)

You can create a SageMaker Edge Manager packaging job with the AWS SDK for Python (Boto3). Before continuing, make sure you have satisfied the [Prerequisites](p. 3035).

To request an edge packaging job, use `CreateEdgePackagingJob`. You need to provide a name to your edge packaging job, the name of your SageMaker Neo compilation job, your role Amazon resource name (ARN), a name for your model, a version for your model, and the Amazon S3 bucket URI where you want to store the output of your packaging job. Note that Edge Manager packaging job names and SageMaker Neo compilation job names are case-sensitive.

```python
# Import AWS SDK for Python (Boto3)
import boto3

# Create Edge client so you can submit a packaging job
sagemaker_client = boto3.client("sagemaker", region_name='aws-region')

sagemaker_client.create_edge_packaging_job(
    EdgePackagingJobName="edge-packaging-name",
    CompilationJobName="neo-compilation-name",
    RoleArn="arn:aws:iam::99999999999:role/rolename",
    ModelName="sample-model-name",
    ModelVersion="model-version",
    OutputConfig={
        "S3OutputLocation": "s3://your-bucket/",
    }
)
```

You can check the status of an edge packaging job using `DescribeEdgePackagingJob` and providing the case-sensitive edge packaging job name:

```python
response = sagemaker_client.describe_edge_packaging_job(
    EdgePackagingJobName="edge-packaging-name")
```

This returns a dictionary that can be used to poll the status of the packaging job:

```python
# Optional - Poll every 30 sec to check completion status
import time

while True:
    response = sagemaker_client.describe_edge_packaging_job(
        EdgePackagingJobName="edge-packaging-name")

    if response['EdgePackagingJobStatus'] == 'Completed':
        break
    elif response['EdgePackagingJobStatus'] == 'Failed':
        raise RuntimeError('Packaging job failed')
    print('Packaging model...')
    time.sleep(30)
print('Done!')
```
For a list of packaging jobs, use ListEdgePackagingJobs. You can use this API to search for a specific packaging job. Provide a partial name to filter packaging job names for NameContains, a partial name for ModelNameContains to filter for jobs in which the model name contains the name you provide. Also specify with which column to sort with SortBy, and by which direction to sort for SortOrder (either Ascending or Descending).

```python
sagemaker_client.list_edge_packaging_jobs(
    "NameContains": "sample",
    "ModelNameContains": "sample",
    "SortBy": "column-name",
    "SortOrder": "Descending"
)
```

To stop a packaging job, use StopEdgePackagingJob and provide the name of your edge packaging job.

```python
sagemaker_client.stop_edge_packaging_job(
    EdgePackagingJobName="edge-packaging-name"
)
```

For a full list of Edge Manager APIs, see the Boto3 documentation.

### The Edge Manager Agent

The Edge Manager agent is an inference engine for your edge devices. Use the agent to make predictions with models loaded onto your edge devices. The agent also collects model metrics and captures data at specific intervals. Sample data is stored in your Amazon S3 bucket.

There are two methods of installing and deploying the Edge Manager agent onto your edge devices:

1. Download the agent as a binary from the Amazon S3 release bucket. For more information, see Download and Set Up the Edge Manager Agent Manually (p. 3041).
2. Use the AWS IoT Greengrass V2 console or the AWS CLI to deploy `aws.greengrass.SageMakerEdgeManager`. See Create the AWS IoT Greengrass V2 Components (p. 3047).

### Download and Set Up the Edge Manager Agent Manually

Download the Edge Manager agent based on your operating system, architecture, and AWS Region. The agent is periodically updated, so you have the option to choose your agent based on release dates and versions. Once you have the agent, create a JSON configuration file. Specify the device IoT thing name, fleet name, device credentials, and other key-value pairs. See Running the Edge Manager agent (p. 3043) for full a list of keys you must specify in the configuration file. You can run the agent as an executable binary or link against it as a dynamic shared object (DSO).

**How the agent works**

The agent runs on the CPU of your devices. The agent runs inference on the framework and hardware of the target device you specified during the compilation job. For example, if you compiled your model for the Jetson Nano, the agent supports the GPU in the provided Deep Learning Runtime (DLR).

The agent is released in binary format for supported operating systems. Check that your operating system is supported and meets the minimum OS requirement in the following table:

**Linux**

Version: Ubuntu 18.04
**Supported Binary Formats:** x86-64 bit (ELF binary) and ARMv8 64 bit (ELF binary)

Windows

**Version:** Windows 10 version 1909

**Supported Binary Formats:** x86-32 bit (DLL) and x86-64 bit (DLL)

### Installing the Edge Manager agent

To use the Edge Manager agent, you first must obtain the release artifacts and a root certificate. The release artifacts are stored in an Amazon S3 bucket in the us-west-2 Region. To download the artifacts, specify your operating system (<OS>) and the <VERSION>.

Based on your operating system, replace <OS> with one of the following:

<table>
<thead>
<tr>
<th>Windows 32-bit</th>
<th>Windows 64-bit</th>
<th>Linux x86-64</th>
<th>Linux ARMv8</th>
</tr>
</thead>
<tbody>
<tr>
<td>windows-x86</td>
<td>windows-x64</td>
<td>linux-x64</td>
<td>linux-armv8</td>
</tr>
</tbody>
</table>

The VERSION is broken into three components: `<MAJOR_VERSION>-.<YYYY-MM-DD>-<SHA-7>`, where:

- `<MAJOR_VERSION>`: The release version. The release version is currently set to 1.
- `<YYYY-MM-DD>`: The time stamp of the artifacts release.
- `<SHA-7>`: The repository commit ID from which the release is built.

You must provide the `<MAJOR_VERSION>` and the time stamp in YYYY-MM-DD format. We suggest you use the latest artifact release time stamp.

Run the following in your command line to get the latest time stamp. Replace <OS> with your operating system:

```bash
aws s3 ls s3://sagemaker-edge-release-store-us-west-2-<OS>/Releases/ | sort -r
```

For example, if you have a Windows 32-bit OS, run:

```bash
aws s3 ls s3://sagemaker-edge-release-store-us-west-2-windows-x86/Releases/ | sort -r
```

This returns:

```
2020-12-01 23:33:36 0
  PRE 1.20201218.81f481f/
  PRE 1.20201207.02d0e97/
```

The return output in this example shows two release artifacts. The first release artifact file notes that the release version has a major release version of 1, a time stamp of 20201218 (in YYYY-MM-DD format), and a 81f481f SHA-7 commit ID.

**Note**

The preceding command assumes you have configured the AWS Command Line Interface. For more information, about how to configure the settings that the AWS CLI uses to interact with AWS, see [Configuring the AWS CLI](#).
Based on your operating system, use the following commands to install the artifacts:

Windows 32-bit

aws s3 cp s3://sagemaker-edge-release-store-us-west-2-windows-x86/Releases/<VERSION>/sha256_hex.shasum .

Windows 64-bit

aws s3 cp s3://sagemaker-edge-release-store-us-west-2-windows-x64/Releases/<VERSION>/.<VERSION>.zip .
aws s3 cp s3://sagemaker-edge-release-store-us-west-2-windows-x64/Releases/<VERSION>/sha256_hex.shasum .

Linux x86-64

aws s3 cp s3://sagemaker-edge-release-store-us-west-2-linux-x64/Releases/<VERSION>/.<VERSION>.tgz .
aws s3 cp s3://sagemaker-edge-release-store-us-west-2-linux-x64/Releases/<VERSION>/sha256_hex.shasum .

Linux ARMv8


You also must download a root certificate. This certificate validates model artifacts signed by AWS before loading them onto your edge devices.

Replace <OS> corresponding to your platform from the list of supported operation systems and replace <REGION> with your AWS Region.

aws s3 cp s3://sagemaker-edge-release-store-us-west-2-<OS>/Certificates/<REGION>/<REGION>.pem .

**Running the Edge Manager agent**

You can run the SageMaker Edge Manager agent as a standalone process in the form of an Executable and Linkable Format (ELF) executable binary or you can link against it as a dynamic shared object (.dll). Linux supports running it as a standalone executable binary and is the preferred mode. Windows supports running it as a shared object (.dll).

On Linux, we recommend that you run the binary via a service that’s a part of your initialization (init) system. If you want to run the binary directly, you can do so in a terminal as shown in the following example. If you have a modern OS, there are no other installations necessary prior to running the agent, since all the requirements are statically built into the executable. This gives you flexibility to run the agent on the terminal, as a service, or within a container.

To run the agent, first create a JSON configuration file. Specify the following key-value pairs:

- sagemaker_edge_core_device_name: The name of the device. This device name needs to be registered along with the device fleet in the SageMaker Edge Manager console.
• `sagemaker_edge_core_device_fleet_name`: The name of the fleet to which the device belongs.

• `sagemaker_edge_core_region`: The AWS Region associated with the device, the fleet and the Amazon S3 buckets. This corresponds to the Region where the device is registered and where the Amazon S3 bucket is created (they are expected to be the same). The models themselves can be compiled with SageMaker Neo in a different Region, this configuration is not related to model compilation Region.

• `sagemaker_edge_core_root_certs_path`: The absolute folder path to root certificates. This is used to validate the device with the relevant AWS account.

• `sagemaker_edge_provider_aws_ca_cert_file`: The absolute path to Amazon Root CA certificate (AmazonRootCA1.pem). This is used to validate the device with the relevant AWS account. AmazonCA is a certificate owned by AWS.

• `sagemaker_edge_provider_aws_cert_file`: The absolute path to AWS IoT signing root certificate (*.pem.crt).

• `sagemaker_edge_provider_aws_cert_pk_file`: The absolute path to AWS IoT private key. (*.pem.key).

• `sagemaker_edge_provider_aws_iot_cred_endpoint`: The AWS IoT credentials endpoint (identifier.iot.region.amazonaws.com). This endpoint is used for credential validation. See Connecting devices to AWS IoT for more information.

• `sagemaker_edge_provider_provider`: This indicates the implementation of the provider interface being used. The provider interface communicates with the end network services for uploads, heartbeats and registration validation. By default this is set to "Aws". We allow custom implementations of the provider interface. It can be set to None for no provider or Custom for custom implementation with the relevant shared object path provided.

• `sagemaker_edge_provider_provider_path`: Provides the absolute path to the provider implementation shared object (.so or .dll file). The "Aws" provider .dll or .so file is provided with the agent release. This field is mandatory.

• `sagemaker_edge_provider_s3_bucket_name`: The name of your Amazon S3 bucket (not the Amazon S3 bucket URI). The bucket must have a sagemaker string within its name.

• `sagemaker_edge_log_verbose` (Boolean): Optional. This sets the debug log. Select either True or False.

• `sagemaker_edge_telemetry_libsystemd_path`: For Linux only, systemd implements the agent crash counter metric. Set the absolute path of libsystemd to turn on the crash counter metric. You can find the default libsystemd path can be found by running `whereis libsystemd` in the device terminal.

• `sagemaker_edge_core_capture_data_destination`: The destination for uploading capture data. Choose either "Cloud" or "Disk". The default is set to "Disk". Setting it to "Disk" writes the input and output tensor(s) and auxiliary data to the local file system at your preferred location of. When writing to "Cloud" use the Amazon S3 bucket name provided in the `sagemaker_edge_provider_s3_bucket_name` configuration.

• `sagemaker_edge_core_capture_data_disk_path`: Set the absolute path in the local file system, into which capture data files are written when "Disk" is the destination. This field is not used when "Cloud" is specified as the destination.

• `sagemaker_edge_core_folder_prefix`: The parent prefix in Amazon S3 where captured data is stored when you specify "Cloud" as the capture data destination (sagemaker_edge_core_capture_data_disk_path). Captured data is stored in a sub-folder under sagemaker_edge_core_capture_data_disk_path if "Disk" is set as the data destination.

• `sagemaker_edge_core_capture_data_buffer_size` (Integer value): The capture data circular buffer size. It indicates the maximum number of requests stored in the buffer.

• `sagemaker_edge_core_capture_data_batch_size` (Integer value): The capture data batch size. It indicates the size of a batch of requests that are handled from the buffer. This value must to be less than sagemaker_edge_core_capture_data_buffer_size. A maximum of half the size of the buffer is recommended for batch size.
• `sagemaker_edge_core_capture_data_push_period_seconds` (Integer value): The capture data push period in seconds. A batch of requests in the buffer is handled when there are batch size requests in the buffer, or when this time period has completed (whichever comes first). This configuration sets that time period.

• `sagemaker_edge_core_capture_data_base64_embed_limit`: The limit for uploading capture data in bytes. Integer value.

Your configuration file should look similar to the following example (with your specific values specified). This example uses the default AWS provider ("Aws") and does not specify a periodic upload.

```json
{
    "sagemaker_edge_core_device_name": "device-name",
    "sagemaker_edge_core_device_fleet_name": "fleet-name",
    "sagemaker_edge_core_region": "region",
    "sagemaker_edge_core_root_certs_path": "<Absolute path to root certificates>",
    "sagemaker_edge_provider_provider": "Aws",
    "sagemaker_edge_provider_provider_path": "/path/to/libprovider-aws.so",
    "sagemaker_edge_core_capture_data_destination": "Cloud",
    "sagemaker_edge_provider_s3_bucket_name": "sagemaker-bucket-name",
    "sagemaker_edge_core_capture_data_buffer_size": 30,
    "sagemaker_edge_core_capture_data_batch_size": 10,
    "sagemaker_edge_core_capture_data_push_period_seconds": 4000,
    "sagemaker_edge_core_capture_data_base64_embed_limit": 2,
    "sagemaker_edge_log_verbose": false
}
```

The release artifact includes a binary executable called `sagemaker_edge_agent_binary` in the `/bin` directory. To run the binary, use the `-a` flag to create a socket file descriptor (.sock) in a directory of your choosing and specify the path of the agent JSON config file you created with the `-c` flag.

```bash
./sagemaker_edge_agent_binary -a <ADDRESS_TO_SOCKET> -c <PATH_TO_CONFIG_FILE>
```

The following example shows the code snippet with a directory and file path specified:

```bash
./sagemaker_edge_agent_binary -a /tmp/sagemaker_edge_agent_example.sock -c sagemaker_edge_config.json
```

In this example, a socket file descriptor named `sagemaker_edge_agent_example.sock` is created in the `/tmp` directory and points to a configuration file that is in the same working directory as the agent called `sagemaker_edge_config.json`.

**Deploy the Model Package and Edge Manager Agent with AWS IoT Greengrass**

SageMaker Edge Manager integrates AWS IoT Greengrass version 2 to simplify accessing, maintaining, and deploying the Edge Manager agent and model to your devices. Without AWS IoT Greengrass V2, setting up your devices and fleets to use SageMaker Edge Manager requires you to manually copy the Edge Manager agent from an Amazon S3 release bucket. You use the agent to make predictions with models loaded onto your edge devices. With AWS IoT Greengrass V2 and SageMaker Edge Manager
integration, you can use AWS IoT Greengrass V2 components. Components are pre-built software modules that can connect your edge devices to AWS services or third-party service via AWS IoT Greengrass.

You must install the AWS IoT Greengrass Core software onto your device(s) if you want to use AWS IoT Greengrass V2 to deploy the Edge Manager agent and your model. For more information about device requirements and how to set up your devices, see Setting up AWS IoT Greengrass core devices in the AWS IoT Greengrass documentation.

You use the following three components to deploy the Edge Manager agent:

- **A pre-built public component**: SageMaker maintains the public Edge Manager component.
- **A autogenerated private component**: The private component is autogenerated when you package your machine learning model with the CreateEdgePackagingJob API and specify GreengrassV2Component for the Edge Manager API field PresetDeploymentType.
- **A custom component**: This is the inference application that is responsible for preprocessing and making inferences on your device. You must create this component. See either ??? (p. 3049) in the SageMaker Edge Manager documentation or Create custom AWS IoT Greengrass components in the AWS IoT Greengrass documentation for more information on how to create custom components.

**Prerequisites**

SageMaker Edge Manager uses AWS IoT Greengrass V2 to simplify the deployment of the Edge Manager agent, your machine learning models, and your inference application to your devices with the use of components. To make it easier to maintain your AWS IAM roles, Edge Manager allows you to reuse your existing AWS IoT role alias. If you do not have one yet, Edge Manager generates a role alias as part of the Edge Manager packaging job. You no longer need to associate a role alias generated from the SageMaker Edge Manager packaging job with your AWS IoT role.

Before you start, you must complete the following prerequisites:

1. Install the AWS IoT Greengrass Core software. For detailed information, see Install the AWS IoT Greengrass Core software.
2. Set up AWS IoT Greengrass V2. For more information, see Install AWS IoT Greengrass Core software with manual resource provisioning. **Note**
   - Make sure the AWS IoT thing name is all lowercase and does not contain characters except (optionally) dashes (-).
   - The IAM Role must start with SageMaker*
3. Attach the following permission and inline policy to the IAM role created during AWS IoT Greengrass V2 setup.
   - Navigate to the IAM console https://console.aws.amazon.com/iam/.
   - Search for the role you created by typing in the role name in the Search field.
   - Choose your role.
   - Next, choose Attach policies.
   - Search for AmazonSageMakerEdgeDeviceFleetPolicy.
   - Select AmazonSageMakerFullAccess (This is an optional step that makes it easier for you to reuse this IAM role in model compilation and packaging).
   - Choose Add inline policy.

```json
{
   "Version":"2012-10-17",
   "Statement":[
   {
```
Choose **Attach policy**.
Choose **Trust relationship**.
Choose **Edit trust relationship**.
Replace the content with the following.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Principal": {
            "Service": "credentials.iot.amazonaws.com"
         },
         "Action": "sts:AssumeRole"
      },
      {
         "Effect": "Allow",
         "Principal": {
            "Service": "sagemaker.amazonaws.com"
         },
         "Action": "sts:AssumeRole"
      }
   ]
}
```

4. Create an Edge Manager device fleet. For information on how to create a fleet, see Set Up Devices and Fleets (p. 3028).
5. Register your device with the same name as your AWS IoT thing name created during the AWS IoT Greengrass V2 setup.
6. Create at least one custom private AWS IoT Greengrass component. This component is the application that runs inference on the device. For more information, see Create a Hello World custom component (p. 3049)

**Note**

- The SageMaker Edge Manager and AWS IoT Greengrass integration only works for AWS IoT Greengrass v2.
- Both your AWS IoT thing name and Edge Manager device name must be the same.
- SageMaker Edge Manager does not load local AWS IoT certificates and call the AWS IoT credential provider endpoint directly. Instead, SageMaker Edge Manager uses the AWS IoT Greengrass v2 TokenExchangeService and it fetches a temporary credential from a TES endpoint.

**Create the AWS IoT Greengrass V2 Components**

AWS IoT Greengrass uses components, a software module that is deployed to and runs on a AWS IoT Greengrass core device. You need (at a minimum) three components:
1. A public Edge Manager Agent AWS IoT Greengrass component which deploys the Edge Manager agent binary.

2. A model component that is autogenerated when you package your machine learning model with either the AWS SDK for Python (Boto3) API or with the SageMaker console. For information, see Create an autogenerated component (p. 3048).

3. A private, custom component to implement the Edge Manager agent client application, and do any preprocessing and post-processing of the inference results. For more information about how to create a custom component, see Create an autogenerated component (p. 3048) or Create custom AWS IoT Greengrass components.

Create an autogenerated component

Generate the model component with the CreateEdgePackagingJob API and specify GreengrassV2Component for the SageMaker Edge Manager packaging job API field PresetDeploymentType. When you call the CreateEdgePackagingJob API, Edge Manager takes your SageMaker Neo-compiled model in Amazon S3 and creates a model component. The model component is automatically stored in your account. You can view any of your components by navigating to the AWS IoT console https://console.aws.amazon.com/iot/. Select Greengrass and then select Core devices. The page has a list of AWS IoT Greengrass core devices associated with your account. If a model component name is not specified in PresetDeploymentConfig, the default name generated consists of "SagemakerEdgeManager" and the name of your Edge Manager agent packaging job. The following example demonstrates how to specify to Edge Manager to create a AWS IoT Greengrass V2 component with the CreateEdgePackagingJob API.

```python
import sagemaker
import boto3

# Create a SageMaker client object to make it easier to interact with other AWS services.
sagemaker_client = boto3.client('sagemaker', region='YOUR_REGION')

# Replace with your IAM Role ARN
sagemaker_role_arn = "arn:aws:iam::<account>:role/*"

# Replace string with the name of your already created S3 bucket.
bucket = 'edge-manager-demo-bucket'

# Specify a name for your edge packaging job.
edge_packaging_name = "edge_packag_job_demo"

# Replace the following string with the name you used for the SageMaker Neo compilation job.
compilation_job_name = "getting-started-demo"

# The name of the model and the model version.
model_name = "sample-model"
model_version = "1.1"

# Output directory in S3 where you want to store the packaged model.
packaging_output_dir = 'packaged_models'
packaging_s3_output = 's3://{}/{}'.format(bucket, packaging_output_dir)

# The name you want your Greengrass component to have.
component_name = "SagemakerEdgeManager" + edge_packaging_name

sagemaker_client.create_edge_packaging_job(
    EdgePackagingJobName=edge_packaging_name,
    CompilationJobName=compilation_job_name,
    RoleArn=sagemaker_role_arn,
    ModelName=model_name,
    ModelVersion=model_version,
    OutputConfig={
```
You can also create the autogenerated component with the SageMaker console. Follow steps 1-6 in Package a Model (Amazon SageMaker Console) (p. 3037)

Enter the Amazon S3 bucket URI where you want to store the output of the packaging job and optional encryption key.

Complete the following to create the model component:

1. Choose **Preset deployment**.
2. Specify the name of the component for the **Component name** field.
3. Optionally, provide a description of the component, a component version, the platform OS, or the platform architecture for the **Component description**, **Component version**, **Platform OS**, and **Platform architecture**, respectively.
4. Choose **Submit**.

Create a Hello World custom component

The custom application component is used to perform inference on the edge device. The component is responsible for loading models to SageMaker Edge Manager, invoking the Edge Manager agent for inference, and unloading the model when the component is shut down. Before you create your component, ensure the agent and application can communicate with Edge Manager. To do this, configure gRPC. The Edge Manager agent uses methods defined in Protobuf Buffers and the gRPC server to establish communication with the client application on the edge device and the cloud.

To use gRPC, you must:

1. Create a gRPC stub using the .proto file provided when you download the Edge Manager agent from Amazon S3 release bucket.
2. Write client code with the language you prefer.

You do not need to define the service in a .proto file. The service .proto files are included in the compressed TAR file when you download the Edge Manager agent release binary from the Amazon S3 release bucket.

Install gRPC and other necessary tools on your host machine and create the gRPC stubs agent_pb2_grpc.py and agent_pb2.py in Python. Make sure you have agent.proto in your local directory.

```bash
pip install grpcio
pip install grpcio-tools
python3 -m grpc_tools.protoc --proto_path=. --python_out=. --grpc_python_out=. agent.proto
```

The preceding code generates the gRPC client and server interfaces from your .proto service definition. In other words, it creates the gRPC model in Python. The API directory contains the Protobuf specification for communicating with the agent.

Next, use the gRPC API to write a client and server for your service (2). The following example script, edge_manager_python_example.py, uses Python to load, list, and unload a yolov3 model to the edge device.
import grpc
from PIL import Image
import agent_pb2
import agent_pb2_grpc
import os

model_path = '<PATH-TO-SagemakerEdgeManager-COMPONENT>'
ageant_socket = 'unix:///tmp/aws.greengrass.SageMakerEdgeManager.sock'
ageant_channel = grpc.insecure_channel(agent_socket, options=((grpc.enable_http_proxy', 0),))
ageant_client = agent_pb2_grpc.AgentStub(agent_channel)

def list_models():
    return agent_client.ListModels(agent_pb2.ListModelsRequest())

def list_model_tensors(models):
    return {
        model.name: {
            'inputs': model.input_tensor_metadatas,
            'outputs': model.output_tensor_metadatas
        }
    for model in list_models().models
}

def load_model(model_name, model_path):
    load_request = agent_pb2.LoadModelRequest()
    load_request.url = model_path
    load_request.name = model_name
    return agent_client.LoadModel(load_request)

def unload_model(name):
    unload_request = agent_pb2.UnLoadModelRequest()
    unload_request.name = name
    return agent_client.UnLoadModel(unload_request)

def predict_image(model_name, image_path):
    image_tensor = agent_pb2.Tensor()
    image_tensor.byte_data = Image.open(image_path).tobytes()
    image_tensor_metadata = list_model_tensors(list_models())[model_name]['inputs'][0]
    image_tensor.tensor_metadata.name = image_tensor_metadata.name
    image_tensor.tensor_metadata.data_type = image_tensor_metadata.data_type
    for shape in image_tensor_metadata.shape:
        image_tensor.tensor_metadata.shape.append(shape)
    predict_request = agent_pb2.PredictRequest()
    predict_request.name = model_name
    predict_request.tensors.append(image_tensor)
    predict_response = agent_client.Predict(predict_request)
    return predict_response

def main():
    try:
        unload_model('your-model')
    except:
        pass
    print('LoadModel...', end='')
try:
    load_model('your-model', model_path)
    print('done.')
except Exception as e:
    print()
    print(e)
    print('Model already loaded!')

print('ListModels...', end='')
try:
    print(list_models())
    print('done.')
except Exception as e:
    print()
    print(e)
    print('List model failed!')

print('Unload model...', end='')
try:
    unload_model('your-model')
    print('done.')
except Exception as e:
    print()
    print(e)
    print('unload model failed!')

if __name__ == '__main__':
    main()

Ensure model_path points to the name of the AWS IoT Greengrass component containing the model if you use the same client code example.

You can create your AWS IoT Greengrass V2 Hello World component once you have generated your gRPC stubs and you have your Hello World code ready. To do so:

- Upload your edge_manager_python_example.py, agent_pb2_grpc.py, and agent_pb2.py to your Amazon S3 bucket and note down their Amazon S3 path.
- Create a private component in the AWS IoT Greengrass V2 console and define the recipe for your component. Specify the Amazon S3 URI to your Hello World application and gRPC stub in the following recipe.

```yaml
---
RecipeFormatVersion: 2020-01-25
ComponentName: com.sagemaker.edgePythonExample
ComponentVersion: 1.0.0
ComponentDescription: Sagemaker Edge Manager Python example
ComponentPublisher: Amazon Web Services, Inc.
ComponentDependencies:
  aws.greengrass.SageMakerEdgeManager:
    VersionRequirement: '>=1.0.0'
    DependencyType: HARD
Manifests:
- Platform:
  os: linux
    architecture: "/amd64|x86/"
Lifecycle:
  install: |-  
    apt-get install python3-pip
    pip3 install grpcio
    pip3 install grpcio-tools
    pip3 install protobuf
    pip3 install Pillow
```
run:
  script: |- 
    python3 {{[artifacts:path]}}/edge_manager_python_example.py
```
Artifacts:
  - URI: <code-s3-path>
  - URI: <pb2-s3-path>
  - URI: <pb2-grpc-s3-path>
```

For detailed information about creating a Hello World recipe, see Create your first component in the AWS IoT Greengrass documentation.

**Deploy the components to your device**

Deploy your components with the AWS IoT console or with the AWS CLI.

**To deploy your components (console)**

Deploy your AWS IoT Greengrass components with the AWS IoT console.

1. In the AWS IoT Greengrass console at https://console.aws.amazon.com/iot/ navigation menu, choose **Deployments**.
2. On the **Components** page, on the **Public components** tab, choose `aws.greengrass.SageMakerEdgeManager`
3. On the `aws.greengrass.SageMakerEdgeManager` page, choose **Deploy**
4. From **Add to deployment**, choose one of the following:
   a. To merge this component to an existing deployment on your target device, choose **Add to existing deployment**, and then select the deployment that you want to revise.
   b. To create a new deployment on your target device, choose **Create new deployment**. If you have an existing deployment on your device, choosing this step replaces the existing deployment.
5. On the **Specify target** page, do the following:
   a. Under **Deployment information**, enter or modify the friendly name for your deployment.
   b. Under **Deployment targets**, select a target for your deployment, and choose **Next**. You cannot change the deployment target if you are revising an existing deployment.
6. On the **Select components** page, under **My components**, choose:
   - `com.<CUSTOM-COMPONENT-NAME>`
   - `aws.greengrass.SageMakerEdgeManager`
   - `SagemakerEdgeManager.<YOUR-PACKAGING-JOB>`
7. On the **Configure components** page, choose `com.greengrass.SageMakerEdgeManager`, and do the following.
   a. Choose **Configure component**
   b. Under **Configuration update**, in **Configuration to merge**, enter the following configuration.

    ```
    {
      "DeviceFleetName": "device-fleet-name",
      "BucketName": "DOC-EXAMPLE-BUCKET"
    }
    ```

    Replace **device-fleet-name** with the name of the edge device fleet that you created, and replace **DOC-EXAMPLE-BUCKET** with the name of the Amazon S3 bucket that is associated with your device fleet.
   c. Choose **Confirm**, and then choose **Next**.
8. On the **Configure advanced settings** page, keep the default configuration settings, and choose **Next**.
9. On the **Review** page, choose **Deploy**.
To deploy your components (AWS CLI)

1. Create a deployment.json file to define the deployment configuration for your SageMaker Edge Manager components. This file should look like the following example.

```json
{
    "targetArn": "targetArn",
    "components": {
        "aws.greengrass.SageMakerEdgeManager": {
            "componentVersion": 1.0.0,
            "configurationUpdate": {
                "merge": {
                    "DeviceFleetName": "device-fleet-name",
                    "BucketName": "DOC-EXAMPLE-BUCKET"
                }
            }
        },
        "com.greengrass.SageMakerEdgeManager.ImageClassification": {
            "componentVersion": 1.0.0,
            "configurationUpdate": {
            }
        },
        "com.greengrass.SageMakerEdgeManager.ImageClassification.Model": {
            "componentVersion": 1.0.0,
            "configurationUpdate": {
            }
        } ...
    }
}
```

- In the targetArn field, replace `targetArn` with the Amazon Resource Name (ARN) of the thing or thing group to target for the deployment, in the following format:
  - Thing: `arn:aws:iot:region:account-id:thing/thingName`
  - Thing group: `arn:aws:iot:region:account-id:thinggroup/thingGroupName`
- In the merge field, replace `device-fleet-name` with the name of the edge device fleet that you created, and replace `DOC-EXAMPLE-BUCKET` with the name of the Amazon S3 bucket that is associated with your device fleet.
- Replace the component versions for each component with the latest available version.

2. Run the following command to deploy the components on the device:

```bash
aws greengrassv2 create-deployment \
    --cli-input-json file://path/to/deployment.json
```

The deployment can take several minutes to complete. In the next step, check the component log to verify that the deployment completed successfully and to view the inference results.

For more information about deploying components to individual devices or groups of devices, see Deploy AWS IoT Greengrass components to devices.

**Deploy the Model Package Directly with SageMaker Edge Manager Deployment API**

SageMaker Edge Manager provides a deployment API that you can use to deploy models to device targets without AWS IoT Greengrass. It is useful in situations where you want to update models independently of firmware updates or application deployment mechanisms. You can use the API to integrate your edge deployments into a CI/CD workflow to automatically deploy models once you have
validated your model for accuracy. The API also has convenient rollback and staged rollout options for you to ensure models work well in a particular environment before wider rollout.

To use the Edge Manager deployment API first compile and package your model. For information on how to compile and package your model, see Train, Compile, and Package Your Model (p. 3017). The following sections of this guide show how you can create edge deployments using SageMaker API, after you have compiled and packaged your models.

Topics
- Create an edge deployment plan (p. 3054)
- Start the edge deployment (p. 3055)
- Check the status of the deployment (p. 3055)

Create an edge deployment plan

You can create an edge deployment plan with the CreateEdgeDeploymentPlan API. The deployment plan can have multiple stages. You can configure each stage to rollout the deployment to a subset of edge devices (by percentage, or by device name). You can also configure how rollout failures are handled at each stage.

The following code snippet shows how you can create an edge deployment plan with 1 stage to deploy a compiled and package model to 2 specific edge devices:

```python
import boto3
client = boto3.client("sagemaker")

client.create_edge_deployment_plan(
    EdgeDeploymentPlanName="edge-deployment-plan-name",
    DeviceFleetName="device-fleet-name",
    ModelConfigs=[
        {
            "EdgePackagingJobName": "edge-packaging-job-name",
            "ModelHandle": "model-handle"
        }
    ],
    Stages=[
        {
            "StageName": "stage-name",
            "DeviceSelectionConfig": {
                "DeviceSubsetType": "SELECTION",
                "DeviceNames": ["device-name-1", "device-name-2"]
            },
            "DeploymentConfig": {
                "FailureHandlingPolicy": "ROLLBACK_ON_FAILURE"
            }
        }
    ]
)
```

Instead of specific devices, if you want to deploy to the model to a percentage of devices in your fleet, then set the value of DeviceSubsetType to "PERCENTAGE" and replace "DeviceNames": ["device-name-1", "device-name-2"] with "Percentage": desired-percentage in the above example.

Stages can be added after the deployment plan has been created with the CreateEdgeDeploymentStage API, in case you want to start rolling out new stages after validating your test rollout success. For more information about deployment stages see DeploymentStage.
Start the edge deployment

After creating the deployment plan and the deployment stages, you can start the deployment with the `StartEdgeDeploymentStage` API.

```
client.start_edge_deployment_stage(
    EdgeDeploymentPlanName="edge-deployment-plan-name",
    StageName="stage-name"
)
```

Check the status of the deployment

You can check the status of the edge deployment with the `DescribeEdgeDeploymentPlan` API.

```
client.describe_edge_deployment_plan(
    EdgeDeploymentPlanName="edge-deployment-plan-name"
)
```

Manage Model

The Edge Manager agent can load multiple models at a time and make inference with loaded models on edge devices. The number of models the agent can load is determined by the available memory on the device. The agent validates the model signature and loads into memory all the artifacts produced by the edge packaging job. This step requires all the required certificates described in previous steps to be installed along with rest of the binary installation. If the model’s signature cannot be validated, then loading of the model fails with appropriate return code and reason.

SageMaker Edge Manager agent provides a list of Model Management APIs that implement control plane and data plane APIs on edge devices. Along with this documentation, we recommend going through the sample client implementation which shows canonical usage of the below described APIs.

The proto file is available as a part of the release artifacts (inside the release tarball). In this doc, we list and describe the usage of APIs listed in this proto file.

**Note**

There is one-to-one mapping for these APIs on Windows release and a sample code for an application implementation in C# shared with the release artifacts for Windows. Below instructions are for running the Agent as a standalone process, applicable for the release artifacts for Linux.

Extract the archive based on your OS. Where VERSION is broken into three components: `<MAJOR_VERSION>.-<YYYY-MM-DD>-<SHA-7>`. See Installing the Edge Manager agent (p. 3042) for information on how to obtain the release version `<MAJOR_VERSION>`, time stamp of the release artifact `<YYYY-MM-DD>`, and the repository commit ID (SHA-7)

**Linux**

The zip archive can be extracted with the command:

```
tar -xvfz <VERSION>.tgz
```

**Windows**

The zip archive can be extracted with the UI or command:
unzip <VERSION>.tgz

The release artifact hierarchy (after extracting the tar/zip archive) is shown below. The agent proto file is available under api/.

```
0.20201205.7ee4b0b
### bin
#       ### sagemaker_edge_agent_binary
#       ### sagemaker_edge_agent_client_example
### docs
### api
#       ### agent.proto
### attributions
#       ### agent.txt
#       ### core.txt
### examples
### ipc_example
### CMakeLists.txt
### sagemaker_edge_client.cc
### sagemaker_edge_client_example.cc
### sagemaker_edge_client.hh
### sagemaker_edge.proto
### README.md
### shm.cc
### shm.hh
### street_small.bmp
```

Topics
- Load Model (p. 3056)
- Unload Model (p. 3057)
- List Models (p. 3058)
- Describe Model (p. 3058)
- Capture Data (p. 3059)
- Get Capture Status (p. 3060)
- Predict (p. 3061)

Load Model

The Edge Manager agent supports loading multiple models. This API validates the model signature and loads into memory all the artifacts produced by the EdgePackagingJob operation. This step requires all the required certificates to be installed along with rest of the agent binary installation. If the model's signature cannot be validated then this step fails with appropriate return code and error messages in the log.

```c
// perform load for a model
// Note:
// 1. currently only local filesystem paths are supported for loading models.
// 2. multiple models can be loaded at the same time, as limited by available device memory
// 3. users are required to unload any loaded model to load another model.
// Status Codes:
// 1. OK - load is successful
// 2. UNKNOWN - unknown error has occurred
// 3. INTERNAL - an internal error has occurred
// 4. NOT_FOUND - model doesn't exist at the url
// 5. ALREADY_EXISTS - model with the same name is already loaded
// 6. RESOURCE_EXHAUSTED - memory is not available to load the model
```
// 7. FAILED_PRECONDITION - model is not compiled for the machine.
//
rpc LoadModel(LoadModelRequest) returns (LoadModelResponse);

Input

//
// request for LoadModel rpc call
//
message LoadModelRequest {
  string url = 1;
  string name = 2;  // Model name needs to match regex "^[a-zA-Z0-9\-]*[a-zA-Z0-9]+"$
}

Output

//
// response for LoadModel rpc call
//
message LoadModelResponse {
  Model model = 1;
}

//
// Model represents the metadata of a model
// url - url representing the path of the model
// name - name of model
// input_tensor_metadatas - TensorMetadata array for the input tensors
// output_tensor_metadatas - TensorMetadata array for the output tensors
//
// Note:
// 1. input and output tensor metadata could empty for dynamic models.
//
message Model {
  string url = 1;
  string name = 2;
  repeated TensorMetadata input_tensor_metadatas = 3;
  repeated TensorMetadata output_tensor_metadatas = 4;
}

Unload Model

Unloads a previously loaded model. It is identified via the model alias which was provided during LoadModel. If the alias is not found or model is not loaded then returns error.

//
// perform unload for a model
// Status Codes:
// 1. OK - unload is successful
// 2. UNKNOWN - unknown error has occurred
// 3. INTERNAL - an internal error has occurred
// 4. NOT_FOUND - model doesn’t exist
//
rpc UnLoadModel(UnLoadModelRequest) returns (UnLoadModelResponse);

Input

//

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Manage Model

// request for UnLoadModel rpc call
//
message UnLoadModelRequest {
  string name = 1; // Model name needs to match regex "^[a-zA-Z0-9](-*[a-zA-Z0-9])*$"
}

Output

// // response for UnLoadModel rpc call
//
message UnLoadModelResponse {}

List Models

Lists all the loaded models and their aliases.

// // lists the loaded models
// Status Codes:
// 1. OK - unload is successful
// 2. UNKNOWN - unknown error has occurred
// 3. INTERNAL - an internal error has occurred
// rpc ListModels(ListModelsRequest) returns (ListModelsResponse);

Input

// // request for ListModels rpc call
//
message ListModelsRequest {}

Output

// // response for ListModels rpc call
//
message ListModelsResponse {
  repeated Model models = 1;
}

Describe Model

Describes a model that is loaded on the agent.

// // Status Codes:
// 1. OK - load is successful
// 2. UNKNOWN - unknown error has occurred
// 3. INTERNAL - an internal error has occurred
// 4. NOT_FOUND - model doesn’t exist at the url
// rpc DescribeModel(DescribeModelRequest) returns (DescribeModelResponse);
Input

```protobuf
// request for DescribeModel rpc call
message DescribeModelRequest {
  string name = 1;
}
```

Output

```protobuf
// response for DescribeModel rpc call
message DescribeModelResponse {
  Model model = 1;
}
```

Capture Data

Allows the client application to capture input and output tensors in Amazon S3 bucket, and optionally the auxiliary. The client application is expected to pass a unique capture ID along with each call to this API. This can be later used to query status of the capture.

```protobuf
// allows users to capture input and output tensors along with auxiliary data.
// Status Codes:
// 1. OK - data capture successfully initiated
// 2. UNKNOWN - unknown error has occurred
// 3. INTERNAL - an internal error has occurred
// 5. ALREADY_EXISTS - capture initiated for the given capture_id
// 6. RESOURCE_EXHAUSTED - buffer is full cannot accept any more requests.
// 7. OUT_OF_RANGE - timestamp is in the future.
// 8. INVALID_ARGUMENT - capture_id is not of expected format.
// rpc CaptureData(CaptureDataRequest) returns (CaptureDataResponse);
```

Input

```protobuf
enum Encoding {
  CSV = 0;
  JSON = 1;
  NONE = 2;
  BASE64 = 3;
}
```

```protobuf
// AuxiliaryData represents a payload of extra data to be capture along with inputs and outputs of inference
// encoding - supports the encoding of the data
// data - represents the data of shared memory, this could be passed in two ways:
// a. send across the raw bytes of the multi-dimensional tensor array
// b. send a SharedMemoryHandle which contains the posix shared memory segment id and offset in bytes to location of multi-dimensional tensor array.
message AuxiliaryData {
  string name = 1;
  Encoding encoding = 2;
  oneof data {
```
// Tensor represents a tensor, encoded as contiguous multi-dimensional array.
// tensor_metadata - represents metadata of the shared memory segment
// data_or_handle - represents the data of shared memory, this could be passed in two ways:
// a. send across the raw bytes of the multi-dimensional tensor array
// b. send a SharedMemoryHandle which contains the posix shared memory segment id and offset in bytes to location of multi-dimensional tensor array.

message Tensor {
  TensorMetadata tensor_metadata = 1;  //optional in the predict request
  oneof data {
    bytes byte_data = 4;
    // will only be used for input tensors
    SharedMemoryHandle shared_memory_handle = 5;
  }
}

// request for CaptureData rpc call
// message CaptureDataRequest {
  string model_name = 1;  //uid
  string capture_id = 2;  //uuid string
  Timestamp inference_timestamp = 3;
  repeated Tensor input_tensors = 4;
  repeated Tensor output_tensors = 5;
  repeated AuxilaryData inputs = 6;
  repeated AuxilaryData outputs = 7;
}

Output

// response for CaptureData rpc call
// message CaptureDataResponse {}

Get Capture Status

Depending on the models loaded the input and output tensors can be large (for many edge devices). Capture to the cloud can be time consuming. So the CaptureData() is implemented as an asynchronous operation. A capture ID is a unique identifier that the client provides during capture data call, this ID can be used to query the status of the asynchronous call.

 rpc GetCaptureDataStatus(GetCaptureDataStatusRequest) returns (GetCaptureDataStatusResponse);
Input

```protobuf
// request for GetCaptureDataStatus rpc call
message GetCaptureDataStatusRequest {
  string capture_id = 1;
}
```

Output

```protobuf
enum CaptureDataStatus {
  FAILURE = 0;
  SUCCESS = 1;
  IN_PROGRESS = 2;
  NOT_FOUND = 3;
}

// response for GetCaptureDataStatus rpc call
message GetCaptureDataStatusResponse {
  CaptureDataStatus status = 1;
}
```

**Predict**

The `predict` API performs inference on a previously loaded model. It accepts a request in the form of a tensor that is directly fed into the neural network. The output is the output tensor (or scalar) from the model. This is a blocking call.

```protobuf
// perform inference on a model.
// Note:
// 1. users can chose to send the tensor data in the protobuf message or
// through a shared memory segment on a per tensor basis, the Predict
// method with handle the decode transparently.
// 2. serializing large tensors into the protobuf message can be quite expensive,
// based on our measurements it is recommended to use shared memory of
// tenors larger than 256KB.
// 3. SMEdge IPC server will not use shared memory for returning output tensors,
// i.e., the output tensor data will always send in byte form encoded
// in the tensors of PredictResponse.
// 4. currently SMEdge IPC server cannot handle concurrent predict calls, all
// these call will be serialized under the hood. this shall be addressed
// in a later release.
// Status Codes:
// 1. OK - prediction is successful
// 2. UNKNOWN - unknown error has occurred
// 3. INTERNAL - an internal error has occurred
// 4. NOT_FOUND - when model not found
// 5. INVALID_ARGUMENT - when tenors types mismatch
// rpc Predict(PredictRequest) returns (PredictResponse);
```

Input

```protobuf
// request for Predict rpc call
```
/ message PredictRequest {
  string name = 1;
  repeated Tensor tensors = 2;
}

// Tensor represents a tensor, encoded as contiguous multi-dimensional array.
// tensor_metadata - represents metadata of the shared memory segment
// data_or_handle - represents the data of shared memory, this could be passed in
// two ways:
// a. send across the raw bytes of the multi-dimensional tensor
// array
// b. send a SharedMemoryHandle which contains the posix shared
// memory segment
// id and offset in bytes to location of multi-dimensional
// tensor array.
// message Tensor {
  TensorMetadata tensor_metadata = 1; //optional in the predict request
  oneof data {
    bytes byte_data = 4;
      // will only be used for input tensors
    SharedMemoryHandle shared_memory_handle = 5;
  }
}

// TensorMetadata represents the metadata for a tensor
// name - name of the tensor
// data_type - data type of the tensor
// shape - array of dimensions of the tensor
// message TensorMetadata {
  string name = 1;
  DataType data_type = 2;
  repeated int32 shape = 3;
}

// SharedMemoryHandle represents a posix shared memory segment
// offset - offset in bytes from the start of the shared memory segment.
// segment_id - shared memory segment id corresponding to the posix shared memory
// segment.
// size - size in bytes of shared memory segment to use from the offset position.
Optimize model performance using Neo

Neo is a capability of Amazon SageMaker that enables machine learning models to train once and run anywhere in the cloud and at the edge.

If you are a first time user of SageMaker Neo, we recommend you check out the Getting Started with Edge Devices section to get step-by-step instructions on how to compile and deploy to an edge device.

What is SageMaker Neo?

Generally, optimizing machine learning models for inference on multiple platforms is difficult because you need to hand-tune models for the specific hardware and software configuration of each platform. If you want to get optimal performance for a given workload, you need to know the hardware architecture, instruction set, memory access patterns, and input data shapes, among other factors. For traditional software development, tools such as compilers and profilers simplify the process. For machine learning, most tools are specific to the framework or to the hardware. This forces you into a manual trial-and-error process that is unreliable and unproductive.

Neo automatically optimizes Gluon, Keras, MXNet, PyTorch, TensorFlow, TensorFlow-Lite, and ONNX models for inference on Android, Linux, and Windows machines based on processors from Ambarella, ARM, Intel, Nvidia, NXP, Qualcomm, Texas Instruments, and Xilinx. Neo is tested with computer vision models available in the model zoos across the frameworks. SageMaker Neo supports compilation and deployment for two main platforms: cloud instances (including Inferentia) and edge devices.

For more information about supported frameworks and cloud instance types you can deploy to, see Supported Instance Types and Frameworks (p. 3078) for cloud instances.

For more information about supported frameworks, edge devices, operating systems, chip architectures, and common machine learning models tested by SageMaker Neo for edge devices, see Supported Frameworks, Devices, Systems, and Architectures (p. 3105) for edge devices.

How it Works

Neo consists of a compiler and a runtime. First, the Neo compilation API reads models exported from various frameworks. It converts the framework-specific functions and operations into a framework-agnostic intermediate representation. Next, it performs a series of optimizations. Then it generates
binary code for the optimized operations, writes them to a shared object library, and saves the model definition and parameters into separate files. Neo also provides a runtime for each target platform that loads and executes the compiled model.

You can create a Neo compilation job from either the SageMaker console, the AWS Command Line Interface (AWS CLI), a Python notebook, or the SageMaker SDK. For information on how to compile a model, see Use Neo to Compile a Model (p. 3065). With a few CLI commands, an API invocation, or a few clicks, you can convert a model for your chosen platform. You can deploy the model to a SageMaker endpoint or on an AWS IoT Greengrass device quickly.

Neo can optimize models with parameters either in FP32 or quantized to INT8 or FP16 bit-width.

**Neo Sample Notebooks**

For sample notebooks that use SageMaker Neo to train, compile, optimize, and deploy machine learning models to make inferences, see:

- MNIST Training, Compilation and Deployment with MXNet Module
- MNIST Training, Compilation and Deployment with Tensorflow Module
- Deploying pre-trained PyTorch vision models with SageMaker Neo
- Model Optimization with an Image Classification Example
- Model Optimization with XGBoost Example

For instructions on how to run these example notebooks in SageMaker, see Example Notebooks (p. 306). If you need instructions on how to create a notebook instance to run these examples, see Use Amazon SageMaker Notebook Instances (p. 291). To navigate to the relevant example in your notebook instance,
choose the Amazon SageMaker Examples tab to see a list of all of the SageMaker samples. To open a notebook, choose its Use tab, then choose Create copy.

**Use Neo to Compile a Model**

This section shows how to create, describe, stop, and list compilation jobs. The following options are available in Amazon SageMaker Neo for managing the compilation jobs for machine learning models: the Neo CLI, the Amazon SageMaker console, or the Amazon SageMaker SDK.

**Topics**
- Prepare Model for Compilation (p. 3065)
- Compile a Model (AWS Command Line Interface) (p. 3071)
- Compile a Model (Amazon SageMaker Console) (p. 3073)
- Compile a Model (Amazon SageMaker SDK) (p. 3078)

**Prepare Model for Compilation**

SageMaker Neo requires machine learning models satisfy specific input data shape. The input shape required for compilation depends on the deep learning framework you use. Once your model input shape is correctly formatted, save your model according to the requirements below. Once you have a saved model, compress the model artifacts.

**Topics**
- What input data shapes does SageMaker Neo expect? (p. 3065)
- Saving Models for SageMaker Neo (p. 3066)

**What input data shapes does SageMaker Neo expect?**

Before you compile your model, make sure your model is formatted correctly. Neo expects the name and shape of the expected data inputs for your trained model with JSON format or list format. The expected inputs are framework specific.

Below are the input shapes SageMaker Neo expects:

**Keras**

Specify the name and shape (NCHW format) of the expected data inputs using a dictionary format for your trained model. Note that while Keras model artifacts should be uploaded in NHWC (channel-last) format, DataInputConfig should be specified in NCHW (channel-first) format. The dictionary formats required are as follows:

- For one input: `{'input_1':[1,3,224,224]}`
- For two inputs: `{'input_1': [1,3,224,224], 'input_2':[1,3,224,224]}`

**MXNet/ONNX**

Specify the name and shape (NCHW format) of the expected data inputs using a dictionary format for your trained model. The dictionary formats required are as follows:

- For one input: `{'data':[1,3,1024,1024]}`
- For two inputs: `{'var1': [1,1,28,28], 'var2':[1,1,28,28]}`
PyTorch

Specify the name and shape (NCHW format) of the expected data inputs using a dictionary format for your trained model. Alternatively, you can specify the shape only using a list format. The dictionary formats required are as follows:

- For one input in dictionary format: {'input0':[1,3,224,224]}
- For one input in list format: [[1,3,224,224]]
- For two inputs in dictionary format: {'input0':[1,3,224,224], 'input1':[1,3,224,224]}
- For two inputs in list format: [[1,3,224,224], [1,3,224,224]]

TensorFlow

Specify the name and shape (NHWC format) of the expected data inputs using a dictionary format for your trained model. The dictionary formats required are as follows:

- For one input: {'input':[1,1024,1024,3]}
- For two inputs: {'data1': [1,28,28,1], 'data2':[1,28,28,1]}

TFLite

Specify the name and shape (NHWC format) of the expected data inputs using a dictionary format for your trained model. The dictionary formats required are as follows:

- For one input: {'input':[1,224,224,3]}

Note

SageMaker Neo only supports TensorFlow Lite for edge device targets. For a list of supported SageMaker Neo edge device targets, see the SageMaker Neo Devices (p. 3107) page. For a list of supported SageMaker Neo cloud instance targets, see the SageMaker Neo Supported Instance Types and Frameworks (p. 3078) page.

XGBoost

An input data name and shape are not needed.

Saving Models for SageMaker Neo

The following code examples show how to save your model to make it compatible with Neo. Models must be packaged as compressed tar files (*.tar.gz).

Keras

Keras models require one model definition file (.h5).

There are two options for saving your Keras model in order to make it compatible for SageMaker Neo:

1. Export to .h5 format with model.save("<model-name>", save_format="h5").
2. Freeze the SavedModel after exporting.

Below is an example of how to export a tf.keras model as a frozen graph (option two):

```python
import os
import tensorflow as tf
from tensorflow.keras.applications.resnet50 import ResNet50
from tensorflow.keras import backend
```
tf.keras.backend.set_learning_phase(0)
model = tf.keras.applications.ResNet50(weights='imagenet', include_top=False,
    input_shape=(224, 224, 3), pooling='avg')
model.summary()

# Save as a SavedModel
export_dir = 'saved_model/
model.save(export_dir, save_format='tf')

# Freeze saved model
input_node_names = [inp.name.split(':')[0] for inp in model.inputs]
output_node_names = [output.name.split(':')[0] for output in model.outputs]
print("Input names: ", input_node_names)
with tf.Session() as sess:
    loaded = tf.saved_model.load(sess, export_dir=export_dir, tags=["serve"])
    frozen_graph = tf.graph_util.convert_variables_to_constants(sess,
        sess.graph.as_graph_def(),
        output_node_names)
    tf.io.write_graph(graph_or_graph_def=frozen_graph, logdir=".", name="frozen_graph.pb",
        as_text=False)

import tarfile
tar = tarfile.open("frozen_graph.tar.gz", "w:gz")
tar.add("frozen_graph.pb")
tar.close()

Warning
Do not export your model with the SavedModel class using model.save(<path>,
    save_format='tf'). This format is suitable for training, but it is not suitable for inference.

MXNet

MXNet models must be saved as a single symbol file *-symbol.json and a single parameter *.params
files.

Gluon Models

Define the neural network using the HybridSequential Class. This will run the code in the style of
symbolic programming (as opposed to imperative programming).

def get_net():
    net = nn.HybridSequential()  # Here we use the class HybridSequential.
    net.add(nn.Dense(256, activation='relu'),
        nn.Dense(128, activation='relu'),
        nn.Dense(2))
    net.initialize()
    return net

# Define an input to compute a forward calculation.
x = nd.random.normal(shape=(1, 512))
net = get_net()

# During the forward calculation, the neural network will automatically infer
# the shape of the weight parameters of all the layers based on the shape of
# the input.
net(x)

# hybridize model
net.hybridize()
net(x)
Amazon SageMaker Developer Guide
Compile Models

# export model
net.export('<model_name>') # this will create model-symbol.json and model-0000.params
files
import tarfile
tar = tarfile.open("<model_name>.tar.gz", "w:gz")
for name in ["<model_name>-0000.params", "<model_name>-symbol.json"]:
tar.add(name)
tar.close()

For more information about hybridizing models, see the MXNet hybridize documentation.
Gluon Model Zoo (GluonCV)
GluonCV model zoo models come pre-hybridized. So you can just export them.
import numpy as np
import mxnet as mx
import gluoncv as gcv
from gluoncv.utils import export_block
import tarfile
net = gcv.model_zoo.get_model('<model_name>', pretrained=True) # For example, choose
<model_name> as resnet18_v1
export_block('<model_name>', net, preprocess=True, layout='HWC')
tar = tarfile.open("<model_name>.tar.gz", "w:gz")
for name in ["<model_name>-0000.params", "<model_name>-symbol.json"]:
tar.add(name)
tar.close()

Non Gluon Models
All non-Gluon models when saved to disk use *-symbol and *.params ﬁles. They are therefore
already in the correct format for Neo.
# Pass the following 3 parameters: sym, args, aux
mx.model.save_checkpoint('<model_name>',0,sym,args,aux) # this will create
<model_name>-symbol.json and <model_name>-0000.params files
import tarfile
tar = tarfile.open("<model_name>.tar.gz", "w:gz")
for name in ["<model_name>-0000.params", "<model_name>-symbol.json"]:
tar.add(name)
tar.close()

PyTorch
PyTorch models must be saved as a deﬁnition ﬁle (.pt or .pth) with input datatype of float32.
To save your model, use torch.jit.trace followed by torch.save. This will save an object to a
disk ﬁle and by default uses python pickle (pickle_module=pickle) to save the objects and some
metadata. Next, convert the saved model to a compressed tar ﬁle.
import torchvision
import torch
model = torchvision.models.resnet18(pretrained=True)

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model.eval()
inp = torch.rand(1, 3, 224, 224)
model_trace = torch.jit.trace(model, inp)

# Save your model. The following code saves it with the .pth file extension
model_trace.save('model.pth')

# Save as a compressed tar file
import tarfile
with tarfile.open('model.tar.gz', 'w:gz') as f:
    f.add('model.pth')
    f.close()

**TensorFlow**

TensorFlow requires one .pb or one .pbtxt file and a variables directory that contains variables. For frozen models, only one .pb or .pbtxt file is required.

**Pre-Trained Model**

The following code example shows how to use the tar Linux command to compress your model. Run the following in your terminal or in a Jupyter notebook (if you use a Jupyter notebook, insert the ! magic command at the beginning of the statement):

```bash
# Download SSD_Mobilenet trained model
!wget http://download.tensorflow.org/models/object_detection/ssd_mobilenet_v2_coco_2018_03_29.tar.gz

# unzip the compressed tar file
!tar xvf ssd_mobilenet_v2_coco_2018_03_29.tar.gz

# Compress the tar file and save it in a directory called 'model.tar.gz'
!tar czvf model.tar.gz ssd_mobilenet_v2_coco_2018_03_29/frozen_inference_graph.pb
```

The command flags used in this example accomplish the following:

- c: Create an archive
- z: Compress the archive with gzip
- v: Display archive progress
- f: Specify the filename of the archive

**Built-In Estimators**

Built-in estimators are either made by framework-specific containers or algorithm-specific containers. Estimator objects for both the built-in algorithm and framework-specific estimator saves the model in the correct format for you when you train the model using the built-in `.fit` method.

For example, you can use a `sagemaker.TensorFlow` to define a TensorFlow estimator:

```python
from sagemaker.tensorflow import TensorFlow
estimator = TensorFlow(entry_point='mnist.py',
    role=role,  # param role can be arn of a sagemaker execution role
    framework_version='1.15.3',
    py_version='py3',
    training_steps=1000,
    evaluation_steps=100,
    instance_count=2,
    instance_type='ml.c4.xlarge')
```
Then train the model with `.fit` built-in method:

```python
estimator.fit(inputs)
```

Before finally compiling model with the build in `compile_model` method:

```python
# Specify output path of the compiled model
output_path = '/'.join(estimator.output_path.split('/')[:-1])

# Compile model
optimized_estimator = estimator.compile_model(target_instance_family='ml_c5',
                                           input_shape={'data':[1, 784]},  # Batch size 1, 3 channels,
                                           output_path=output_path,
                                           framework='tensorflow', framework_version='1.15.3')
```

You can also use the `sagemaker.estimator.Estimator` Class to initialize an estimator object for training and compiling a built-in algorithm with the `compile_model` method from the SageMaker Python SDK:

```python
import sagemaker
from sagemaker.image_uris import retrieve

sagemaker_session = sagemaker.Session()
aws_region = sagemaker_session.boto_region_name

# Specify built-in algorithm training image
training_image = retrieve(framework='image-classification',
                          region=aws_region, image_scope='training')

# Create estimator object for training
estimator = sagemaker.estimator.Estimator(image_uri=training_image,
                                          role=role,  #param role can be arn of a sagemaker
                                          execution role
                                          instance_count=1,
                                          instance_type='ml.p3.8xlarge',
                                          volume_size = 50,
                                          max_run = 360000,
                                          input_mode= 'File',
                                          output_path=s3_training_output_location,
                                          base_job_name='image-classification-training')

# Setup the input data_channels to be used later for training.
train_data = sagemaker.inputs.TrainingInput(s3_training_data_location,
                                            content_type='application/x-recordio',
                                            s3_data_type='S3Prefix')
validation_data = sagemaker.inputs.TrainingInput(s3_validation_data_location,
                                                content_type='application/x-recordio',
                                                s3_data_type='S3Prefix')
data_channels = {'train': train_data, 'validation': validation_data}

# Train model
estimator.fit(inputs=data_channels, logs=True)

# Compile model with Neo
optimized_estimator = estimator.compile_model(target_instance_family='ml_c5',
                                             ...)
Compile Models

input_shape={'data':[1, 3, 224, 224],
            'softmax_label':[1],
            output_path=s3_compilation_output_location,
            framework='mxnet',
            framework_version='1.7')

For more information about compiling models with the SageMaker Python SDK, see Compile a Model (Amazon SageMaker SDK) (p. 3078).

Compile a Model (AWS Command Line Interface)

This section shows how to manage Amazon SageMaker Neo compilation jobs for machine learning models using AWS Command Line Interface (CLI). You can create, describe, stop, and list the compilation jobs.

1. Create a Compilation Job

   With the CreateCompilationJob API operation, you can specify the data input format, the S3 bucket in which to store your model, the S3 bucket to which to write the compiled model, and the target hardware device or platform.

   The following table demonstrates how to configure CreateCompilationJob API based on whether your target is a device or a platform.

   **Device Example**

   ```json
   {
   "CompilationJobName": "neo-compilation-job-demo",
   "RoleArn": "arn:aws:iam::<your-account>:role/service-role/AmazonSageMaker-ExecutionRole-yyyyymmdTHHMMSS",
   "InputConfig": {
      "S3Uri": "s3://<your-bucket>/sagemaker/neo-compilation-job-demo-data/train",
      "DataInputConfig": "{'data': [1,3,1024,1024]}",
      "Framework": "MXNET"
   },
   "OutputConfig": {
      "S3OutputLocation": "s3://<your-bucket>/sagemaker/neo-compilation-job-demo-data/compile",
      "TargetDevice": "ml_c5"
   },
   "StoppingCondition": {
      "MaxRuntimeInSeconds": 300
   }
   }
   ```

   You can optionally specify the framework version you used with the FrameworkVersion field if you used the PyTorch framework to train your model and your target device is a ml_* target.

   ```json
   {
   "CompilationJobName": "neo-compilation-job-demo",
   "RoleArn": "arn:aws:iam::<your-account>:role/service-role/AmazonSageMaker-ExecutionRole-yyyyymmdTHHMMSS",
   "InputConfig": {
      "S3Uri": "s3://<your-bucket>/sagemaker/neo-compilation-job-demo-data/train",
      "DataInputConfig": "{'data': [1,3,1024,1024]}",
      "Framework": "PYTORCH"
   },
   "OutputConfig": {
      "S3OutputLocation": "s3://<your-bucket>/sagemaker/neo-compilation-job-demo-data/compile",
      "TargetDevice": "ml_c5"
   },
   "StoppingCondition": {
      "MaxRuntimeInSeconds": 300
   }
   }
   ```

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# excluding ml_inf. Supported values are 1.4 or 1.5 or 1.6. Default is 1.6
"FrameworkVersion": "1.6"
},
"OutputConfig": {
  "S3OutputLocation": "s3://your-bucket/sagemaker/neo-compilation-job-demo-data/compile",
  # A target device specification example for a ml_c5 instance family
  "TargetDevice": "ml_c5",
  # When compiling for ml_* instances using PyTorch framework, use the
  "CompilerOptions" field in
  # OutputConfig to provide the correct data type ("dtype") of the model’s
  input. Default assumed is "float32"
  "CompilerOptions": {
    "dtype": 'long'}
},
"StoppingCondition": {
  "MaxRuntimeInSeconds": 300
}
}

Note
This API field is only supported for PyTorch.

Platform Example

```
{
  "CompilationJobName": "neo-test-compilation-job",
  "RoleArn": "arn:aws:iam::your-account:role/service-role/AmazonSageMaker-ExecutionRole-yyyyymmddThhmmss",
  "InputConfig": {
    "S3Uri": "s3://your-bucket/sagemaker/neo-compilation-job-demo-data/train",
    "DataInputConfig": {
      "data": [1,3,1024,1024]
    },
    "Framework": "MXNET"
  },
  "OutputConfig": {
    "S3OutputLocation": "s3://your-bucket/sagemaker/neo-compilation-job-demo-data/compile",
    # A target platform configuration example for a p3.2xlarge instance
    "TargetPlatform": {
      "Os": "LINUX",
      "Arch": "X86_64",
      "Accelerator": "NVIDIA"
    },
    "CompilerOptions": {
      "cuda-ver": '10.0', 'trt-ver': '6.0.1', 'gpu-code': 'sm_70'
    },
    "StoppingCondition": {
      "MaxRuntimeInSeconds": 300
    }
  }
}
```

Note
For the OutputConfig API operation, the TargetDevice and TargetPlatform API operations are mutually exclusive. You have to choose one of the two options.

To find the JSON string examples of DataInputConfig depending on frameworks, see What input data shapes Neo expects.

For more information about setting up the configurations, see the InputConfig, OutputConfig, and TargetPlatform API operations in the SageMaker API reference.

2. After you configure the JSON file, run the following command to create the compilation job:
aws sagemaker create-compilation-job
--cli-input-json file://job.json
--region us-west-2

# You should get CompilationJobArn

3. Describe the compilation job by running the following command:

```bash
da sagemaker describe-compilation-job
--compilation-job-name $JOB_NM
--region us-west-2
```

4. Stop the compilation job by running the following command:

```bash
da sagemaker stop-compilation-job
--compilation-job-name $JOB_NM
--region us-west-2
```

# There is no output for compilation-job operation

5. List the compilation job by running the following command:

```bash
da sagemaker list-compilation-jobs
--region us-west-2
```

**Compile a Model (Amazon SageMaker Console)**

You can create an Amazon SageMaker Neo compilation job in the Amazon SageMaker console.

1. In the Amazon SageMaker console, choose **Compilation jobs**, and then choose **Create compilation job**.

2. On the **Create compilation job** page, under **Job name**, enter a name. Then select an **IAM role**.
3. If you don’t have an IAM role, choose **Create a new role**.

4. On the **Create an IAM role** page, choose **Any S3 bucket**, and choose **Create role**.
5. Non PyTorch Frameworks

Within the **Input configuration** section, enter the full path of the Amazon S3 bucket URI that contains your model artifacts in the **Location of model artifacts** input field. Your model artifacts must be in a compressed tarball file format (.tar.gz).

For the **Data input configuration** field, enter the JSON string that specifies the shape of the input data. For **Machine learning framework**, choose the framework of your choice.

To find the JSON string examples of input data shapes depending on frameworks, see [What input data shapes Neo expects](#).

**PyTorch Framework**

Similar instructions apply for compiling PyTorch models. However, if you trained with PyTorch and are trying to compile the model for ml_* (except ml_inf) target, you can optionally specify the version of PyTorch you used.

To find the JSON string examples of input data shapes depending on frameworks, see [What input data shapes Neo expects](#).
Note
When compiling for ml_* instances using PyTorch framework, use Compiler options field in Output Configuration to provide the correct data type (dtype) of the model’s input. The default is set to “float32”.

Output configuration
Amazon SageMaker needs to know where to store the modules compiled with this job. Learn more

- Target device
  Choose the target device or the machine learning instance that you want to run your model on after the compilation has completed.
- Target platform
  Control the target platform that you want your model to run on, such as OS, architecture, and accelerators.

Target device
Amazon SageMaker needs to know where you intend to deploy your model to an Amazon SageMaker ML instance or to an AWS IoT Greengrass device.

Compiler options - optional
Specify additional parameters for compiler options in JSON format.

S3 Output location
Amazon SageMaker needs the path to the S3 bucket or folder where you want to store the compiled module.

Encryption key – optional
Encrypt your data. Choose an existing KMS key or enter a key's ARN.

Warning
If you specify an Amazon S3 bucket URI path that leads to .pth file, you will receive the following error after starting compilation: ClientError: InputConfiguration: Unable to untar input model. Please confirm the model is a tar.gz file

6. Go to the Output configuration section. Choose where you want to deploy your model. You can deploy your model to a Target device or a Target platform. Target devices include cloud and edge devices. Target platforms refer to specific OS, architecture, and accelerators you want your model to run on.

For S3 Output location, enter the path to the S3 bucket where you want to store the model. You can optionally add compiler options in JSON format under the Compiler options section.
7. Check the status of the compilation job when started. This status of the job can be found at the top of the Compilation Job page, as shown in the following screenshot. You can also check the status of it in the Status column.

8. Check the status of the compilation job when completed. You can check the status in the Status column as shown in the following screenshot.
Compile a Model (Amazon SageMaker SDK)

You can use the `compile_model` API in the Amazon SageMaker SDK for Python to compile a trained model and optimize it for specific target hardware. The API should be invoked on the estimator object used during model training.

**Note**

You must set `MMS_DEFAULT_RESPONSE_TIMEOUT` environment variable to 500 when compiling the model with MXNet or PyTorch. The environment variable is not needed for TensorFlow.

The following is an example of how you can compile a model using the `trained_model_estimator` object:

```python
# Replace the value of expected_trained_model_input below and
# specify the name & shape of the expected inputs for your trained model
expected_trained_model_input = {'data':[1, 784]}

# Replace the example target_instance_family below to your preferred target_instance_family
compiled_model = trained_model_estimator.compile_model(target_instance_family='ml_c5',
                                                      input_shape=expected_trained_model_input,
                                                      output_path='insert s3 output path',
                                                      env={'MMS_DEFAULT_RESPONSE_TIMEOUT': '500'})
```

The code compiles the model, saves the optimized model at `output_path`, and creates a SageMaker model that can be deployed to an endpoint. Sample notebooks of using the SDK for Python are provided in the Neo Model Compilation Sample Notebooks section.

Cloud Instances

Amazon SageMaker Neo provides compilation support for popular machine learning frameworks such as TensorFlow, PyTorch, MXNet, and more. You can deploy your compiled model to cloud instances and AWS Inferentia instances. For a full list of supported frameworks and instances types, see Supported Instances Types and Frameworks.

You can compile your model in one of three ways: through the AWS CLI, the SageMaker Console, or the SageMaker SDK for Python. See, Use Neo to Compile a Model for more information. Once compiled, your model artifacts are stored in the Amazon S3 bucket URI you specified during the compilation job. You can deploy your compiled model to cloud instances and AWS Inferentia instances using the SageMaker SDK for Python, AWS SDK for Python (Boto3), AWS CLI, or the AWS console.

If you deploy your model using AWS CLI, the console, or Boto3, you must select a Docker image Amazon ECR URI for your primary container. See Neo Inference Container Images for a list of Amazon ECR URIs.

**Topics**

- Supported Instance Types and Frameworks (p. 3078)
- Deploy a Model (p. 3082)
- Request Inferences from a Deployed Service (p. 3099)
- Inference Container Images (p. 3102)

**Supported Instance Types and Frameworks**

Amazon SageMaker Neo supports popular deep learning frameworks for both compilation and deployment. You can deploy your model to cloud instances, AWS Inferentia instance types, or Amazon Elastic Inference accelerators.
The following describes frameworks SageMaker Neo supports and the target cloud instances you can compile and deploy to. For information on how to deploy your compiled model to a cloud or Inferentia instance, see Deploy a Model with Cloud Instances. For information on how to deploy your compiled model with Elastic Inference accelerators, see Use EI on Amazon SageMaker Hosted Endpoints (p. 3137).

Cloud Instances

SageMaker Neo supports the following deep learning frameworks for CPU and GPU cloud instances:

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>MXNet</td>
<td>1.8.0</td>
<td>Supports 1.8.0 or earlier</td>
<td>Image Classification, Object Detection, Semantic Segmentation, Pose Estimation, Activity Recognition</td>
<td>One symbol file (.json) and one parameter file (.params)</td>
<td>GluonCV v0.8.0</td>
</tr>
<tr>
<td>ONNX</td>
<td>1.7.0</td>
<td>Supports 1.7.0 or earlier</td>
<td>Image Classification, SVM</td>
<td>One model file (.onnx)</td>
<td></td>
</tr>
<tr>
<td>Keras</td>
<td>2.2.4</td>
<td>Supports 2.2.4 or earlier</td>
<td>Image Classification</td>
<td>One model definition file (.h5)</td>
<td></td>
</tr>
<tr>
<td>PyTorch</td>
<td>1.4, 1.5, 1.6, 1.7 or 1.8</td>
<td>Supports 1.4, 1.5, 1.6, 1.7 and 1.8</td>
<td>Image Classification</td>
<td>One model definition file (.pt or .pth) with input dtype of float32</td>
<td></td>
</tr>
<tr>
<td>TensorFlow</td>
<td>1.15.3 or 2.9</td>
<td>Supports 1.15.3 and 2.9</td>
<td>Image Classification</td>
<td>For saved models, one .pb or one .pbtxt file and a variables directory that contains variables For frozen models, only one .pb or .pbtxt file</td>
<td></td>
</tr>
<tr>
<td>XGBoost</td>
<td>1.3.3</td>
<td>Supports 1.3.3 or earlier</td>
<td>Decision Trees</td>
<td>One XGBoost model file (.model) where the number of</td>
<td></td>
</tr>
</tbody>
</table>
Cloud Instances

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>nodes in a tree is less than 2^31</td>
</tr>
</tbody>
</table>

**Note**

"Model Version" is the version of the framework used to train and export the model.

**Instance Types**

You can deploy your SageMaker compiled model to one of the cloud instances listed below:

<table>
<thead>
<tr>
<th>Instance</th>
<th>Compute Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>ml_c4</td>
<td>Standard</td>
</tr>
<tr>
<td>ml_c5</td>
<td>Standard</td>
</tr>
<tr>
<td>ml_m4</td>
<td>Standard</td>
</tr>
<tr>
<td>ml_m5</td>
<td>Standard</td>
</tr>
<tr>
<td>ml_p2</td>
<td>Accelerated computing</td>
</tr>
<tr>
<td>ml_p3</td>
<td>Accelerated computing</td>
</tr>
<tr>
<td>ml_g4dn</td>
<td>Accelerated computing</td>
</tr>
</tbody>
</table>

For information on the available vCPU, memory, and price per hour for each instance type, see Amazon SageMaker Pricing.

**Note**

When compiling for ml_* instances using PyTorch framework, use Compiler options field in Output Configuration to provide the correct data type (dtype) of the model's input. The default is set to "float32".

**AWS Inferentia**

SageMaker Neo supports the following deep learning frameworks for Inferentia:

<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>MXNet</td>
<td>1.5 or 1.8</td>
<td>Supports 1.8, 1.5 and earlier</td>
<td>Image Classification, Object Detection, Semantic</td>
<td>One symbol file (.json) and one parameter file (.params)</td>
<td>GluonCV v0.8.0</td>
</tr>
<tr>
<td>-----------</td>
<td>------------------</td>
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</tr>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Segmentation, Pose Estimation, Activity Recognition</td>
<td></td>
</tr>
<tr>
<td>PyTorch</td>
<td>1.7, 1.8 or 1.9</td>
<td>Supports 1.9 and earlier</td>
<td>Image Classification</td>
<td>One model definition file (.pt or .pth) with input dtype of float32</td>
<td></td>
</tr>
<tr>
<td>TensorFlow</td>
<td>1.15 or 2.5</td>
<td>Supports 2.5, 1.15 and earlier</td>
<td>Image Classification</td>
<td>For saved models, one .pb or one .pbtxt file and a variables directory that contains variables. For frozen models, only one .pb or .pbtxt file.</td>
<td></td>
</tr>
</tbody>
</table>

**Note**

"Model Version" is the version of the framework used to train and export the model.

You can deploy your SageMaker Neo-compiled model to AWS Inferentia-based Amazon EC2 Inf1 instances. AWS Inferentia is Amazon's first custom silicon chip designed to accelerate deep learning. Currently, you can use the ml_inf1 instance to deploy your compiled models.

**Amazon Elastic Inference**

SageMaker Neo supports the following deep learning frameworks for Elastic Inference:

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>TensorFlow</td>
<td>2.3.2</td>
<td>Supports 2.3</td>
<td>Image Classification, Object Detection, Semantic Segmentation, Pose Estimation, Activity Recognition</td>
<td>For saved models, one .pb or one .pbtxt file and a variables directory that contains variables. For frozen models, only one .pb or .pbtxt file.</td>
</tr>
</tbody>
</table>
You can deploy your SageMaker Neo-compiled model to an Elastic Inference Accelerator. For more information, see Use EI on Amazon SageMaker Hosted Endpoints (p. 3137).

**Deploy a Model**

To deploy an Amazon SageMaker Neo-compiled model to an HTTPS endpoint, you must configure and create the endpoint for the model using Amazon SageMaker hosting services. Currently, developers can use Amazon SageMaker APIs to deploy modules on to ml.c5, ml.c4, ml.m5, ml.m4, ml.p3, ml.p2, and ml.inf1 instances.

For **Inf1 instances**, models need to be compiled specifically for ml.inf1 instances. Models compiled for other instance types are not guaranteed to work with ml.inf1 instances.

For **Elastic Inference accelerators**, models need to be compiled specifically for ml_eia2 devices. For information on how to deploy your compiled model to an Elastic Inference accelerator, see Use EI on Amazon SageMaker Hosted Endpoints (p. 3137).

When you deploy a compiled model, you need to use the same instance for the target that you used for compilation. This creates a SageMaker endpoint that you can use to perform inferences. You can deploy a Neo-compiled model using any of the following: Amazon SageMaker SDK for Python, SDK for Python (Boto3), AWS Command Line Interface, and the SageMaker console [https://console.aws.amazon.com/SageMaker].

**Note**
For deploying a model using AWS CLI, the console, or Boto3, see Neo Inference Container Images to select the inference image URI for your primary container.

**Topics**

- Prerequisites (p. 3082)
- Deploy a Compiled Model Using SageMaker SDK (p. 3088)
- Deploy a Compiled Model Using Boto3 (p. 3091)
- Deploy a Compiled Model Using the AWS CLI (p. 3092)
- Deploy a Compiled Model Using the Console (p. 3094)

**Prerequisites**

**Note**
Follow the instructions in this section if you compiled your model using AWS SDK for Python (Boto3), AWS CLI, or the SageMaker console.

To create a SageMaker Neo-compiled model, you need the following:

1. A Docker image Amazon ECR URI. You can select one that meets your needs from this list.
2. An entry point script file:
   a. **For PyTorch and MXNet models:**

   *If you trained your model using SageMaker*, the training script must implement the functions described below. The training script serves as the entry point script during inference. In the example detailed in MNIST Training, Compilation and Deployment with MXNet Module and SageMaker Neo, the training script (mnist.py) implements the required functions.

   *If you did not train your model using SageMaker*, you need to provide an entry point script (inference.py) file that can be used at the time of inference. Based on the framework—MXNet or PyTorch—the inference script location must conform to the SageMaker Python SDK Model Directory Structure for MxNet or Model Directory Structure for PyTorch.
When using Neo Inference Optimized Container images with **PyTorch** and **MXNet** on CPU and GPU instance types, the inference script must implement the following functions:

- **model_fn**: Loads the model. (Optional)
- **input_fn**: Converts the incoming request payload into a numpy array.
- **predict_fn**: Performs the prediction.
- **output_fn**: Converts the prediction output into the response payload.
- Alternatively, you can define **transform_fn** to combine **input_fn**, **predict_fn**, and **output_fn**.

The following are examples of inference.py script within a directory named code (code/inference.py) for **PyTorch** and **MXNet (Gluon and Module)**. The examples first load the model and then serve it on image data on a GPU:

**MXNet Module**

```python
import numpy as np
import json
import mxnet as mx
import neomx  # noqa: F401
from collections import namedtuple

Batch = namedtuple('Batch', ['data'])

# Change the context to mx.cpu() if deploying to a CPU endpoint
ctx = mx.gpu()

def model_fn(model_dir):
    # The compiled model artifacts are saved with the prefix 'compiled'
    sym, arg_params, aux_params = mx.model.load_checkpoint('compiled', 0)
    mod = mx.mod.Module(symbol=sym, context=ctx, label_names=None)
    exe = mod.bind(for_training=False,
                   data_shapes=[('data', (1,3,224,224))],
                   label_shapes=mod._label_shapes)
    mod.set_params(arg_params, aux_params, allow_missing=True)
    # Run warm-up inference on empty data during model load (required for GPU)
    data = mx.nd.empty((1,3,224,224), ctx=ctx)
    mod.forward(Batch([data]))
    return mod

def transform_fn(mod, image, input_content_type, output_content_type):
    # pre-processing
    decoded = mx.image.imdecode(image)
    resized = mx.image.resize_short(decoded, 224)
    cropped, crop_info = mx.image.center_crop(resized, (224, 224))
    normalized = mx.image.color_normalize(cropped.astype(np.float32) / 255,
                                           mean=mx.nd.array([0.485, 0.456, 0.406]),
                                           std=mx.nd.array([0.229, 0.224, 0.225]))
    transposed = normalized.transpose((2, 0, 1))
    batchified = transposed.expand_dims(axis=0)
    casted = batchified.astype(dtype='float32')
    processed_input = casted.as_in_context(ctx)

    # prediction/inference
    mod.forward(Batch([processed_input]))

    # post-processing
    prob = mod.get_outputs()[0].asnumpy().tolist()
```

prob_json = json.dumps(prob)
return prob_json, output_content_type

**MXNet Gluon**

```python
import numpy as np
import json
import mxnet as mx
import neomx  # noqa: F401

# Change the context to mx.cpu() if deploying to a CPU endpoint
ctx = mx.gpu()

def model_fn(model_dir):
    # The compiled model artifacts are saved with the prefix 'compiled'
    block = mx.gluon.nn.SymbolBlock.imports('compiled-symbol.json',
                                           ['data'],
                                           'compiled-0000.params',
                                           ctx=ctx)

    # Hybridize the model & pass required options for Neo: static_alloc=True &
    # static_shape=True
    block.hybridize(static_alloc=True, static_shape=True)

    # Run warm-up inference on empty data during model load (required for GPU)
    data = mx.nd.empty((1,3,224,224), ctx=ctx)
    warm_up = block(data)
    return block

def input_fn(image, input_content_type):
    # pre-processing
    decoded = mx.image.imdecode(image)
    resized = mx.image.resize_short(decoded, 224)
    cropped, crop_info = mx.image.center_crop(resized, (224, 224))
    normalized = mx.image.color_normalize(cropped.astype(np.float32) / 255,
                                           mean=mx.nd.array([0.485, 0.456, 0.406]),
                                           std=mx.nd.array([0.229, 0.224, 0.225]))
    transposed = normalized.transpose((2, 0, 1))
    batchified = transposed.expand_dims(axis=0)
    casted = batchified.astype(dtype='float32')
    processed_input = casted.as_in_context(ctx)
    return processed_input

def predict_fn(processed_input_data, block):
    # prediction/inference
    prediction = block(processed_input_data)
    return prediction

def output_fn(prediction, output_content_type):
    # post-processing
    prob = prediction.asnumpy().tolist()
    prob_json = json.dumps(prob)
    return prob_json, output_content_type

**PyTorch 1.4 and Older**

```python
import os
import torch
import torch.nn.parallel
import torch.optim
import torch.utils.data
import torch.utils.data.distributed
import torchvision.transforms as transforms
```
```
from PIL import Image
import io
import json
import pickle

def model_fn(model_dir):
    """Load the model and return it.
    Providing this function is optional.
    There is a default model_fn available which will load the model
    compiled using SageMaker Neo. You can override it here.
    
    Keyword arguments:
    model_dir -- the directory path where the model artifacts are present
    """

    # The compiled model is saved as "compiled.pt"
    model_path = os.path.join(model_dir, 'compiled.pt')
    with torch.neo.config(model_dir=model_dir, neo_runtime=True):
        model = torch.jit.load(model_path)
        device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        model = model.to(device)
        # We recommend that you run warm-up inference during model load
        sample_input_path = os.path.join(model_dir, 'sample_input.pkl')
        with open(sample_input_path, 'rb') as input_file:
            model_input = pickle.load(input_file)
        if torch.is_tensor(model_input):
            model_input = model_input.to(device)
        elif isinstance(model_input, tuple):
            model_input = (inp.to(device) for inp in model_input if
            torch.is_tensor(inp))
        else:
            print("Only supports a torch tensor or a tuple of torch tensors")
        return model

def transform_fn(model, request_body, request_content_type,
                 response_content_type):
    """Run prediction and return the output.
    The function
    1. Pre-processes the input request
    2. Runs prediction
    3. Post-processes the prediction output.
    """

    # preprocess
    decoded = Image.open(io.BytesIO(request_body))
    preprocess = transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(
            mean=[
                0.485, 0.456, 0.406],
            std=[
                0.229, 0.224, 0.225]),
    ])
    normalized = preprocess(decoded)
    batchified = normalized.unsqueeze(0)
    # predict
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    batchified = batchified.to(device)
    output = model.forward(batchified)
```
import os
import torch
import torch.nn.parallel
import torch.optim
import torch.utils.data
import torch.utils.data.distributed
import torchvision.transforms as transforms
from PIL import Image
import io
import json
import pickle

def model_fn(model_dir):
    """Load the model and return it."
    # The compiled model is saved as "model.pt"
    model_path = os.path.join(model_dir, 'model.pt')
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    model = torch.jit.load(model_path, map_location=device)
    model = model.to(device)
    return model

def transform_fn(model, request_body, request_content_type, response_content_type):
    """Run prediction and return the output."
    # preprocess
    decoded = Image.open(io.BytesIO(request_body))
    preprocess = transforms.Compose([
        transforms.Resize(256),
        transforms.CenterCrop(224),
        transforms.ToTensor(),
        transforms.Normalize(mean=[
            0.485, 0.456, 0.406], std=[
            0.229, 0.224, 0.225]),
    ])
    normalized = preprocess(decoded)
    batchified = normalized.unsqueeze(0)

    # predict
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    batchified = batchified.to(device)
    output = model.forward(batchified)
    return json.dumps(output.cpu().numpy().tolist()), response_content_type
b. For inf1 instances or onnx, xgboost, keras container images

For all other Neo Inference-optimized container images, or inferentia instance types, the entry point script must implement the following functions for Neo Deep Learning Runtime:

- neo_preprocess: Converts the incoming request payload into a numpy array.
- neo_postprocess: Converts the prediction output from Neo Deep Learning Runtime into the response body.

**Note**
The preceding two functions do not use any of the functionalities of MXNet, PyTorch, or TensorFlow.

For examples of how to use these functions, see Neo Model Compilation Sample Notebooks.

c. For TensorFlow models

If your model requires custom pre- and post-processing logic before data is sent to the model, then you must specify an entry point script inference.py file that can be used at the time of inference. The script should implement either a either a pair of input_handler and output_handler functions or a single handler function.

**Note**
Note that if handler function is implemented, input_handler and output_handler are ignored.

The following is a code example of inference.py script that you can put together with the compile model to perform custom pre- and post-processing on an image classification model. The SageMaker client sends the image file as an application/x-image content type to the input_handler function, where it is converted to JSON. The converted image file is then sent to the TensorFlow Model Server (TFX) using the REST API.

```python
import json
import numpy as np
import json
import io
from PIL import Image
from tensorflow_serving.apis import predict_pb2
from tensorflow_serving.apis import prediction_service_pb2

def input_handler(data, context):
    """ Pre-process request input before it is sent to TensorFlow Serving REST API ""

    Args:
    data (obj): the request data, in format of dict or string
    context (Context): an object containing request and configuration details

    Returns:
    (dict): a JSON-serializable dict that contains request body and headers
    """
    f = data.read()
    f = io.BytesIO(f)
    image = Image.open(f).convert('RGB')
    batch_size = 1
    image = np.asarray(image.resize((512, 512)))
    image = np.concatenate([image[np.newaxis, :, :] * batch_size]
    image = json.dumps(
        "signature_name": "serving_default",
        "instances":
            image.tolist()"
    return body
```
def output_handler(data, context):
    """Post-process TensorFlow Serving output before it is returned to the client.
    Args:
    data (obj): the TensorFlow serving response
    context (Context): an object containing request and configuration details
    Returns:
    (bytes, string): data to return to client, response content type
    """
    if data.status_code != 200:
        raise ValueError(data.content.decode('utf-8'))
    response_content_type = context.accept_header
    prediction = data.content
    return prediction, response_content_type

If there is no custom pre- or post-processing, the SageMaker client converts the file image to JSON in a similar way before sending it over to the SageMaker endpoint.

For more information, see the Deploying to TensorFlow Serving Endpoints in the SageMaker Python SDK.

3. The Amazon S3 bucket URI that contains the compiled model artifacts.

Deploy a Compiled Model Using SageMaker SDK

You must satisfy the prerequisites section if the model was compiled using AWS SDK for Python (Boto3), AWS CLI, or the Amazon SageMaker console. Follow one of the following use cases to deploy a model compiled with SageMaker Neo based on how you compiled your model.

Topics
- If you compiled your model using the SageMaker SDK (p. 3088)
- If you compiled your model using MXNet or PyTorch (p. 3088)
- If you compiled your model using Boto3, SageMaker console, or the CLI for TensorFlow (p. 3090)

If you compiled your model using the SageMaker SDK

The sagemaker.Model object handle for the compiled model supplies the deploy() function, which enables you to create an endpoint to serve inference requests. The function lets you set the number and type of instances that are used for the endpoint. You must choose an instance for which you have compiled your model. For example, in the job compiled in Compile a Model (Amazon SageMaker SDK) section, this is ml_c5.

predictor = compiled_model.deploy(initial_instance_count = 1, instance_type = 'ml.c5.4xlarge')

# Print the name of newly created endpoint
print(predictor.endpoint_name)

If you compiled your model using MXNet or PyTorch

Create the SageMaker model and deploy it using the deploy() API under the framework-specific Model APIs. For MXNet, it is MXNetModel and for PyTorch, it is PyTorchModel. When you are creating and deploying an SageMaker model, you must set MMS_DEFAULT_RESPONSE_TIMEOUT environment variable to 500 and specify the entry_point parameter as the inference script (inference.py) and the source_dir parameter as the directory location (code) of the inference script. To prepare the inference script (inference.py) follow the Prerequisites step.
The following example shows how to use these functions to deploy a compiled model using the SageMaker SDK for Python:

**MXNet**

```python
from sagemaker.mxnet import MXNetModel

# Create SageMaker model and deploy an endpoint
sm_mxnet_compiled_model = MXNetModel(
    model_data='insert S3 path of compiled MXNet model archive',
    role='AmazonSageMaker-ExecutionRole',
    entry_point='inference.py',
    source_dir='code',
    framework_version='1.8.0',
    py_version='py3',
    image_uri='insert appropriate ECR Image URI for MXNet',
    env={'MMS_DEFAULT_RESPONSE_TIMEOUT': '500'},
)

# Replace the example instance_type below to your preferred instance_type
predictor = sm_mxnet_compiled_model.deploy(initial_instance_count = 1, instance_type = 'ml.p3.2xlarge')

# Print the name of newly created endpoint
print(predictor.endpoint_name)
```

**PyTorch 1.4 and Older**

```python
from sagemaker.pytorch import PyTorchModel

# Create SageMaker model and deploy an endpoint
sm_pytorch_compiled_model = PyTorchModel(
    model_data='insert S3 path of compiled PyTorch model archive',
    role='AmazonSageMaker-ExecutionRole',
    entry_point='inference.py',
    source_dir='code',
    framework_version='1.4.0',
    py_version='py3',
    image_uri='insert appropriate ECR Image URI for PyTorch',
    env={'MMS_DEFAULT_RESPONSE_TIMEOUT': '500'},
)

# Replace the example instance_type below to your preferred instance_type
predictor = sm_pytorch_compiled_model.deploy(initial_instance_count = 1, instance_type = 'ml.p3.2xlarge')

# Print the name of newly created endpoint
print(predictor.endpoint_name)
```

**PyTorch 1.5 and Newer**

```python
from sagemaker.pytorch import PyTorchModel

# Create SageMaker model and deploy an endpoint
sm_pytorch_compiled_model = PyTorchModel(
    model_data='insert S3 path of compiled PyTorch model archive',
    role='AmazonSageMaker-ExecutionRole',
    entry_point='inference.py',
    source_dir='code',
    framework_version='1.5',
    py_version='py3',
    image_uri='insert appropriate ECR Image URI for PyTorch',
)
```
# Replace the example instance_type below to your preferred instance_type
predictor = sm_pytorch_compiled_model.deploy(initial_instance_count = 1, instance_type = 'ml.p3.2xlarge')

# Print the name of newly created endpoint
print(predictor.endpoint_name)

**Note**
The AmazonSageMakerFullAccess and AmazonS3ReadOnlyAccess policies must be attached to the AmazonSageMaker-ExecutionRole IAM role.

If you compiled your model using Boto3, SageMaker console, or the CLI for TensorFlow

Construct a TensorFlowModel object, then call deploy:

```python
role='AmazonSageMaker-ExecutionRole'
model_path='S3 path for model file'
framework_image='inference container arn'
tf_model = TensorFlowModel(model_data=model_path,
                           framework_version='1.15.3',
                           role=role,
                           image_uri=framework_image)
instance_type='ml.c5.xlarge'
predictor = tf_model.deploy(instance_type=instance_type,
                            initial_instance_count=1)
```

See Deploying directly from model artifacts for more information.

You can select a Docker image Amazon ECR URI that meets your needs from this list.

For more information on how to construct a TensorFlowModel object, see the SageMaker SDK.

**Note**
Your first inference request might have high latency if you deploy your model on a GPU. This is because an optimized compute kernel is made on the first inference request. We recommend that you make a warm-up file of inference requests and store that alongside your model file before sending it off to a TFX. This is known as “warming up” the model.

The following code snippet demonstrates how to produce the warm-up file for image classification example in the prerequisites section:

```python
import tensorflow as tf
from tensorflow_serving.apis import classification_pb2
from tensorflow_serving.apis import inference_pb2
from tensorflow_serving.apis import model_pb2
from tensorflow_serving.apis import predict_pb2
from tensorflow_serving.apis import prediction_log_pb2
import numpy as np

with tf.python_io.TFRecordWriter("tf_serving_warmup_requests") as writer:
    img = np.random.uniform(0, 1, size=[224, 224, 3]).astype(np.float32)
    img = np.expand_dims(img, axis=0)
    test_data = np.repeat(img, 1, axis=0)
    request = predict_pb2.PredictRequest()
    request.model_spec.name = 'compiled_models'
    request.model_spec.signature_name = 'serving_default'
    request.inputs["Placeholder:0'].CopyFrom(tf.compat.v1.make_tensor_proto(test_data, shape=test_data.shape, dtype=tf.float32))
```

---

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log = prediction_log_pb2.PredictionLog(
predict_log=prediction_log_pb2.PredictLog(request=request))
writer.write(log.SerializeToString())

For more information on how to “warm up” your model, see the TensorFlow TFX page.

Deploy a Compiled Model Using Boto3

You must satisfy the prerequisites section if the model was compiled using AWS SDK for Python (Boto3), AWS CLI, or the Amazon SageMaker console. Follow the steps below to create and deploy a SageMaker Neo-compiled model using Amazon Web Services SDK for Python (Boto3).

Topics
• Deploy the Model (p. 3091)

Deploy the Model

After you have satisfied the prerequisites, use the create_model, create_endpoint_config, and create_endpoint APIs.

The following example shows how to use these APIs to deploy a model compiled with Neo:

```python
import boto3
client = boto3.client('sagemaker')

# create sagemaker model
create_model_api_response = client.create_model(
    ModelName='my-sagemaker-model',
    PrimaryContainer={
        'Image': '<insert the ECR Image URI>',
        'ModelDataUrl': 's3://path/to/model/artifact/model.tar.gz',
        'Environment': {}
    },
    ExecutionRoleArn='ARN for AmazonSageMaker-
    ExecutionRole'
)

print ('create_model API response', create_model_api_response)

# create sagemaker endpoint config
create_endpoint_config_api_response = client.create_endpoint_config(
    EndpointConfigName='sagemaker-neomxnet-endpoint-configuration',
    ProductionVariants=[
        {'VariantName': '<provide your variant name>',
         'ModelName': 'my-sagemaker-model',
         'InitialInstanceCount': 1,
         'InstanceType': '<provide your instance type here>'
        },
    ],
)

print ('create_endpoint_config API response', create_endpoint_config_api_response)

# create sagemaker endpoint
create_endpoint_api_response = client.create_endpoint(
    EndpointName='<provide your endpoint name>',
    EndpointConfigName='<insert your endpoint config name>',
)```
Note
The AmazonSageMakerFullAccess and AmazonS3ReadOnlyAccess policies must be
attached to the AmazonSageMaker-ExecutionRole IAM role.

For full syntax of create_model, create_endpoint_config, and create_endpoint APIs, see
create_model, create_endpoint_config, and create_endpoint, respectively.

If you did not train your model using SageMaker, specify the following environment variables:

MXNet and PyTorch

"Environment": {
    "SAGEMAKER_PROGRAM": "inference.py",
    "SAGEMAKER_SUBMIT_DIRECTORY": "/opt/ml/model/code",
    "SAGEMAKER_CONTAINER_LOG_LEVEL": "20",
    "SAGEMAKER_REGION": "insert your region",
    "MMS_DEFAULT_RESPONSE_TIMEOUT": "500"
}

TensorFlow

"Environment": {
    "SAGEMAKER_PROGRAM": "inference.py",
    "SAGEMAKER_SUBMIT_DIRECTORY": "/opt/ml/model/code",
    "SAGEMAKER_CONTAINER_LOG_LEVEL": "20",
    "SAGEMAKER_REGION": "insert your region"
}

If you trained your model using SageMaker, specify the environment variable
SAGEMAKER_SUBMIT_DIRECTORY as the full Amazon S3 bucket URI that contains the training script.

Deploy a Compiled Model Using the AWS CLI

You must satisfy the prerequisites section if the model was compiled using AWS SDK for Python (Boto3),
AWS CLI, or the Amazon SageMaker console. Follow the steps below to create and deploy a SageMaker
Neo-compiled model using the AWS CLI.

Topics
• Deploy the Model (p. 3092)

Deploy the Model

After you have satisfied the prerequisites, use the create-model, create-endpoint-config, and
create-endpoint AWS CLI commands. The following steps explain how to use these commands to
deploy a model compiled with Neo:

Create a Model

From Neo Inference Container Images, select the inference image URI and then use create-model API
to create a SageMaker model. You can do this with two steps:

1. Create a create_model.json file. Within the file, specify the name of the model, the image URI, the
   path to the model.tar.gz file in your Amazon S3 bucket, and your SageMaker execution role:
Cloud Instances

```
{
    "ModelName": "insert model name",
    "PrimaryContainer": {
        "Image": "insert the ECR Image URI",
        "ModelDataUrl": "insert S3 archive URL",
        "Environment": {"See details below"}
    },
    "ExecutionRoleArn": "ARN for AmazonSageMaker-ExecutionRole"
}
```

If you trained your model using SageMaker, specify the following environment variable:

```
"Environment": {
    "SAGEMAKER_SUBMIT_DIRECTORY": "[Full S3 path for *.tar.gz file containing the training script]"
}
```

If you did not train your model using SageMaker, specify the following environment variables:

**MXNet and PyTorch**

```
"Environment": {
    "SAGEMAKER_PROGRAM": "inference.py",
    "SAGEMAKER_SUBMIT_DIRECTORY": "/opt/ml/model/code",
    "SAGEMAKER_CONTAINER_LOG_LEVEL": "20",
    "SAGEMAKER_REGION": "insert your region",
    "MMS_DEFAULT_RESPONSE_TIMEOUT": "500"
}
```

**TensorFlow**

```
"Environment": {
    "SAGEMAKER_PROGRAM": "inference.py",
    "SAGEMAKER_SUBMIT_DIRECTORY": "/opt/ml/model/code",
    "SAGEMAKER_CONTAINER_LOG_LEVEL": "20",
    "SAGEMAKER_REGION": "insert your region"
}
```

**Note**
The AmazonSageMakerFullAccess and AmazonS3ReadOnlyAccess policies must be attached to the AmazonSageMaker-ExecutionRole IAM role.

2. Run the following command:

```
aws sagemaker create-model --cli-input-json file://create_model.json
```

For the full syntax of the create-model API, see [create-model](https://docs.aws.amazon.com/sagemaker/latest/dg/API_CreateModel.html).

**Create an Endpoint Configuration**

After creating a SageMaker model, create the endpoint configuration using the create-endpoint-config API. To do this, create a JSON file with your endpoint configuration specifications. For example, you can use the following code template and save it as create_config.json:

```
{
    "EndpointConfigName": "<provide your endpoint config name>",
    "ProductionVariants": [
```
Now run the following AWS CLI command to create your endpoint configuration:

```bash
aws sagemaker create-endpoint-config --cli-input-json file://create_config.json
```

For the full syntax of the `create-endpoint-config` API, see `create-endpoint-config`.

Create an Endpoint

After you have created your endpoint configuration, create an endpoint using the `create-endpoint` API:

```bash
aws sagemaker create-endpoint --endpoint-name '<provide your endpoint name>' --endpoint-config-name '<insert your endpoint config name>'
```

For the full syntax of the `create-endpoint` API, see `create-endpoint`.

Deploy a Compiled Model Using the Console

You must satisfy the prerequisites section if the model was compiled using AWS SDK for Python (Boto3), the AWS CLI, or the Amazon SageMaker console. Follow the steps below to create and deploy a SageMaker Neo-compiled model using the SageMaker console [https://console.aws.amazon.com/SageMaker](https://console.aws.amazon.com/SageMaker).

Topics

- Deploy the Model (p. 3094)

Deploy the Model

After you have satisfied the prerequisites, use the following steps to deploy a model compiled with Neo:

1. Choose Models, and then choose Create models from the Inference group. On the Create model page, complete the Model name, IAM role, and VPC fields (optional), if needed.
2. To add information about the container used to deploy your model, choose Add container container, then choose Next. Complete the Container input options, Location of inference code image, and Location of model artifacts, and optionally, Container host name, and Environmental variables fields.
3. To deploy Neo-compiled models, choose the following:

- **Container input options**: Choose *Provide model artifacts and inference image*.
- **Location of inference code image**: Choose the inference image URI from *Neo Inference Container Images*, depending on the AWS Region and kind of application.
- **Location of model artifact**: Enter the Amazon S3 bucket URI of the compiled model artifact generated by the Neo compilation API.
- **Environment variables**:
  - Leave this field blank for *SageMaker XGBoost*.
  - If you trained your model using SageMaker, specify the environment variable `SAGEMAKER_SUBMIT_DIRECTORY` as the Amazon S3 bucket URI that contains the training script.
  - If you did not train your model using SageMaker, specify the following environment variables:

<table>
<thead>
<tr>
<th>Key</th>
<th>Values for MXNet and PyTorch</th>
<th>Values TensorFlow</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAGEMAKER_PROGRAM</td>
<td>inference.py</td>
<td>inference.py</td>
</tr>
<tr>
<td>SAGEMAKER_SUBMIT_DIRECTORY</td>
<td>/opt/ml/model/code</td>
<td>/opt/ml/model/code</td>
</tr>
<tr>
<td>SAGEMAKER_CONTAINER_LOG_LEVEL</td>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>Key</td>
<td>Values for MXNet and PyTorch</td>
<td>Values TensorFlow</td>
</tr>
<tr>
<td>-----------------------------------</td>
<td>-------------------------------</td>
<td>------------------</td>
</tr>
<tr>
<td>SAGEMAKER_REGION</td>
<td>&lt;your region&gt;</td>
<td>&lt;your region&gt;</td>
</tr>
<tr>
<td>MMS_DEFAULT_RESPONSE_TIMEOUT</td>
<td>500</td>
<td>Leave this field blank for TF</td>
</tr>
</tbody>
</table>

4. Confirm that the information for the containers is accurate, and then choose Create model. On the Create model landing page, choose Create endpoint.

5. In Create and configure endpoint diagram, specify the Endpoint name. For Attach endpoint configuration, choose Create a new endpoint configuration.

6. In New endpoint configuration page, specify the Endpoint configuration name.
7. Choose **Edit** next to the name of the model and specify the correct **Instance type** on the **Edit Production Variant** page. It is imperative that the **Instance type** value match the one specified in your compilation job.
8. Choose **Save**.

9. On the **New endpoint configuration** page, choose **Create endpoint configuration**, and then choose **Create endpoint**.

### Request Inferences from a Deployed Service

If you have followed instructions in Deploy a Model (p. 3082), you should have a SageMaker endpoint set up and running. Regardless of how you deployed your Neo-compiled model, there are three ways you can submit inference requests:

**Topics**
- Request Inferences from a Deployed Service (Amazon SageMaker SDK) (p. 3099)
- Request Inferences from a Deployed Service (Boto3) (p. 3101)
- Request Inferences from a Deployed Service (AWS CLI) (p. 3102)

**Request Inferences from a Deployed Service (Amazon SageMaker SDK)**

Use the following the code examples to request inferences from your deployed service based on the framework you used to train your model. The code examples for the different frameworks are similar. The main difference is that TensorFlow requires `application/json` as the content type.
PyTorch and MXNet

If you are using PyTorch v1.4 or later or MXNet 1.7.0 or later and you have an Amazon SageMaker endpoint InService, you can make inference requests using the predictor package of the SageMaker SDK for Python.

Note
The API varies based on the SageMaker SDK for Python version:

- For version 1.x, use the RealTimePredictor and Predict API.
- For version 2.x, use the Predictor and the Predict API.

The following code example shows how to use these APIs to send an image for inference:

SageMaker Python SDK v1.x

```python
from sagemaker.predictor import RealTimePredictor

endpoint = 'insert name of your endpoint here'

# Read image into memory
payload = None
with open("image.jpg", 'rb') as f:
    payload = f.read()

predictor = RealTimePredictor(endpoint=endpoint, content_type='application/x-image')
inference_response = predictor.predict(data=payload)
print (inference_response)
```

SageMaker Python SDK v2.x

```python
from sagemaker.predictor import Predictor

endpoint = 'insert name of your endpoint here'

# Read image into memory
payload = None
with open("image.jpg", 'rb') as f:
    payload = f.read()

predictor = Predictor(endpoint)
inference_response = predictor.predict(data=payload)
print (inference_response)
```

TensorFlow

The following code example shows how to use the SageMaker Python SDK API to send an image for inference:

```python
from sagemaker.predictor import Predictor
from PIL import Image
import numpy as np
import json

endpoint = 'insert the name of your endpoint here'

# Read image into memory
image = Image.open(input_file)
batch_size = 1
image = np.asarray(image.resize((224, 224)))
```
Request Inferences from a Deployed Service (Boto3)

You can submit inference requests using SageMaker SDK for Python (Boto3) client and `invoke_endpoint()` API once you have an SageMaker endpoint InService. The following code example shows how to send an image for inference:

**PyTorch and MXNet**

```python
import boto3
import json

endpoint = 'insert name of your endpoint here'

runtime = boto3.Session().client('sagemaker-runtime')

# Read image into memory
with open(image, 'rb') as f:
    payload = f.read()

# Send image via InvokeEndpoint API
response = runtime.invoke_endpoint(EndpointName=endpoint, ContentType='application/x-image', Body=payload)

# Unpack response
result = json.loads(response['Body'].read().decode())
```

**TensorFlow**

For TensorFlow submit an input with `application/json` for the content type.

```python
from PIL import Image
import numpy as np
import json
import boto3

client = boto3.client('sagemaker-runtime')

input_file = 'path/to/image'
image = Image.open(input_file)
batch_size = 1
image = np.array(image.resize((224, 224)))/128.0 - 1

body = json.dumps({"instances": image.tolist()})
ioc_predictor_endpoint_name = 'insert name of your endpoint here'
content_type = 'application/json'
ioc_response = client.invoke_endpoint(EndpointName=ioc_predictor_endpoint_name, Body=body, ContentType=content_type)
```

**XGBoost**

For an XGBoost application, you should submit a CSV text instead:

```python
image = image / 128 - 1
image = np.concatenate([image[np.newaxis, :, :]] * batch_size)
body = json.dumps({"instances": image.tolist()})
predictor = Predictor(endpoint)
inference_response = predictor.predict(data=body)
print(inference_response)
```
import boto3
import json

endpoint = 'insert your endpoint name here'
runtime = boto3.Session().client('sagemaker-runtime')

csv_text = '1,-1.0,1.0,1.5,2.6'
# Send CSV text via InvokeEndpoint API
response = runtime.invoke_endpoint(EndpointName=endpoint, ContentType='text/csv',
Body=csv_text)
# Unpack response
result = json.loads(response['Body'].read().decode())

Note that BYOM allows for a custom content type. For more information, see runtime_InvokeEndpoint.

Request Inferences from a Deployed Service (AWS CLI)

Inference requests can be made with the sagemaker-runtime invoke-endpoint once you have an Amazon SageMaker endpoint InService. You can make inference requests with the AWS Command Line Interface (AWS CLI). The following example shows how to send an image for inference:

```
aws sagemaker-runtime invoke-endpoint --endpoint-name 'insert name of your endpoint here'
--body fileb://image.jpg --content-type=application/x-image output_file.txt
```

An output_file.txt with information about your inference requests is made if the inference was successful.

For TensorFlow submit an input with application/json as the content type.

```
aws sagemaker-runtime invoke-endpoint --endpoint-name 'insert name of your endpoint here'
--body fileb://input.json --content-type=application/json output_file.txt
```

Inference Container Images

Based on your use case, replace the highlighted portion in the inference image URI template provided below with appropriate values.

**Amazon SageMaker XGBoost**

```
aws_account_id.dkr.ecr.aws_region.amazonaws.com/xgboost-neo:latest
```

Replace `aws_account_id` from the table at the end of this page based on the `aws_region` you used.

**Keras**

```
aws_account_id.dkr.ecr.aws_region.amazonaws.com/sagemaker-neo-keras:fx_version-instance_type-py3
```

Replace `aws_account_id` from the table at the end of this page based on the `aws_region` you used.

Replace `fx_version` with 2.2.4.

Replace `instance_type` with either cpu or gpu.
MXNet

CPU or GPU instance types

\[
\text{aws_account_id}.dkr.ecr.\text{aws_region}.amazonaws.com/sagemaker-inference-mxnet:\text{fx_version}-\text{instance_type}-py3
\]

Replace \text{aws_account_id} from the table at the end of this page based on the \text{aws_region} you used.

Replace \text{fx_version} with 1.8.0.

Replace \text{instance_type} with either cpu or gpu.

Inferentia instance types

\[
\text{aws_account_id}.dkr.ecr.\text{aws_region}.amazonaws.com/sagemaker-neo-mxnet:\text{fx_version}-\text{instance_type}-py3
\]

Replace \text{aws_region} with either us-east-1 or us-west-2.

Replace \text{aws_account_id} from the table at the end of this page based on the \text{aws_region} you used.

Replace \text{fx_version} with 1.5.1.

Replace \text{instance_type} with inf.

ONNX

\[
\text{aws_account_id}.dkr.ecr.\text{aws_region}.amazonaws.com/sagemaker-neo-onnx:\text{fx_version}-\text{instance_type}-py3
\]

Replace \text{aws_account_id} from the table at the end of this page based on the \text{aws_region} you used.

Replace \text{fx_version} with 1.5.0.

Replace \text{instance_type} with either cpu or gpu.

PyTorch

CPU or GPU instance types

\[
\text{aws_account_id}.dkr.ecr.\text{aws_region}.amazonaws.com/sagemaker-inference-pytorch:\text{fx_version}-\text{instance_type}-py3
\]

Replace \text{aws_account_id} from the table at the end of this page based on the \text{aws_region} you used.

Replace \text{fx_version} with 1.4, 1.5, 1.6, 1.7 or 1.8.

Replace \text{instance_type} with either cpu or gpu.

Inferentia instance types

\[
\text{aws_account_id}.dkr.ecr.\text{aws_region}.amazonaws.com/sagemaker-neo-pytorch:\text{fx_version}-\text{instance_type}-py3
\]
Replace `aws_region` with either `us-east-1` or `us-west-2`.

Replace `aws_account_id` from the table at the end of this page based on the `aws_region` you used.

Replace `fx_version` with `1.5.1`.

Replace `instance_type` with `inf`.

**TensorFlow**

CPU or GPU instance types

```
aws_account_id.dkr.ecr.aws_region.amazonaws.com/sagemaker-inference-tensorflow:fix_version-instance_type-py3
```

Replace `aws_account_id` from the table at the end of this page based on the `aws_region` you used.

Replace `fx_version` with `1.15.3` or `2.9`.

Replace `instance_type` with either `cpu` or `gpu`.

Inferentia instance types

```
aws_account_id.dkr.ecr.aws_region.amazonaws.com/sagemaker-neo-tensorflow:fx_version-instance_type-py3
```

Replace `aws_account_id` from the table at the end of this page based on the `aws_region` you used. Note that for instance type `inf` only `us-east-1` and `us-west-2` are supported.

Replace `fx_version` with `1.15.0`.

Replace `instance_type` with `inf`.

The following table maps `aws_account_id` with `aws_region`. Use this table to find the correct inference image URI you need for your application.

<table>
<thead>
<tr>
<th>aws_account_id</th>
<th>aws_region</th>
</tr>
</thead>
<tbody>
<tr>
<td>785573368785</td>
<td>us-east-1</td>
</tr>
<tr>
<td>007439368137</td>
<td>us-east-2</td>
</tr>
<tr>
<td>710691900526</td>
<td>us-west-1</td>
</tr>
<tr>
<td>301217895009</td>
<td>us-west-2</td>
</tr>
<tr>
<td>802834080501</td>
<td>eu-west-1</td>
</tr>
<tr>
<td>205493899709</td>
<td>eu-west-2</td>
</tr>
<tr>
<td>254080097072</td>
<td>eu-west-3</td>
</tr>
<tr>
<td>601324751636</td>
<td>eu-north-1</td>
</tr>
<tr>
<td>966458181534</td>
<td>eu-south-1</td>
</tr>
<tr>
<td>746233611703</td>
<td>eu-central-1</td>
</tr>
</tbody>
</table>
Edge Devices

Amazon SageMaker Neo provides compilation support for popular machine learning frameworks. You can deploy your Neo-compiled edge devices such as the Raspberry Pi 3, Texas Instruments' Sitara, Jetson TX1, and more. For a full list of supported frameworks and edge devices, see Supported Frameworks, Devices, Systems, and Architectures.

You must configure your edge device so that it can use AWS services. One way to do this is to install DLR and Boto3 to your device. To do this, you must set up the authentication credentials. See Boto3 AWS Configuration for more information. Once your model is compiled and your edge device is configured, you can download the model from Amazon S3 to your edge device. From there, you can use the Deep Learning Runtime (DLR) to read the compiled model and make inferences.

For first-time users, we recommend you check out the Getting Started guide. This guide walks you through how to set up your credentials, compile a model, deploy your model to a Raspberry Pi 3, and make inferences on images.

Topics
- Supported Frameworks, Devices, Systems, and Architectures (p. 3105)
- Deploy Models (p. 3115)
- Getting Started with Neo on Edge Devices (p. 3116)

Supported Frameworks, Devices, Systems, and Architectures

Amazon SageMaker Neo supports common machine learning frameworks, edge devices, operating systems, and chip architectures. Find out if Neo supports your framework, edge device, OS, and chip architecture by selecting one of the topics below.

You can find a list of models that have been tested by the Amazon SageMaker Neo Team in the Tested Models (p. 3109) section.
Note

- Ambarella devices require additional files to be included within the compressed TAR file before it is sent for compilation. For more information, see Troubleshoot Ambarella Errors (p. 3127).
- TIM-VX (libtim-vx.so) is required for i.MX 8M Plus. For information on how to build TIM-VX, see the TIM-VX GitHub repository.

Topics

- Supported Frameworks (p. 3106)
- Supported Devices, Chip Architectures, and Systems (p. 3107)
- Tested Models (p. 3109)

Supported Frameworks

Amazon SageMaker Neo supports the following frameworks.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>MXNet</td>
<td>1.8</td>
<td>Supports 1.8 or earlier</td>
<td>Image Classification, Object Detection, Semantic Segmentation, Pose Estimation, Activity Recognition</td>
<td>One symbol file (.json) and one parameter file (.params)</td>
<td>GluonCV v0.8.0</td>
</tr>
<tr>
<td>ONNX</td>
<td>1.7</td>
<td>Supports 1.7 or earlier</td>
<td>Image Classification, SVM</td>
<td>One model file (.onnx)</td>
<td></td>
</tr>
<tr>
<td>Keras</td>
<td>2.2</td>
<td>Supports 2.2 or earlier</td>
<td>Image Classification</td>
<td>One model definition file (.h5)</td>
<td></td>
</tr>
<tr>
<td>PyTorch</td>
<td>1.7, 1.8</td>
<td>Supports 1.7, 1.8 or earlier</td>
<td>Image Classification, Object Detection</td>
<td>One model definition file (.pth)</td>
<td></td>
</tr>
<tr>
<td>TensorFlow</td>
<td>1.15, 2.4, 2.5 (only for ml.inf1.* instances)</td>
<td>Supports 1.15, 2.4, 2.5 (only for ml.inf1.* instances) or earlier</td>
<td>Image Classification, Object Detection</td>
<td>*For saved models, one .pb or one .pbtxt file and a variables directory that contains variables *For frozen models,</td>
<td></td>
</tr>
</tbody>
</table>
Amazon SageMaker Developer Guide

Edge Devices

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>TensorFlow-Lite</td>
<td>1.15</td>
<td>Supports 1.15 or earlier</td>
<td>Image Classification, Object Detection</td>
<td>only one .pb or .pbtxt file</td>
<td></td>
</tr>
<tr>
<td>XGBoost</td>
<td>1.3</td>
<td>Supports 1.3 or earlier</td>
<td>Decision Trees</td>
<td>One XGBoost model file (.model) where the number of nodes in a tree is less than $2^{31}$</td>
<td></td>
</tr>
<tr>
<td>DARKNET</td>
<td></td>
<td></td>
<td>Image Classification, Object Detection (Yolo model is not supported)</td>
<td>One config (.cfg) file and one weights (.weights) file</td>
<td></td>
</tr>
</tbody>
</table>

Supported Devices, Chip Architectures, and Systems

Amazon SageMaker Neo supports the following devices, chip architectures, and operating systems.

**Devices**

You can select a device using the dropdown list in the Amazon SageMaker console or by specifying the TargetDevice in the output configuration of the CreateCompilationJob API.

You can choose from one of the following edge devices:

<table>
<thead>
<tr>
<th>Device List</th>
<th>System on a Chip (SoC)</th>
<th>Operating System</th>
<th>Architecture</th>
<th>Accelerator</th>
<th>Compiler Options Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>aisage</td>
<td>Linux</td>
<td>ARM64</td>
<td>Mali</td>
<td></td>
<td></td>
</tr>
<tr>
<td>amba_cv2</td>
<td>CV2</td>
<td>Arch Linux</td>
<td>ARM64</td>
<td>cvflow</td>
<td></td>
</tr>
<tr>
<td>amba_cv22</td>
<td>CV22</td>
<td>Arch Linux</td>
<td>ARM64</td>
<td>cvflow</td>
<td></td>
</tr>
<tr>
<td>amba_cv25</td>
<td>CV25</td>
<td>Arch Linux</td>
<td>ARM64</td>
<td>cvflow</td>
<td></td>
</tr>
<tr>
<td>coreml</td>
<td>iO, macOS</td>
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<tr>
<td>deplens</td>
<td>Intel Atom</td>
<td>Linux</td>
<td>X86_64</td>
<td>Intel Graphics</td>
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</tr>
<tr>
<td>imx8qm</td>
<td>NXP imx8</td>
<td>Linux</td>
<td>ARM64</td>
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<td></td>
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<td>imx8mplus</td>
<td>i.MX 8M Plus</td>
<td>Linux</td>
<td>ARM64</td>
<td>NPU</td>
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<tr>
<td>Device List</td>
<td>System on a Chip (SoC)</td>
<td>Operating System</td>
<td>Architecture</td>
<td>Accelerator</td>
<td>Compiler Options Example</td>
</tr>
<tr>
<td>-----------------</td>
<td>------------------------</td>
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<td>-------------</td>
<td>--------------------------</td>
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<tr>
<td>jacinto_tda4vm</td>
<td>TDA4VM</td>
<td>Linux</td>
<td>ARM</td>
<td>TDA4VM</td>
<td></td>
</tr>
<tr>
<td>jetson_nano</td>
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<td>jetson_tx1</td>
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<td>Linux</td>
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<td>NVIDIA</td>
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<td>NVIDIA</td>
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<td>jetson_xavier</td>
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<td>NVIDIA</td>
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<td>Mali</td>
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<td>qcs603</td>
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<td>Mali</td>
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<td>Linux</td>
<td>ARM_EABIHF</td>
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<td>{'mattr': ['+neon']}</td>
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<td>rasp4b</td>
<td>ARM A72</td>
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<td>Linux</td>
<td>ARM_EABIHF</td>
<td>Mali</td>
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For more information about JSON key-value compiler options for each target device, see the CompilerOptions field in the OutputConfig API data type.

**Systems and Chip Architectures**

The following look-up tables provide information regarding available operating systems and architectures for Neo model compilation jobs.

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**Tested Models**

The following collapsible sections provide information about machine learning models that were tested by the Amazon SageMaker Neo team. Expand the collapsible section based on your framework to check if a model was tested.
Note
This is not a comprehensive list of models that can be compiled with Neo.

See Supported Frameworks (p. 3106) and SageMaker Neo Supported Operators to find out if you can compile your model with SageMaker Neo.

DarkNet

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### TensorFlow-Lite

#### TensorFlow-Lite (FP32)

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Deploy Models

You can deploy the compute module to resource-constrained edge devices by: downloading the compiled model from Amazon S3 to your device and using DLR, or you can use AWS IoT Greengrass.

Before moving on, make sure your edge device must be supported by SageMaker Neo. See, Supported Frameworks, Devices, Systems, and Architectures to find out what edge devices are supported. Make sure that you specified your target edge device when you submitted the compilation job, see Use Neo to Compile a Model.

Deploy a Compiled Model (DLR)

DLR is a compact, common runtime for deep learning models and decision tree models. DLR uses the TVM runtime, Treelite runtime, NVIDIA TensorRT™, and can include other hardware-specific runtimes. DLR provides unified Python/C++ APIs for loading and running compiled models on various devices.

You can install latest release of DLR package using the following pip command:

```
pip install dlr
```

For installation of DLR on GPU targets or non-x86 edge devices, please refer to Releases for prebuilt binaries, or Installing DLR for building DLR from source. For example, to install DLR for Raspberry Pi 3, you can use:
**Deploy a Model (AWS IoT Greengrass)**

AWS IoT Greengrass extends cloud capabilities to local devices. It enables devices to collect and analyze data closer to the source of information, react autonomously to local events, and communicate securely with each other on local networks. With AWS IoT Greengrass, you can perform machine learning inference at the edge on locally generated data using cloud-trained models. Currently, you can deploy models on to all AWS IoT Greengrass devices based on ARM Cortex-A, Intel Atom, and Nvidia Jetson series processors. For more information on deploying a Lambda inference application to perform machine learning inferences with AWS IoT Greengrass, see [How to configure optimized machine learning inference using the AWS Management Console](#).

**Getting Started with Neo on Edge Devices**

This guide to getting started with Amazon SageMaker Neo shows you how to compile a model, set up your device, and make inferences on your device. Most of the code examples use Boto3. We provide commands using AWS CLI where applicable, as well as instructions on how to satisfy prerequisites for Neo.

**Note**
You can run the following code snippets on your local machine, within a SageMaker notebook, within SageMaker Studio, or (depending on your edge device) on your edge device. The setup is similar; however, there are two main exceptions if you run this guide within a SageMaker notebook instance or SageMaker Studio session:

- You do not need to install Boto3.
- You do not need to add the ‘AmazonSageMakerFullAccess’ IAM policy

This guide assumes you are running the following instructions on your edge device.

**Prerequisites**

1. **Install Boto3**

   If you are running these commands on your edge device, you must install the AWS SDK for Python (Boto3). Within a Python environment (preferably a virtual environment), run the following locally on your edge device's terminal or within a Jupyter notebook instance:

   **Terminal**

   ```bash
   pip install boto3
   ```

   **Jupyter Notebook**

   ```bash
   !pip install boto3
   ```

2. **Set Up AWS Credentials**

   You need to set up Amazon Web Services credentials on your device in order to run SDK for Python (Boto3). By default, the AWS credentials should be stored in the file `~/.aws/credentials` on your edge device. Within the credentials file, you should see two environment variables: `aws_access_key_id` and `aws_secret_access_key`.

   In your terminal, run:
$ more ~/.aws/credentials

[default]
aws_access_key_id = YOUR_ACCESS_KEY
aws_secret_access_key = YOUR_SECRET_KEY

The AWS General Reference Guide has instructions on how to get the necessary aws_access_key_id and aws_secret_access_key. For more information on how to set up credentials on your device, see the Boto3 documentation.

3. **Set up an IAM Role and attach policies.**

Neo needs access to your S3 bucket URI. Create an IAM role that can run SageMaker and has permission to access the S3 URI. You can create an IAM role either by using SDK for Python (Boto3), the console, or the AWS CLI. The following example illustrates how to create an IAM role using SDK for Python (Boto3):

```python
import boto3
AWS_REGION = 'aws-region'
# Create an IAM client to interact with IAM
iam_client = boto3.client('iam', region_name=AWS_REGION)
role_name = 'role-name'

For more information on how to create an IAM role with the console, AWS CLI, or through the AWS API, see Creating an IAM user in your AWS account.

Create a dictionary describing the IAM policy you are attaching. This policy is used to create a new IAM role.

```python
policy = {
    'Statement': [
        {
            'Action': 'sts:AssumeRole',
            'Effect': 'Allow',
            'Principal': {'Service': 'sagemaker.amazonaws.com'},
        },
    ],
    'Version': '2012-10-17'
}
``` Create a new IAM role using the policy you defined above:

```python
import json

new_role = iam_client.create_role(
    AssumeRolePolicyDocument=json.dumps(policy),
    Path='/',
    RoleName=role_name
)
```

You need to know what your Amazon Resource Name (ARN) is when you create a compilation job in a later step, so store it in a variable as well.

```python
role_arn = new_role['Role']['Arn']
```
Now that you have created a new role, attach the permissions it needs to interact with Amazon SageMaker and Amazon S3:

```python
iam_client.attach_role_policy(
    RoleName=role_name,
    PolicyArn='arn:aws:iam::aws:policy/AmazonSageMakerFullAccess'
)

iam_client.attach_role_policy(
    RoleName=role_name,
    PolicyArn='arn:aws:iam::aws:policy/AmazonS3FullAccess'
);
```

4. **Create an Amazon S3 bucket to store your model artifacts**

SageMaker Neo will access your model artifacts from Amazon S3

Boto3

```python
# Create an S3 client
s3_client = boto3.client('s3', region_name=AWS_REGION)

# Name buckets
bucket='name-of-your-bucket'

# Check if bucket exists
if boto3.resource('s3').Bucket(bucket) not in boto3.resource('s3').buckets.all():
    s3_client.create_bucket(
        Bucket=bucket,
        CreateBucketConfiguration={
            'LocationConstraint': AWS_REGION
        }
    )
else:
    print(f'Bucket {bucket} already exists. No action needed.')
```

CLI

```
aws s3 mb s3://'name-of-your-bucket' --region specify-your-region

# Check your bucket exists
aws s3 ls s3://'name-of-your-bucket'/
```

5. **Train a machine learning model**

See [Train a Model with Amazon SageMaker](https://docs.aws.amazon.com/sagemaker/latest/dg/model-creation.html) for more information on how to train a machine learning model using Amazon SageMaker. You can optionally upload your locally trained model directly into an Amazon S3 URI bucket.

**Note**

Make sure the model is correctly formatted depending on the framework you used. See [What input data shapes does SageMaker Neo expect?](https://docs.aws.amazon.com/sagemaker/latest/dg/model-creation.html)

If you do not have a model yet, use the `curl` command to get a local copy of the `coco_ssd_mobilenet` model from TensorFlow's website. The model you just copied is an object detection model trained from the [COCO dataset](https://cocodataset.org/). Type the following into your Jupyter notebook:

```
model_zip_filename = './coco_ssd_mobilenet_v1_1.0.zip'
!curl http://storage.googleapis.com/download.tensorflow.org/models/tflite/coco_ssd_mobilenet_v1_1.0_quant_2018_06_29.zip \
```
Note that this particular example was packaged in a .zip file. Unzip this file and repackage it as a compressed tarfile (.tar.gz) before using it in later steps. Type the following into your Jupyter notebook:

```python
# Extract model from zip file
!unzip -u {model_zip_filename}

model_filename = 'detect.tflite'
model_name = model_filename.split('.')[0]

# Compress model into .tar.gz so SageMaker Neo can use it
!tar -czf {model_tar} {model_filename}
```

6. **Upload trained model to an S3 bucket**

Once you have trained your machine learning mode, store it in an S3 bucket.

**Boto3**

```python
# Upload model
s3_client.upload_file(Filename=model_filename, Bucket=bucket, Key=model_filename)
```

**CLI**

Replace `your-model-filename` and `your-S3-bucket` with the name of your S3 bucket.

```bash
aws s3 cp your-model-filename s3://your-S3-bucket
```

**Step 1: Compile the Model**

Once you have satisfied the Prerequisites, you can compile your model with Amazon SageMaker Neo. You can compile your model using the AWS CLI, the console or the Amazon Web Services SDK for Python (Boto3), see Use Neo to Compile a Model. In this example, you will compile your model with Boto3.

To compile a model, SageMaker Neo requires the following information:

1. **The Amazon S3 bucket URI where you stored the trained model.**

   If you followed the prerequisites, the name of your bucket is stored in a variable named `bucket`. The following code snippet shows how to list all of your buckets using the AWS CLI:

   ```bash
   aws s3 ls
   ```

   For example:

   ```bash
   $ aws s3 ls
   2020-11-02 17:08:50 bucket
   ```

2. **The Amazon S3 bucket URI where you want to save the compiled model.**

   The code snippet below concatenates your Amazon S3 bucket URI with the name of an output directory called output:
s3_output_location = f's3://{bucket}/output'

3. **The machine learning framework you used to train your model.**

Define the framework you used to train your model.

```
framework = 'framework-name'
```

For example, if you wanted to compile a model that was trained using TensorFlow, you could either use `tflite` or `tensorflow`. Use `tflite` if you want to use a lighter version of TensorFlow that uses less storage memory.

```
framework = 'tflite'
```

For a complete list of Neo-supported frameworks, see [Supported Frameworks, Devices, Systems, and Architectures](#).

4. **The shape of your model's input.**

Neo requires the name and shape of your input tensor. The name and shape are passed in as key-value pairs. value is a list of the integer dimensions of an input tensor and key is the exact name of an input tensor in the model.

```
data_shape = '{"name": [tensor-shape]}'
```

For example:

```
data_shape = '{"normalized_input_image_tensor": [1, 300, 300, 3]}'
```

**Note**

Make sure the model is correctly formatted depending on the framework you used. See [What input data shapes does SageMaker Neo expect?](#) The key in this dictionary must be changed to the new input tensor's name.

5. **Either the name of the target device to compile for or the general details of the hardware platform**

```
target_device = 'target-device-name'
```

For example, if you want to deploy to a Raspberry Pi 3, use:

```
target_device = 'rasp3b'
```

You can find the entire list of supported edge devices in [Supported Frameworks, Devices, Systems, and Architectures](#).

Now that you have completed the previous steps, you can submit a compilation job to Neo.

```
# Create a SageMaker client so you can submit a compilation job
sagemaker_client = boto3.client('sagemaker', region_name=AWS_REGION)

# Give your compilation job a name
compilation_job_name = 'getting-started-demo'
print(f'Compilation job for {compilation_job_name} started')
```
response = sagemaker_client.create_compilation_job(
    CompilationJobName=compilation_job_name,
    RoleArn=role_arn,
    InputConfig={
        'S3Uri': s3_input_location,
        'DataInputConfig': data_shape,
        'Framework': framework.upper()
    },
    OutputConfig={
        'S3OutputLocation': s3_output_location,
        'TargetDevice': target_device
    },
    StoppingCondition={
        'MaxRuntimeInSeconds': 900
    }
)

# Optional - Poll every 30 sec to check completion status
import time
while True:
    response = sagemaker_client.describe_compilation_job(CompilationJobName=compilation_job_name)
    if response['CompilationJobStatus'] == 'COMPLETED':
        break
    elif response['CompilationJobStatus'] == 'FAILED':
        raise RuntimeError('Compilation failed')
        print('Compiling ...')
        time.sleep(30)
    print('Done!')

If you want additional information for debugging, include the following print statement:

print(response)

If the compilation job is successful, your compiled model is stored in the output Amazon S3 bucket you specified earlier (s3_output_location). Download your compiled model locally:

object_path = f'output/{model}-{target_device}.tar.gz'
neo_compiled_model = f'compiled-{model}.tar.gz'
s3_client.download_file(bucket, object_path, neo_compiled_model)

**Step 2: Set Up Your Device**

You will need to install packages on your edge device so that your device can make inferences. You will also need to either install AWS IoT Greengrass core or Deep Learning Runtime (DLR). In this example, you will install packages required to make inferences for the coco_ssd_mobilenet object detection algorithm and you will use DLR.

1. **Install additional packages**

   In addition to Boto3, you must install certain libraries on your edge device. What libraries you install depends on your use case.

   For example, for the coco_ssd_mobilenet object detection algorithm you downloaded earlier, you need to install **NumPy** for data manipulation and statistics, **PIL** to load images, and **Matplotlib** to generate plots. You also need a copy of TensorFlow if you want to gauge the impact of compiling with Neo versus a baseline.
2. **Install inference engine on your device**

To run your Neo-compiled model, install the Deep Learning Runtime (DLR) on your device. DLR is a compact, common runtime for deep learning models and decision tree models. On x86_64 CPU targets running Linux, you can install the latest release of the DLR package using the following `pip` command:

```
!pip install dlr
```

For installation of DLR on GPU targets or non-x86 edge devices, refer to Releases for prebuilt binaries, or Installing DLR for building DLR from source. For example, to install DLR for Raspberry Pi 3, you can use:

```
```

### Step 3: Make Inferences on Your Device

In this example, you will use Boto3 to download the output of your compilation job onto your edge device. You will then import DLR, download an example images from the dataset, resize this image to match the model's original input, and then you will make a prediction.

1. **Download your compiled model from Amazon S3 to your device and extract it from the compressed tarfile.**

   ```python
   # Download compiled model locally to edge device
   object_path = f'output/{model_name}-{target_device}.tar.gz'
   neo_compiled_model = f'compiled-{model_name}.tar.gz'
   s3_client.download_file(bucket_name, object_path, neo_compiled_model)

   # Extract model from .tar.gz so DLR can use it
   !mkdir ./dlr_model # make a directory to store your model (optional)
   !tar -xzvf ./compiled-detect.tar.gz --directory ./dlr_model
   ```

2. **Import DLR and an initialized DLRModel object.**

   ```python
   import dlr
   device = 'cpu'
   model = dlr.DLRModel('./dlr_model', device)
   ```

3. **Download an image for inferencing and format it based on how your model was trained.**

   For the coco_ssd_mobilenet example, you can download an image from the COCO dataset and then reform the image to 300x300:

   ```python
   from PIL import Image

   # Download an image for model to make a prediction
   input_image_filename = './input_image.jpg'
   !curl https://farm9.staticflickr.com/8325/8077197378_79efb4805e_z.jpg --output {input_image_filename}

   # Format image so model can make predictions
   resized_image = image.resize((300, 300))
   ```
# Troubleshoot Errors

This section contains information about how to understand and prevent common errors, the error messages they generate, and guidance on how to resolve these errors. Before moving on, ask yourself the following questions:

Did you encounter an error before you deployed your model? If yes, see Troubleshoot Neo Compilation Errors.

Did you encounter an error after you compiled your model? If yes, see Troubleshoot Neo Inference Errors.

Did you encounter an error trying to compile your model for Ambarella devices? If yes, see Troubleshoot Ambarella Errors (p. 3127).

## Error Classification Types

This list classifies the user errors you can receive from Neo. These include access and permission errors and load errors for each of the supported frameworks. All other errors are system errors.

### Client permission error

Neo passes the errors for these straight through from the dependent service.

- **Access Denied** when calling sts:AssumeRole
- **Any 400** error when calling Amazon S3 to download or upload a client model
- **PassRole** error

### Load error

Assuming that the Neo compiler successfully loaded .tar.gz from Amazon S3, check whether the tarball contains the necessary files for compilation. The checking criteria is framework-specific:

- **TensorFlow**: Expects only protobuf file (*.pb or *.pbtxt). For saved models, expects one variables folder.
- **Pytorch**: Expect only one pytorch file (*.pth).
- **MXNET**: Expect only one symbol file (*.json) and one parameter file (*.params).
- **XGBoost**: Expect only one XGBoost model file (*.model). The input model has size limitation.

### Compilation error

Assuming that the Neo compiler successfully loaded .tar.gz from Amazon S3, and that the tarball contains necessary files for compilation. The checking criteria is:

```python
# Model is quantized, so convert the image to uint8
x = np.array(resized_image).astype('uint8')

4. **Use DLR to make inferences.**

Finally, you can use DLR to make a prediction on the image you just downloaded:

```python
out = model.run(x)
```

For more examples using DLR to make inferences from a Neo-compiled model on an edge device, see the neo-ai-dlr Github repository.
• **OperatorNotImplemented**: An operator has not been implemented.
• **OperatorAttributeNotImplemented**: The attribute in the specified operator has not been implemented.
• **OperatorAttributeRequired**: An attribute is required for an internal symbol graph, but it is not listed in the user input model graph.
• **OperatorAttributeValueNotValid**: The value of the attribute in the specific operator is not valid.

**Topics**

- Troubleshoot Neo Compilation Errors (p. 3124)
- Troubleshoot Neo Inference Errors (p. 3126)
- Troubleshoot Ambarella Errors (p. 3127)

**Troubleshoot Neo Compilation Errors**

This section contains information about how to understand and prevent common compilation errors, the error messages they generate, and guidance on how to resolve these errors.

**Topics**

- How to Use This Page (p. 3124)
- Framework-Related Errors (p. 3124)
- Infrastructure-Related Errors (p. 3125)
- Check your compilation log (p. 3126)

**How to Use This Page**

Attempt to resolve your error by the going through these sections in the following order:

1. Check that the input of your compilation job satisfies the input requirements. See What input data shapes does SageMaker Neo expect? (p. 3065)
2. Check common framework-specific errors.
3. Check if your error is an infrastructure error.
4. Check your compilation log.

**Framework-Related Errors**

**TensorFlow**

<table>
<thead>
<tr>
<th>Error</th>
<th>Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>InputConfiguration: Exactly one .pb file is allowed for TensorFlow models.</td>
<td>Make sure you only provide one .pb or .pbtxt file.</td>
</tr>
<tr>
<td>InputConfiguration: Exactly one .pb or .pbtxt file is allowed for TensorFlow models.</td>
<td>Make sure you only provide one .pb or .pbtxt file.</td>
</tr>
<tr>
<td>ClientError: InputConfiguration: TVM cannot convert &lt;model zoo&gt; model. Please make sure the framework is supported. See SageMaker Neo Supported Frameworks and Operators.</td>
<td>Check the operator you chose is supported. See SageMaker Neo Supported Frameworks and Operators.</td>
</tr>
<tr>
<td><strong>Error</strong></td>
<td><strong>Solution</strong></td>
</tr>
<tr>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td>you selected is correct. The following operators are not implemented: {&lt;operator name&gt;}</td>
<td></td>
</tr>
</tbody>
</table>

**Keras**

<table>
<thead>
<tr>
<th><strong>Error</strong></th>
<th><strong>Solution</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>InputConfiguration: No h5 file provided in <code>&lt;model path&gt;</code></td>
<td>Check your h5 file is in the Amazon S3 URI you specified. Or Check that the h5 file is correctly formatted.</td>
</tr>
<tr>
<td>InputConfiguration: Multiple h5 files provided, <code>&lt;model path&gt;</code>, when only one is allowed</td>
<td>Check you are only providing one h5 file.</td>
</tr>
<tr>
<td>ClientError: InputConfiguration: Unable to load provided Keras model. Error: 'sample_weight_mode'</td>
<td>Check the Keras version you specified is supported. See supported frameworks for cloud instances and edge devices.</td>
</tr>
<tr>
<td>ClientError: InputConfiguration: Input input has wrong shape in Input Shape dictionary. Input shapes should be provided in NCHW format.</td>
<td>Check that your model input follows NCHW format. See What input data shapes does SageMaker Neo expect?</td>
</tr>
</tbody>
</table>

**MXNet**

<table>
<thead>
<tr>
<th><strong>Error</strong></th>
<th><strong>Solution</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>ClientError: InputConfiguration: Only one parameter file is allowed for MXNet model. Please make sure the framework you select is correct.</td>
<td>SageMaker Neo will select the first parameter file given for compilation.</td>
</tr>
</tbody>
</table>

**Infrastructure-Related Errors**

<table>
<thead>
<tr>
<th><strong>Error</strong></th>
<th><strong>Solution</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>ClientError: InputConfiguration: S3 object does not exist. Bucket: <code>&lt;bucket&gt;</code>, Key: <code>&lt;bucket key&gt;</code></td>
<td>Check the Amazon S3 URI your provided.</td>
</tr>
<tr>
<td>ClientError: InputConfiguration: Bucket <code>&lt;bucket name&gt;</code> is in region <code>&lt;region name&gt;</code> which is different from AWS Sagemaker service region <code>&lt;service region&gt;</code></td>
<td>Create an Amazon S3 bucket that is in the same region as the service.</td>
</tr>
<tr>
<td>ClientError: InputConfiguration: Unable to untar input model. Please confirm the model is a tar.gz file</td>
<td>Check that your model in Amazon S3 is compressed into a tar.gz file.</td>
</tr>
</tbody>
</table>
Check your compilation log

2. Select the region you created the compilation job from the Region dropdown list in the top right.
3. In the navigation pane of the Amazon CloudWatch, choose Logs. Select Log groups.
4. Search for the log group called /aws/sagemaker/CompilationJobs. Select the log group.
5. Search for the logstream named after the compilation job name. Select the log stream.

Troubleshoot Neo Inference Errors

This section contains information about how to prevent and resolve some of the common errors you might encounter upon deploying and/or invoking the endpoint. This section applies to PyTorch 1.4.0 or later and MXNet v1.7.0 or later.

- Make sure the first inference (warm-up inference) on a valid input data is done in model_fn(), if you defined a model_fn in your inference script, otherwise the following error message may be seen on the terminal when predict API is called:

  An error occurred (ModelError) when calling the InvokeEndpoint operation: Received server error (0) from <users-sagemaker-endpoint> with message "Your invocation timed out while waiting for a response from container model. Review the latency metrics for each container in Amazon CloudWatch, resolve the issue, and try again."

- Make sure that the environment variables in the following table are set. If they are not set, the following error message might show up:

  On the terminal:

  An error occurred (ModelError) when calling the InvokeEndpoint operation: Received server error (503) from <users-sagemaker-endpoint> with message "{ "code": 503, "type": "InternalServerErrorException", "message": "Prediction failed" } ".

  In CloudWatch:

  W-9001-model-stdout com.amazonaws.ml.mms.wlm.WorkerLifeCycle - AttributeError: 'NoneType' object has no attribute 'transform'

<table>
<thead>
<tr>
<th>Key</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAGEMAKER_PROGRAM</td>
<td>inference.py</td>
</tr>
<tr>
<td>SAGEMAKER_SUBMIT_DIRECTORY</td>
<td>/opt/ml/model/code</td>
</tr>
<tr>
<td>SAGEMAKER_CONTAINER_LOG_LEVEL</td>
<td>20</td>
</tr>
<tr>
<td>SAGEMAKER_REGION</td>
<td>&lt;your region&gt;</td>
</tr>
</tbody>
</table>

- Make sure that the MMS_DEFAULT_RESPONSE_TIMEOUT environment variable is set to 500 or a higher value while creating the Amazon SageMaker model; otherwise, the following error message may be seen on the terminal:

  An error occurred (ModelError) when calling the InvokeEndpoint operation: Received server error (0) from <users-sagemaker-endpoint> with message "Your invocation timed out while waiting for a response from container model. Review the latency metrics for each container in Amazon CloudWatch, resolve the issue, and try again."
Troubleshoot Ambarella Errors

SageMaker Neo requires models to be packaged in a compressed TAR file (*.tar.gz). Ambarella devices require additional files to be included within the compressed TAR file before it is sent for compilation. Include the following files within your compressed TAR file if you want to compile a model for Ambarella targets with SageMaker Neo:

- A trained model using a framework supported by SageMaker Neo
- A JSON configuration file
- Calibration images

For example, the contents of your compressed TAR file should look similar to the following example:

```plaintext
###amba_config.json
###calib_data
|    ### data1
|    ### data2
|    ### .
|    ### .
|    ### data500
###mobilenet_v1_1.0_0224_frozen.pb
```

The directory is configured as follows:

- `amba_config.json`: Configuration file
- `calib_data`: Folder containing calibration images
- `mobilenet_v1_1.0_0224_frozen.pb`: TensorFlow model saved as a frozen graph

For information about frameworks supported by SageMaker Neo, see Supported Frameworks (p. 3106).

Setting up the Configuration File

The configuration file provides information required by the Ambarella toolchain to compile the model. The configuration file must be saved as a JSON file and the name of the file must end with *config.json. The following chart shows the contents of the configuration file.

<table>
<thead>
<tr>
<th>Key</th>
<th>Description</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>inputs</td>
<td>Dictionary mapping input layers to attribute.</td>
<td><code>{inputs:{&quot;data&quot;: {...}, &quot;data1&quot;:{...}}}</code></td>
</tr>
<tr>
<td>&quot;data&quot;</td>
<td>Input layer name. Note: &quot;data&quot; is an example of the name you can use to label the input layer.</td>
<td>&quot;data&quot;</td>
</tr>
<tr>
<td>shape</td>
<td>Describes the shape of the input to the model. This follows the same conventions that SageMaker Neo uses.</td>
<td>&quot;shape&quot;: &quot;1,3,224,224&quot;</td>
</tr>
<tr>
<td>filepath</td>
<td>Relative path to the directory containing calibration images. These can be binary or image files like JPEG or PNG.</td>
<td>&quot;filepath&quot;: &quot;calib_data/&quot;</td>
</tr>
<tr>
<td>Key</td>
<td>Description</td>
<td>Example</td>
</tr>
<tr>
<td>------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>--------------------</td>
</tr>
<tr>
<td>colorformat</td>
<td>Color format that model expects. This will be used while converting images to binary. Supported values: [RGB, BGR]. Default is RGB.</td>
<td>&quot;colorformat&quot;:&quot;RGB&quot;</td>
</tr>
<tr>
<td>mean</td>
<td>Mean value to be subtracted from the input. Can be a single value or a list of values. When the mean is given as a list the number of entries must match the channel dimension of the input.</td>
<td>&quot;mean&quot;:128.0</td>
</tr>
<tr>
<td>scale</td>
<td>Scale value to be used for normalizing the input. Can be a single value or a list of values. When the scale is given as a list, the number of entries must match the channel dimension of the input.</td>
<td>&quot;scale&quot;: 255.0</td>
</tr>
</tbody>
</table>

The following is a sample configuration file:

```json
{
   "inputs": {
      "data": {
         "shape": "1, 3, 224, 224",
         "filepath": "calib_data/",
         "colorformat": "RGB",
         "mean": [128, 128, 128],
         "scale": [128.0, 128.0, 128.0]
      }
   }
}
```

**Calibration Images**

Quantize your trained model by providing calibration images. Quantizing your model improves the performance of the CVFlow engine on an Ambarella System on a Chip (SoC). The Ambarella toolchain uses the calibration images to determine how each layer in the model should be quantized to achieve optimal performance and accuracy. Each layer is quantized independently to INT8 or INT16 formats. The final model has a mix of INT8 and INT16 layers after quantization.

**How many images should you use?**

It is recommended that you include between 100–200 images that are representative of the types of scenes the model is expected to handle. The model compilation time increases linearly to the number of calibration images in the input file.

**What are the recommended image formats?**

Calibration images can be in a raw binary format or image formats such as JPG and PNG.

Your calibration folder can contain a mixture of images and binary files. If the calibration folder contains both images and binary files, the toolchain first converts the images to binary files. Once the conversion
is complete, it uses the newly generated binary files along with the binary files that were originally in the folder.

**Can I convert the images into binary format first?**

Yes. You can convert the images to the binary format with open-source packages such as OpenCV or PIL. Crop and resize the images so they satisfy the input layer of your trained model.

**Mean and Scale**

You can specify mean and scaling pre-processing options to the Amberalla toolchain. These operations are embedded into the network and are applied during inference on each input. Do not provide processed data if you specify the mean or scale. More specifically, do not provide data you have subtracted the mean from or have applied scaling to.

**Check your compilation log**

For information on checking compilation log for Ambarella devices, see [Check your compilation log](p. 3126).

## Use Amazon SageMaker Elastic Inference (EI)

By using Amazon Elastic Inference (EI), you can speed up the throughput and decrease the latency of getting real-time inferences from your deep learning models that are deployed as Amazon SageMaker hosted models, but at a fraction of the cost of using a GPU instance for your endpoint. EI allows you to add inference acceleration to a hosted endpoint for a fraction of the cost of using a full GPU instance. Add an EI accelerator in one of the available sizes to a deployable model in addition to a CPU instance type, and then add that model as a production variant to an endpoint configuration that you use to deploy a hosted endpoint. You can also add an EI accelerator to a SageMaker notebook instance so that you can test and evaluate inference performance when you are building your models.

Elastic Inference is supported in EI-enabled versions of TensorFlow, Apache MXNet, and PyTorch. To use any other deep learning framework, export your model by using ONNX, and then import your model into MXNet. You can then use your model with EI as an MXNet model. For information about importing an ONNX model into MXNet, see [Importing an ONNX model into MXNet](p. 3130).

**Topics**

- How EI Works (p. 3129)
- Choose an EI Accelerator Type (p. 3130)
- Use EI in a SageMaker Notebook Instance (p. 3130)
- Use EI on a Hosted Endpoint (p. 3131)
- Frameworks that Support EI (p. 3131)
- Use EI with SageMaker Built-in Algorithms (p. 3131)
- EI Sample Notebooks (p. 3131)
- Set Up to Use EI (p. 3132)
- Attach EI to a Notebook Instance (p. 3135)
- Use EI on Amazon SageMaker Hosted Endpoints (p. 3137)

**How EI Works**

Amazon Elastic Inference accelerators are network attached devices that work along with SageMaker instances in your endpoint to accelerate your inference calls. Elastic Inference accelerates inference by allowing you to attach fractional GPUs to any SageMaker instance. You can select the client instance
Choose an EI Accelerator Type

Choose an EI Accelerator Type

Consider the following factors when choosing an accelerator type for a hosted model:

- Models, input tensors and batch sizes influence the amount of accelerator memory you need. Start with an accelerator type that provides at least as much memory as the file size of your trained model. Factor in that a model might use significantly more memory than the file size at runtime.
- Demands on CPU compute resources, main system memory, and GPU-based acceleration and accelerator memory vary significantly between different kinds of deep learning models. The latency and throughput requirements of the application also determine the amount of compute and acceleration you need. Thoroughly test different configurations of instance types and EI accelerator sizes to make sure you choose the configuration that best fits the performance needs of your application.

For more information on selecting an EI accelerator, see:

- Amazon Elastic Inference Overview
- Choosing an Instance and Accelerator Type for Your Model
- Optimizing costs in Amazon Elastic Inference with TensorFlow

Use EI in a SageMaker Notebook Instance

Typically, you build and test machine learning models in a SageMaker notebook before you deploy them for production. You can attach EI to your notebook instance when you create the notebook instance. You can set up an endpoint that is hosted locally on the notebook instance by using the local mode supported by TensorFlow, MXNet, and PyTorch estimators and models in the Amazon SageMaker Python SDK to test inference performance. Elastic Inference enabled PyTorch is not currently supported on notebook instances. For instructions on how to attach EI to a notebook instance and set up a local

<table>
<thead>
<tr>
<th>Accelerator Type</th>
<th>F32 Throughput in TFLOPS</th>
<th>F16 Throughput in TFLOPS</th>
<th>Memory in GB</th>
</tr>
</thead>
<tbody>
<tr>
<td>ml.eia2.medium</td>
<td>1</td>
<td>8</td>
<td>2</td>
</tr>
<tr>
<td>ml.eia2.large</td>
<td>2</td>
<td>16</td>
<td>4</td>
</tr>
<tr>
<td>ml.eia2.xlarge</td>
<td>4</td>
<td>32</td>
<td>8</td>
</tr>
<tr>
<td>ml.eia1.medium</td>
<td>1</td>
<td>8</td>
<td>1</td>
</tr>
<tr>
<td>ml.eia1.large</td>
<td>2</td>
<td>16</td>
<td>2</td>
</tr>
<tr>
<td>ml.eia1.xlarge</td>
<td>4</td>
<td>32</td>
<td>4</td>
</tr>
</tbody>
</table>
Use EI on a Hosted Endpoint

When you are ready to deploy your model for production to provide inferences, you create a SageMaker hosted endpoint. You can attach EI to the instance where your endpoint is hosted to increase its performance at providing inferences. For instructions on how to attach EI to a hosted endpoint instance, see Use EI on Amazon SageMaker Hosted Endpoints.

Frameworks that Support EI

Amazon Elastic Inference is designed to be used with AWS enhanced versions of TensorFlow, Apache MXNet, or PyTorch machine learning frameworks. These enhanced versions of the frameworks are automatically built into containers when you use the Amazon SageMaker Python SDK, or you can download them as binary files and import them in your own Docker containers.

You can download the EI-enabled TensorFlow binary files from the public amazonei-tensorflow Amazon S3 bucket to the TensorFlow serving containers. For more information about building a container that uses the EI-enabled version of TensorFlow, see Amazon Elastic Inference with TensorFlow in SageMaker.

You can download the EI-enabled MXNet binary files from the public amazonei-apachemxnet Amazon S3 bucket to the MXNet serving containers. For more information about building a container that uses the EI-enabled version of MXNet, see Amazon Elastic Inference with MXNet in SageMaker.

You can download the EI-enabled PyTorch binary files from the public amazonei-pytorch Amazon S3 bucket to the PyTorch serving containers. For more information about building a container that uses the EI-enabled version of PyTorch, see Amazon Elastic Inference with PyTorch in SageMaker.

To use Elastic Inference in a hosted endpoint, you can choose any of the following frameworks depending on your needs.

- SageMaker Python SDK - Deploy TensorFlow models
- SageMaker Python SDK - Deploy MXNet models
- SageMaker Python SDK - Deploy PyTorch models

If you need to create a custom container for deploying your model that is complex and requires extensions to a framework that the SageMaker pre-built containers do not support, use the low-level AWS SDK for Python (Boto 3).

Use EI with SageMaker Built-in Algorithms

Currently, the Image Classification - MXNet (p. 2172) and Object Detection - MXNet (p. 2196) built-in algorithms support EI. For an example that uses the Image Classification algorithm with EI, see End-to-End Multiclass Image Classification Example.

EI Sample Notebooks

The following Sample notebooks provide examples of using EI in SageMaker:

- Using Amazon Elastic Inference with MXNet on Amazon SageMaker
- Using Amazon Elastic Inference with MXNet on an Amazon SageMaker Notebook Instance
- Using Amazon Elastic Inference with Neo-compiled TensorFlow model on SageMaker
• Using Amazon Elastic Inference with a pre-trained TensorFlow Serving model on SageMaker

Set Up to Use EI

Use the instructions in this topic only if one of the following applies to you:

• You want to use a customized role or permission policy.
• You want to use a VPC for your hosted model or notebook instance.

Note
If you already have an execution role that has the AmazonSageMakerFullAccess managed policy attached (this is true for any IAM role that you create when you create a notebook instance, training job, or model in the console) and you are not connecting to an EI model or notebook instance in a VPC, you do not need to make any of these changes to use EI in Amazon SageMaker.

Topics
• Set Up Required Permissions (p. 3132)
• Use a Custom VPC to Connect to EI (p. 3134)

Set Up Required Permissions

To use EI in SageMaker, the role that you use to open a notebook instance or create a deployable model must have a policy with the required permissions attached. You can attach the AmazonSageMakerFullAccess managed policy, which contains the required permissions, to the role, or you can add a custom policy that has the required permissions. For information about creating an IAM role, see Creating a Role for an AWS Service (Console) in the AWS Identity and Access Management User Guide. For information about attaching a policy to a role, see Adding and Removing IAM Policies.

Add these permissions specifically for connecting EI in an IAM policy.

```json
{
  "Effect": "Allow",
  "Action": [
    "elastic-inference:Connect",
    "ec2:DescribeVpcEndpoints"
  ],
  "Resource": "*"
}
```

The following IAM policy is the complete list of required permissions to use EI in SageMaker.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "elastic-inference:Connect",
        "ec2:DescribeVpcEndpoints"
      ],
      "Resource": "*"
    },
    {
      "Effect": "Allow",
      "Action": [
        "elastic-inference:CreateAccelerator",
        "elastic-inference:DeleteAccelerator",
        "elastic-inference:ListAccelerators",
        "elastic-inference:CreateInferenceInstance",
        "elastic-inference:DescribeInferenceInstance",
        "elastic-inference:DeleteInferenceInstance",
        "elastic-inference:ListInferenceInstances",
        "elastic-inference:StartInferenceInstance",
        "elastic-inference:StopInferenceInstance",
        "elastic-inference:ListAccelerators",
        "elastic-inference:ListInferenceInstances"
      ],
      "Resource": "*"
    }
  ]
}
```
"Action": [  
  "sagemaker:*"
],  
"Resource": "*"
},  

{  
  "Effect": "Allow",  
  "Action": [  
    "ecr:GetAuthorizationToken",  
    "ecr:GetDownloadUrlForLayer",  
    "ecr:BatchGetImage",  
    "ecr:BatchCheckLayerAvailability",  
    "cloudwatch:PutMetricData",  
    "cloudwatch:PutMetricAlarm",  
    "cloudwatch:DescribeAlarms",  
    "cloudwatch:DeleteAlarms",  
    "ec2:CreateNetworkInterface",  
    "ec2:CreateNetworkInterfacePermission",  
    "ec2:DeleteNetworkInterface",  
    "ec2:DeleteNetworkInterfacePermission",  
    "ec2:DescribeNetworkInterfaces",  
    "ec2:DescribeVpcs",  
    "ec2:DescribeDhcpOptions",  
    "ec2:DescribeSubnets",  
    "ec2:DescribeSecurityGroups",  
    "application-autoscaling:DeleteScalingPolicy",  
    "application-autoscaling:DeleteScheduledAction",  
    "application-autoscaling:DeregisterScalableTarget",  
    "application-autoscaling:DescribeScalingActivities",  
    "application-autoscaling:DescribeScalingPolicies",  
    "application-autoscaling:DescribeScheduledActions",  
    "application-autoscaling:PutScalingPolicy",  
    "application-autoscaling:PutScheduledAction",  
    "application-autoscaling:RegisterScalableTarget",  
    "logs:CreateLogGroup",  
    "logs:CreateLogStream",  
    "logs:DescribeLogStreams",  
    "logs:GetLogEvents",  
    "logs:PutLogEvents"
  ],  
  "Resource": "*"
},  

{  
  "Effect": "Allow",  
  "Action": [  
    "s3:GetObject",  
    "s3:PutObject",  
    "s3:DeleteObject"
  ],  
  "Resource": [  
    "arn:aws:s3:::*SageMaker*",  
    "arn:aws:s3:::*Sagemaker*",  
    "arn:aws:s3:::*sagemaker*"
  ]
},  

{  
  "Effect": "Allow",  
  "Action": [  
    "s3:CreateBucket",  
    "s3:GetBucketLocation",  
    "s3:ListBucket",  
    "s3:ListAllMyBuckets"
  ],  
  "Resource": "*"
}
Use a Custom VPC to Connect to EI

To use EI with SageMaker in a VPC, you need to create and configure two security groups, and set up a PrivateLink VPC interface endpoint. EI uses VPC interface endpoint to communicate with SageMaker endpoints in your VPC. The security groups you create are used to connect to the VPC interface endpoint.

Set up Security Groups to Connect to EI

To use EI within a VPC, you need to create two security groups:

- A security group to control access to the VPC interface endpoint that you will set up for EI.
- A security group that allows SageMaker to call into the first security group.

To configure the two security groups

1. Create a security group with no outbound connections. You will attach this to the VPC endpoint interface you create in the next section.
2. Create a second security group with no inbound connections, but with an outbound connection to the first security group.
3. Edit the first security group to allow inbound connections only to the second security group and all outbound connections.
For more information about VPC security groups, see Security Groups for Your VPC in the Amazon Virtual Private Cloud User Guide.

Set up a VPC Interface Endpoint to Connect to EI

To use EI with SageMaker in a custom VPC, you need to set up a VPC interface endpoint (PrivateLink) for the EI service.

- Set up a VPC interface endpoint (PrivateLink) for the EI. Follow the instructions at Creating an Interface Endpoint. In the list of services, choose com.amazonaws.<region>.elastic-inference.runtime. For Security group, make sure you select the first security group you created in the previous section to the endpoint.
- When you set up the interface endpoint, choose all of the Availability Zones where EI is available. EI fails if you do not set up at least two Availability Zones. For information about VPC subnets, see VPCs and Subnets.

Attach EI to a Notebook Instance

To test and evaluate inference performance using EI, you can attach EI to a notebook instance when you create or update a notebook instance. You can then use EI in local mode to host a model at an endpoint hosted on the notebook instance. You should test various sizes of notebook instances and EI accelerators to evaluate the configuration that works best for your use case.

Set Up to Use EI

To use EI locally in a notebook instance, create a notebook instance with an EI instance.

To create a notebook instance with an EI instance

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the navigation pane, choose Notebook instances.
3. Choose Create notebook instance.
4. For Notebook instance name, provide a unique name for your notebook instance.
5. For notebook instance type, choose a CPU instance such as ml.t2.medium.
6. For Elastic Inference (EI), choose an instance from the list, such as ml.eia2.medium.
7. For IAM role, choose an IAM role that has the required permissions to use SageMaker and EI.
8. (Optional) For VPC - Optional, if you want the notebook instance to use a VPC, choose one from the available list. Otherwise, leave it as No VPC. If you use a VPC follow the instructions at Use a Custom VPC to Connect to EI (p. 3134).
9. (Optional) For Lifecycle configuration - optional, either leave it as No configuration or choose a lifecycle configuration. For more information, see Customize a Notebook Instance Using a Lifecycle Configuration Script (p. 299).
10. (Optional) For Encryption key - optional, Optional) If you want SageMaker to use an AWS Key Management Service (AWS KMS) key to encrypt data in the ML storage volume attached to the notebook instance, specify the key.
11. (Optional) For Volume Size In GB - optional, leave the default value of 5.
12. (Optional) For Tags, add tags to the notebook instance. A tag is a label you assign to help manage your notebook instances. A tag consists of a key and a value, both of which you define.
13. Choose Create Notebook Instance.

After you create your notebook instance with EI attached, you can create a Jupyter notebook and set up an EI endpoint that is hosted locally on the notebook instance.
Use EI in Local Mode in SageMaker

To use EI locally in an endpoint hosted on a notebook instance, use local mode with the Amazon SageMaker Python SDK versions of either the TensorFlow, MXNet, or PyTorch estimators or models. For more information about local mode support in the SageMaker Python SDK, see https://github.com/aws/sagemaker-python-sdk#sagemaker-python-sdk-overview.

Use EI in Local Mode with SageMaker TensorFlow Estimators and Models

To use EI with TensorFlow in local mode, specify `local` for `instance_type` and `local_sagemaker_notebook` for `accelerator_type` when you call the `deploy` method of an estimator or a model object. For more information about Amazon SageMaker Python SDK TensorFlow estimators and models, see https://sagemaker.readthedocs.io/en/stable/frameworks/tensorflow/index.html.

The following code shows how to use local mode with an estimator object. To call the `deploy` method, you must have previously either:

- Trained the model by calling the `fit` method of an estimator.
- Pass a model artifact when you initialize the model object.

```python
# Deploys the model to a local endpoint
tf_predictor = tf_model.deploy(initial_instance_count=1,
                                instance_type='local',
                                accelerator_type='local_sagemaker_notebook')
```

Use EI in Local Mode with SageMaker Apache MXNet Estimators and Models

To use EI with MXNet in local mode, specify `local` for `instance_type` and `local_sagemaker_notebook` for `accelerator_type` when you call the `deploy` method of an estimator or a model object. For more information about Amazon SageMaker Python SDK MXNet estimators and models, see https://sagemaker.readthedocs.io/en/stable/frameworks/mxnet/index.html.

The following code shows how to use local mode with an estimator object. You must have previously called the `fit` method of the estimator to train the model.

```python
# Deploys the model to a local endpoint
mxnet_predictor = mxnet_estimator.deploy(initial_instance_count=1,
                                          instance_type='local',
                                          accelerator_type='local_sagemaker_notebook')
```

For a complete example of using EI in local mode with MXNet, see the sample notebook at https://sagemaker-examples.readthedocs.io/en/latest/sagemaker-python-sdk/mxnet_mnist/mxnet_mnist_elastic_inference_local.html.
Use EI in Local Mode with SageMaker PyTorch Estimators and Models

To use EI with PyTorch in local mode, when you call the deploy method of an estimator or a model object, specify local for instance_type and local_sagemaker_notebook for accelerator_type. For more information about Amazon SageMaker Python SDK PyTorch estimators and models, see SageMaker PyTorch Estimators and Models.

The following code shows how to use local mode with an estimator object. You must have previously called the fit method of the estimator to train the model.

```python
# Deploys the model to a local endpoint
pytorch_predictor = pytorch_estimator.deploy(initial_instance_count=1,
                                          instance_type='local',
                                          accelerator_type='local_sagemaker_notebook')
```

Use EI on Amazon SageMaker Hosted Endpoints

To use Elastic Inference (EI) in Amazon SageMaker with a hosted endpoint for real-time inference, specify an EI accelerator when you create the deployable model to be hosted at that endpoint. You can do this in one of the following ways:

- Use the Amazon SageMaker Python SDK versions of either the TensorFlow, MXNet, or PyTorch and the SageMaker pre-built containers for TensorFlow, MXNet, and PyTorch
- Build your own container, and use the low-level SageMaker API (Boto 3). You will need to import the EI-enabled version of either TensorFlow, MXNet, or PyTorch from the provided Amazon S3 locations into your container, and use one of those versions to write your training script.
- Use either the Image Classification - MXNet (p. 2172) or Object Detection - MXNet (p. 2196) built-in algorithms, and use the AWS SDK for Python (Boto3) to run your training job and create your deployable model and hosted endpoint.

Topics

- Use EI with a SageMaker TensorFlow Container (p. 3137)
- Use EI with a SageMaker MXNet Container (p. 3138)
- Use EI with a SageMaker PyTorch Container (p. 3138)
- Use EI with Your Own Container (p. 3139)

Use EI with a SageMaker TensorFlow Container


SageMaker provides default model training and inference code for your convenience. For custom file formats, you might need to implement custom model training and inference code.

Use an Estimator Object

To use an estimator object with EI, when you use the deploy method, include the accelerator_type input argument. The estimator returns a predictor object, which we call its deploy method, as shown in the example code.

```python
# Deploy an estimator using EI (using the accelerator_type input argument)
```
predictor = estimator.deploy(initial_instance_count=1,
    instance_type='ml.m4.xlarge',
    accelerator_type='ml.eia2.medium')

Use a Model Object

To use a model object with EI, when you use the deploy method, include the `accelerator_type` input argument. The estimator returns a predictor object, which we call its deploy method, as shown in the example code.

```python
# Deploy a model using EI (using the accelerator_type input argument)
predictor = model.deploy(initial_instance_count=1,
    instance_type='ml.m4.xlarge',
    accelerator_type='ml.eia2.medium')
```
For information about using PyTorch in the Amazon SageMaker Python SDK, see SageMaker PyTorch Estimators and Models.

For your convenience, SageMaker provides default model training and inference code. For custom file formats, you might need to write custom model training and inference code.

Use an Estimator Object

To use an estimator object with EI, when you use the deploy method, include the `accelerator_type` input argument. The estimator returns a predictor object, which we call its deploy method, as shown in this example code.

```
# Deploy an estimator using EI (using the accelerator_type input argument)
predictor = estimator.deploy(initial_instance_count=1,
                              instance_type='ml.m4.xlarge',
                              accelerator_type='ml.eia2.medium')
```

Use a Model Object

To use a model object with EI, when you use the deploy method, include the `accelerator_type` input argument. The model returns a predictor object, which we call its deploy method, as shown in this example code.

```
# Deploy a model using EI (using the accelerator_type input argument)
predictor = model.deploy(initial_instance_count=1,
                          instance_type='ml.m4.xlarge',
                          accelerator_type='ml.eia2.medium')
```

Use EI with Your Own Container

To use EI with a model in a custom container that you build, use the low-level AWS SDK for Python (Boto 3). download and import the AWS EI-enabled versions of TensorFlow, Apache MXNet, or PyTorch machine learning frameworks, and write your training script using those frameworks.

Import the EI Version of TensorFlow, MXNet, or PyTorch into Your Docker Container

To use EI with your own container, you need to import either the Amazon EI TensorFlow Serving library, the Amazon EI Apache MXNet library, or the Elastic Inference enabled PyTorch library into your container. The EI-enabled versions of TensorFlow and MXNet are currently available as binary files stored in Amazon S3 locations. You can download the EI-enabled binary for TensorFlow from the Amazon S3 bucket at console.aws.amazon.com/s3/buckets/amazonei-tensorflow. For information about building a container that uses the EI-enabled version of TensorFlow, see https://github.com/aws/sagemaker-tensorflow-container#building-the-sagemaker-elastic-inference-tensorflow-serving-container. You can download the EI-enabled binary for Apache MXNet from the public Amazon S3 bucket at console.aws.amazon.com/s3/buckets/amazonei-apachemxnet. For information about building a container that uses the EI-enabled version of MXNet, see https://github.com/aws/sagemaker-mxnet-container#building-the-sagemaker-elastic-inference-mxnet-container. You can download the Elastic Inference enabled binary for PyTorch from the public Amazon S3 bucket at console.aws.amazon.com/s3/buckets/amazonei-pytorch. For information about building a container that uses the Elastic Inference enabled version of PyTorch, see Building your image.

Create an EI Endpoint with AWS SDK for Python (Boto 3)

To create an endpoint by using AWS SDK for Python (Boto 3), you first create an endpoint configuration. The endpoint configuration specifies one or more models (called production variants) that you want to host at the endpoint. To attach EI to one or more of the production variants hosted at the endpoint, you
specify one of the EI instance types as the `AcceleratorType` field for that `ProductionVariant`. You then pass that endpoint configuration when you create the endpoint.

### Create an Endpoint Configuration

To use EI, you need to specify an accelerator type in the endpoint configuration.

```python
# Create Endpoint Configuration
from time import gmtime, strftime

endpoint_config_name = 'ImageClassificationEndpointConfig-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
print(endpoint_config_name)
create_endpoint_config_response = sagemaker.create_endpoint_config(
    EndpointConfigName = endpoint_config_name,
    ProductionVariants=[[
        'InstanceType':'ml.m4.xlarge',
        'InitialInstanceCount':1,
        'ModelName':model_name,
        'VariantName':'AllTraffic',
        'AcceleratorType':'ml.eia2.medium']])
print("Endpoint Config Arn: " + create_endpoint_config_response['EndpointConfigArn'])
```

### Create an Endpoint

After you create an endpoint configuration with an accelerator type, you can create an endpoint.

```python
endpoint_name = 'ImageClassificationEndpoint-' + strftime("%Y-%m-%d-%H-%M-%S", gmtime())
endpoint_response = sagemaker.create_endpoint(
    EndpointName=endpoint_name,
    EndpointConfigName=endpoint_config_name)
```

After creating the endpoint, you can invoke it using the `invoke_endpoint` method in a Boto3 runtime object, as you would any other endpoint.

## Best practices to minimize interruptions during GPU driver upgrades

SageMaker Model Deployment upgrades GPU drivers on the ML instances for Real-time, Batch, and Asynchronous Inference options over time to provide customers access to improvements from the driver providers. Below you can see the GPU version supported for each Inference option. Different driver versions can change how your model interacts with the GPUs. Below are some strategies to help you understand how your application works with different driver versions.

### Current versions and supported instance families

Amazon SageMaker Inference supports the following drivers and instance families:

<table>
<thead>
<tr>
<th>Service</th>
<th>GPU</th>
<th>Driver version</th>
<th>Instance types</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real-time</td>
<td>NVIDIA</td>
<td>470.57.02</td>
<td>ml.p2.<em>, ml.p3.</em>, ml.p4d.<em>, ml.g4dn.</em>, ml.g5.*</td>
</tr>
</tbody>
</table>
Troubleshoot your model container with GPU capabilities

If you encounter an issue when running your GPU workload, see the following guidance:

**GPU card detection failure or NVIDIA initialization error**

Run the `nvidia-smi` (NVIDIA System Management Interface) command from within the Docker container. If the NVIDIA System Management Interface detects a GPU detection error or NVIDIA initialization error, it will return the following error message:

```
Failed to initialize NVML: Driver/library version mismatch
```

Based on your use case, follow these best practices to resolve the failure or error:

- Follow the best practice recommendation described in the If you bring your own (BYO) model containers (p. 3142) dropdown.
- Follow the best practice recommendation described in the If you use a CUDA compatibility layer (p. 3142) dropdown.

Refer to the NVIDIA System Management Interface page on the NVIDIA website for more information.

**Best practices for working with mismatched driver versions**

The following provides information on how to update your GPU driver:

**The driver my container depends on is lower than the version on the ML GPU instance**

No action is required. NVIDIA provides backwards compatibility.

**The driver my container depends on is greater than the version on the ML GPU instances**

If it is a minor version difference, no action is required. NVIDIA provides minor version forward compatibility.

If it is a major version difference, the CUDA Compatibility Package will need to be installed. Please refer to CUDA Compatibility Package in the NVIDIA documentation.
Important

The CUDA Compatibility Package is not backwards compatible so it needs to be disabled if the driver version on the instance is greater than the CUDA Compatibility Package version.

If you bring your own (BYO) model containers

Ensure no NVIDIA driver packages are bundled in the image which could cause conflict with on host NVIDIA driver version.

If you use a CUDA compatibility layer

To verify if the platform Nvidia driver version supports the CUDA Compatibility Package version installed in the model container, see the CUDA documentation. If the platform Nvidia driver version does not support the CUDA Compatibility Package version, you can disable or remove the CUDA Compatibility Package from the model container image. If the CUDA compatibility libs version is supported by the latest Nvidia driver version, we suggest that you enable the CUDA Compatibility Package based on the detected Nvidia driver version for future compatibility by adding the code snippet below into the container start up shell script (at the ENTRYPOINT script).

The script demonstrates how to dynamically switch the use of the CUDA Compatibility Package based on the detected Nvidia driver version on the deployed host for your model container. When SageMaker releases a newer Nvidia driver version, the installed CUDA Compatibility Package can be turned off automatically if the CUDA application is supported natively on the new driver.

```
#!/bin/bash

verlte() {
    [ "$1" = "$2" ] || [ "$2" = `echo -e "$1
$2" | sort -V | head -n1` ]
}

if [ -f /usr/local/cuda/compat/libcuda.so.1 ]; then
cat /usr/local/cuda/version.txt
CUDA_COMPAT_MAX_DRIVER_VERSION=$(readlink /usr/local/cuda/compat/libcuda.so.1 |cut -d'.' -f 3-)
echo "CUDA compat package requires Nvidia driver #${CUDA_COMPAT_MAX_DRIVER_VERSION}"
NVIDIA_DRIVER_VERSION=$(sed -n 's/^NVRM.*Kernel Module \([0-9.]*\).*$/\1/p' /proc/driver/nvidia/version 2>/dev/null || true)
echo "Current installed Nvidia driver version is ${NVIDIA_DRIVER_VERSION}"
if [ $(verlte ${CUDA_COMPAT_MAX_DRIVER_VERSION} ${NVIDIA_DRIVER_VERSION}) ]; then
echo "Setup CUDA compatibility libs path to LD_LIBRARY_PATH"
    export LD_LIBRARY_PATH=/usr/local/cuda/compat:$LD_LIBRARY_PATH
    echo $LD_LIBRARY_PATH
else
echo "Skip CUDA compat libs setup as newer Nvidia driver is installed"
fi
else
echo "Skip CUDA compat libs setup as package not found"
fi
```

Model Hosting FAQs

Refer to the following FAQ items for answers to commonly asked questions about SageMaker Inference Hosting.

General Hosting

The following FAQ items answer common general questions for SageMaker Inference.
Q: What deployment options does Amazon SageMaker provide?

A: After you build and train models, Amazon SageMaker provides four options to deploy them so you can start making predictions. Real-Time Inference is suitable for workloads with millisecond latency requirements, payload sizes up to 6 MB, and processing times of up to 60 seconds. Batch Transform is ideal for offline predictions on large batches of data that are available up front. Asynchronous Inference is designed for workloads that do not have sub-second latency requirements, payload sizes up to 1 GB, and processing times of up to 15 minutes. With Serverless Inference, you can quickly deploy machine learning models for inference without having to configure or manage the underlying infrastructure, and you pay only for the compute capacity used to process inference requests, which is ideal for intermittent workloads.

Q: How do I choose a model deployment option in SageMaker?

A: The following diagram can help you choose a SageMaker Hosting model deployment option.

The preceding diagram walks you through the following decision process. If you want to process requests in batches, you might want to choose Batch Transform. Otherwise, if you want to receive inference for each request to your model, you might want to choose Asynchronous Inference, Serverless Inference, or Real-Time Inference. You can choose Asynchronous Inference if you have long processing times or large payloads and want to queue requests. You can choose Serverless Inference if your workload has unpredictable or intermittent traffic. You can choose Real-Time Inference if you have sustained traffic and need lower and consistent latency for your requests.

Q: I've heard SageMaker Inference is expensive. What's the best way to optimize my cost when hosting models?

A: To optimize your costs with SageMaker Inference, you should choose the right hosting option for your use case. You can also use Inference features such as Amazon SageMaker Savings Plans, model optimization with SageMaker Neo, Multi-Model Endpoints and Multi-Container Endpoints, or autoscaling. For tips on how to optimize your Inference costs, see Inference cost optimization best practices (p. 2980).

Q: Why should I use Amazon SageMaker Inference Recommender?

A: You should use Amazon SageMaker Inference Recommender if you need recommendations for the right endpoint configuration to improve performance and reduce costs. Previously, data scientists who wanted to deploy their models had to run manual benchmarks to select the right endpoint configuration. First, they had to select the right machine learning instance type out of more than 70
available instance types based on the resource requirements of their models and sample payloads, and then optimize the model to account for differing hardware. Then, they had to conduct extensive load tests to validate that latency and throughput requirements were met and that the costs were low. Inference Recommender eliminates this complexity by helping you do the following:

- Get started in minutes with an instance recommendation.
- Conduct load tests across instance types to get recommendations on your endpoint configuration within hours.
- Automatically tune container and model server parameters as well as perform model optimizations for a given instance type.

**Q:** What is a model server?

**A:** SageMaker endpoints are HTTP REST endpoints that use a containerized web server, which includes a model server. These containers are responsible for loading up and serving requests for a machine learning model. They implement a web server that responds to /invocations and /ping on port 8080.

Common model servers include TensorFlow Serving, TorchServe and Multi Model Server. SageMaker framework containers have these model servers built in.

**Q:** What is Bring Your Own Container with Amazon SageMaker?

**A:** Everything in SageMaker Inference is containerized. SageMaker provides managed containers for popular frameworks such as TensorFlow, SKlearn, and HuggingFace. For a comprehensive updated list of those images, see Available Images.

Sometimes there are custom frameworks for which you might need to build a container. This approach is known as Bring Your Own Container or BYOC. With the BYOC approach, you provide the Docker image to set up your framework or library. Then, you push the image to Amazon Elastic Container Registry (Amazon ECR) so that you can use the image with SageMaker. For an example of a BYOC approach, see Overview of Containers for Amazon SageMaker.

Alternatively, instead of building an image from scratch, you can extend a container. You can take one of the base images that SageMaker provides and add your dependencies on top of it in your Dockerfile.

**Q:** Do I need to train my models on SageMaker to host them on SageMaker endpoints?

**A:** SageMaker offers the capacity to bring your own trained framework model that you've trained outside of SageMaker and deploy it on any of the SageMaker hosting options.

SageMaker requires you to package the model in a model.tar.gz file and have a specific directory structure. Each framework has its own model structure (see the following question for example structures). For more information, see the SageMaker Python SDK documentation for TensorFlow, PyTorch, and MXNet.

While you can choose from prebuilt framework images such as TensorFlow, PyTorch, and MXNet to host your trained model, you can also build your own container to host your trained models on SageMaker endpoints. For a walkthrough, see the example Jupyter notebook Building your own algorithm container.

**Q:** How should I structure my model if I want to deploy on SageMaker but not train on SageMaker?

**A:** SageMaker requires your model artifacts to be compressed in a .tar.gz file, or a tarball. SageMaker automatically extracts this .tar.gz file into the /opt/ml/model/ directory in your container. The tarball shouldn't contain any symlinks or unnecessary files. If you are making use of one of the framework
containers, such as TensorFlow, PyTorch, or MXNet, the container expects your TAR structure to be as follows:

**TensorFlow**

```
model.tar.gz/
  |--[model_version_number]/
  |   |--variables
  |   |--saved_model.pb
  code/
    |--inference.py
    |--requirements.txt
```

**PyTorch**

```
model.tar.gz/
  |- model.pth
  |- code/
    |- inference.py
    |- requirements.txt  # only for versions 1.3.1 and higher
```

**MXNet**

```
model.tar.gz/
  |- model-symbol.json
  |- model-shapes.json
  |- model-0000.params
  |- code/
    |- inference.py
    |- requirements.txt # only for versions 1.6.0 and higher
```

**Q: When invoking a SageMaker endpoint, I can provide a ContentType and Accept MIME Type. Which one is used to identify the data type being sent and received?**

A: ContentType is the MIME type of the input data in the request body (the MIME type of the data you are sending to your endpoint). The model server uses the ContentType to determine if it can handle the type provided or not.

Accept is the MIME type of the inference response (the MIME type of the data your endpoint returns). The model server uses the Accept type to determine if it can handle returning the type provided or not.

Common MIME types include text/csv, application/json, and application/jsonlines.

**Q: What are the supported data formats for SageMaker Inference?**

A: SageMaker passes any request onto the model container without modification. The container must contain the logic to deserialize the request. For information about the formats defined for built-in algorithms, see [Common Data Formats for Inference](#). If you are building your own container or using a SageMaker Framework container, you can include the logic to accept a request format of your choice.

Similarly, SageMaker also returns the response without modification, and then the client must deserialize the response. In case of the built-in algorithms, they return responses in specific formats. If you are building your own container or using a SageMaker Framework container, you can include the logic to return a response in the format you choose.

**Q: How do I invoke my endpoint with binary data such as videos or images?**

Use the [Invoke Endpoint](#) API call to make inference against your endpoint.
When passing your input as a payload to the InvokeEndpoint API, you must provide the correct type of input data that your model expects. When passing a payload in the InvokeEndpoint API call, the request bytes are forwarded directly to the model container. For example, for an image, you may use application/jpeg for the ContentType, and make sure that your model can perform inference on this type of data. This applies for JSON, CSV, video, or any other type of input with which you may be dealing.

Another factor to consider is payload size limits. In terms of real-time and serverless endpoints, the payload limit is 6 MB. You can split your video into multiple frames and invoke the endpoint with each frame individually. Alternatively, if your use case permits, you can send the whole video in the payload using an asynchronous endpoint, which supports up to 1 GB payloads.

For an example that showcases how to run computer vision inference on large videos with Asynchronous Inference, see this blog post.

**Real-Time Inference**

The following FAQ items answer common questions for SageMaker Real-Time Inference.

**Q: How do I create a SageMaker endpoint?**

**A:** You can create a SageMaker endpoint through AWS-supported tooling such as the AWS SDKs, the SageMaker Python SDK, the AWS Management Console, AWS CloudFormation, and the AWS Cloud Development Kit (AWS CDK).

There are three key entities in endpoint creation: a SageMaker model, a SageMaker endpoint configuration, and a SageMaker endpoint. The SageMaker model points towards the model data and image you are using. The endpoint configuration defines your production variants, which might include the instance type and instance count. You can then use either the create_endpoint API call or the .deploy() call for SageMaker to create an endpoint using the metadata from your model and endpoint configuration.

**Q: Do I need to use the SageMaker Python SDK to create/invoke endpoints?**

**A:** No, you can use the various AWS SDKs (see Invoke/Create for available SDKs) or even call the corresponding web APIs directly.

**Q: What is the difference between Multi-Model Endpoints (MME) and Multi Model Server (MMS)?**

**A:** A Multi-Model Endpoint is a Real-Time Inference option that SageMaker provides. With Multi-Model Endpoints, you can host thousands of models behind one endpoint. Multi Model Server is an open-source framework for serving machine learning models. It provides the HTTP front-end and model management capabilities required by multi-model endpoints to host multiple models within a single container, load models into and unload models out of the container dynamically, and perform inference on a specified loaded model.

**Q: What are the different model deployment architectures supported by Real-Time Inference?**

**A:** SageMaker Real-Time Inference supports various model deployment architecture such as Multi-Model Endpoints, Multi-Container Endpoints, and Serial Inference Pipelines.

**Multi-Model Endpoints (MME)** – MME allows customers to deploy 1000s of hyper-personalized models in a cost effective way. All the models are deployed on a shared-resource fleet. MME works best when the models are of similar size and latency and belong to the same ML framework. These endpoints are ideal for when you have don’t need to call the same model at all times. You can dynamically load respective models onto the SageMaker endpoint to serve your request.
Multi-Container Endpoints (MCE) – MCE allows customers to deploy 15 different containers with diverse ML frameworks and functionalities with no cold starts while only using one SageMaker endpoint. You can directly invoke these containers. MCE is best for when you want to keep all the models in memory.

Serial Inference Pipelines (SIP) – You can use SIP to chain together 2-15 containers on a single endpoint. SIP is mostly suitable for combining preprocessing and model inference in one endpoint and for low latency operations.

Serverless Inference

The following FAQ items answer common questions for Amazon SageMaker Serverless Inference.

Q: What is Amazon SageMaker Serverless Inference?
A: Serverless Inference (p. 2923) is a purpose-built serverless model serving option that makes it easy to deploy and scale ML models. Serverless Inference endpoints automatically start compute resources and scale them in and out depending on traffic, eliminating the need for you to choose instance type, run provisioned capacity, or manage scaling. You can optionally specify the memory requirements for your serverless endpoint. You pay only for the duration of running the inference code and the amount of data processed, not for idle periods.

Q: Why should I use Serverless Inference?
A: Serverless Inference simplifies the developer experience by eliminating the need to provision capacity up front and manage scaling policies. Serverless Inference can scale instantly from tens to thousands of inferences within seconds based on the usage patterns, making it ideal for ML applications with intermittent or unpredictable traffic. For example, a chatbot service used by a payroll processing company experiences an increase in inquiries at the end of the month while traffic is intermittent for rest of the month. Provisioning instances for the entire month in such scenarios is not cost-effective, as you end up paying for idle periods.

Serverless Inference helps address these types of use cases by providing you automatic and fast scaling out of the box without the need for you to forecast traffic up front or manage scaling policies. Additionally, you pay only for the compute time to run your inference code and for data processing, making it ideal for workloads with intermittent traffic.

Q: How do I choose the right memory size for my serverless endpoint?
A: Your serverless endpoint has a minimum RAM size of 1024 MB (1 GB), and the maximum RAM size you can choose is 6144 MB (6 GB). The memory sizes you can choose are 1024 MB, 2048 MB, 3072 MB, 4096 MB, 5120 MB, or 6144 MB. Serverless Inference auto-assigns compute resources proportional to the memory you select. If you choose a larger memory size, your container has access to more vCPUs.

Choose your endpoint's memory size according to your model size. Generally, the memory size should be at least as large as your model size. You may need to benchmark in order to choose the right memory selection for your model based on your latency SLAs. The memory size increments have different pricing; see the Amazon SageMaker pricing page for more information.

Batch Transform

The following FAQ items answer common questions for SageMaker Batch Transform.

Q: How does Batch Transform split my data?
A: For specific file formats such as CSV, RecordIO and TFRecord, SageMaker can split your data into single-record or multi-record mini batches and send this as a payload to your model container. When the value of BatchStrategy is MultiRecord, SageMaker sends the maximum number of records in
each request, up to the \texttt{MaxPayloadInMB} limit. When the value of \texttt{BatchStrategy} is \texttt{SingleRecord}, SageMaker sends individual records in each request.

\textbf{Q: What is the maximum timeout for Batch Transform and payload limit for a single record?}

\textbf{A:} The maximum timeout for Batch Transform is 3600 seconds. The \textit{maximum payload size} for a record (per mini batch) is 100 MB.

\textbf{Q: How do I speed up a Batch Transform job?}

\textbf{A:} If you are using the \texttt{CreateTransformJob} API, you can reduce the time it takes to complete batch transform jobs by using optimal values for parameters such as \texttt{MaxPayloadInMB}, \texttt{MaxConcurrentTransforms}, or \texttt{BatchStrategy}. The ideal value for \texttt{MaxConcurrentTransforms} is equal to the number of compute workers in the batch transform job. If you are using the SageMaker console, you can specify these optimal parameter values in the \textit{Additional configuration} section of the \texttt{Batch transform job configuration} page. SageMaker automatically finds the optimal parameter settings for built-in algorithms. For custom algorithms, provide these values through an \textit{execution-parameters} endpoint.

\textbf{Q: What are the data formats natively supported in Batch Transform?}

\textbf{A:} Batch Transform supports CVS and JSON.

\section*{Asynchronous Inference}

The following FAQ items answer common general questions for SageMaker Asynchronous Inference.

\textbf{Q: What is Amazon SageMaker Asynchronous Inference?}

\textbf{A:} Asynchronous Inference queues incoming requests and processes them asynchronously. This option is ideal for requests with large payload sizes or long processing times that need to be processed as they arrive. Optionally, you can configure auto-scaling settings to scale down the instance count to zero when not actively processing requests.

\textbf{Q: How do I scale my endpoints to 0 when there’s no traffic?}

\textbf{A:} Amazon SageMaker supports automatic scaling (autoscaling) your asynchronous endpoint. Autoscaling dynamically adjusts the number of instances provisioned for a model in response to changes in your workload. Unlike other hosted models SageMaker supports, with Asynchronous Inference you can also scale down your asynchronous endpoints instances to zero. Requests that are received when there are zero instances are queued for processing once the endpoint scales up. For more information, see \textit{Autoscale an asynchronous endpoint}.

Amazon SageMaker Serverless Inference also automatically scales down to zero. You won’t see this because SageMaker manages scaling your serverless endpoints, but if you are not experiencing any traffic, the same infrastructure applies.
Using Docker containers with SageMaker

Amazon SageMaker makes extensive use of Docker containers for build and runtime tasks. SageMaker provides prebuilt Docker images for its built-in algorithms and the supported deep learning frameworks used for training and inference. Using containers, you can train machine learning algorithms and deploy models quickly and reliably at any scale. The topics in this section show how to deploy these containers for your own use cases. For information on how to bring your own containers for use with Amazon SageMaker Studio, see Bring your own SageMaker image (p. 152).

Topics

- Scenarios for Running Scripts, Training Algorithms, or Deploying Models with SageMaker (p. 3149)
- Docker Container Basics (p. 3150)
- Use Prebuilt SageMaker Docker images (p. 3150)
- Adapting Your Own Docker Container to Work with SageMaker (p. 3164)
- Create a container with your own algorithms and models (p. 3180)
- Example Notebooks: Use Your Own Algorithm or Model (p. 3200)
- Troubleshooting your Docker containers (p. 3202)

Scenarios for Running Scripts, Training Algorithms, or Deploying Models with SageMaker

Amazon SageMaker always uses Docker containers when running scripts, training algorithms, and deploying models. However, your level of engagement with containers depends on your use case.

- **Use a built-in SageMaker algorithm or framework.** For most use cases, you can use the built-in algorithms and frameworks without worrying about containers. You can train and deploy these algorithms from the SageMaker console, the AWS Command Line Interface (AWS CLI), a Python notebook, or the Amazon SageMaker Python SDK by specifying the algorithm or framework version when creating your Estimator. The built-in algorithms available are itemized and described in the Use Amazon SageMaker Built-in Algorithms or Pre-trained Models (p. 1096) topic. For more information on the available frameworks, see ML Frameworks and Toolkits (p. 13). For an example of how to train and deploy a built-in algorithm using a Jupyter notebook running in a SageMaker notebook instance, see the Get Started with Amazon SageMaker (p. 33) topic.

- **Use prebuilt SageMaker container images.** Alternatively, you can use the built-in algorithms and frameworks using Docker containers. SageMaker provides containers for its built-in algorithms and prebuilt Docker images for some of the most common machine learning frameworks, such as Apache MXNet, TensorFlow, PyTorch, and Chainer. For a full list of the available SageMaker Images, see Available Deep Learning Containers Images. It also supports machine learning libraries such as scikit-learn and SparkML. If you use the Amazon SageMaker Python SDK, you can deploy the containers by passing the full container URI to their respective SageMaker SDK Estimator class. For the full list of deep learning frameworks currently supported by SageMaker, see Prebuilt SageMaker Docker Images for Deep Learning (p. 3151). For information on the scikit-learn and SparkML prebuilt container images, see Prebuilt Amazon SageMaker Docker Images for Scikit-learn and Spark ML (p. 3151).
For more information about using frameworks with the Amazon SageMaker Python SDK, see their respective topics in Use Machine Learning Frameworks, Python, and R with Amazon SageMaker (p. 13).

- **Extend a prebuilt SageMaker container image.** If you would like to extend a prebuilt SageMaker algorithm or model Docker image, you can modify the SageMaker image to satisfy your needs. For an example, see Extending our PyTorch containers.
- **Adapt an existing container image:** If you would like to adapt a pre-existing container image to work with SageMaker, you need to modify the Docker container to enable either the SageMaker Training or Inference toolkit. For an example that shows how to build your own containers to train and host an algorithm, see Bring Your Own R Algorithm.

# Docker Container Basics

Docker is a program that performs operating system-level virtualization for installing, distributing, and managing software. It packages applications and their dependencies into virtual containers that provide isolation, portability, and security. With Docker, you can ship code faster, standardize application operations, seamlessly move code, and economize by improving resource utilization. For more general information about Docker, see Docker overview.

The following information outlines the most significant aspects of using Docker containers with Amazon SageMaker.

## SageMaker Functions

SageMaker uses Docker containers in the backend to manage training and inference processes. SageMaker abstracts away from this process, so it happens automatically when an estimator is used. While you don't need to use Docker containers explicitly with SageMaker for most use cases, you can use Docker containers to extend and customize SageMaker functionality.

## Containers with SageMaker Studio

SageMaker Studio runs from a Docker container and uses it to manage functionality. As a result, you must create your Docker container following the steps in Bring your own SageMaker image (p. 152).

# Use Prebuilt SageMaker Docker images

Amazon SageMaker provides containers for its built-in algorithms and prebuilt Docker images for some of the most common machine learning frameworks, such as Apache MXNet, TensorFlow, PyTorch, and Chainer. It also supports machine learning libraries such as scikit-learn and SparkML.

You can use these images from your SageMaker notebook instance or SageMaker Studio. You can also extend the prebuilt SageMaker images to include libraries and needed functionality. The following topics give information about the available images and how to use them.

**Note**
For information on Docker images for developing reinforcement learning (RL) solutions in SageMaker, see SageMaker RL Containers.

## Topics

- Prebuilt SageMaker Docker Images for Deep Learning (p. 3151)
- Prebuilt Amazon SageMaker Docker Images for Scikit-learn and Spark ML (p. 3151)
- Train a Deep Graph Network (p. 3153)
- Extend a Prebuilt Container (p. 3156)
Prebuilt SageMaker Docker Images for Deep Learning

SageMaker provides prebuilt Docker images that include deep learning framework libraries and other dependencies needed for training and inference. For a complete list of the available pre-built Docker images, see Deep Learning Containers Images.

If you are not using the Amazon SageMaker Python SDK and one of its estimators to retrieve the pre-built images, you have to retrieve them yourself.

Using the SageMaker Python SDK

With the SageMaker Python SDK, you can train and deploy models using these popular deep learning frameworks. For instructions on installing and using the SDK, see Amazon SageMaker Python SDK. The following table lists the available frameworks and instructions on how to use them with the SageMaker Python SDK:

<table>
<thead>
<tr>
<th>Framework</th>
<th>Instructions</th>
</tr>
</thead>
<tbody>
<tr>
<td>TensorFlow</td>
<td>Using TensorFlow with the SageMaker Python SDK</td>
</tr>
<tr>
<td>MXNet</td>
<td>Using MXNet with the SageMaker Python SDK</td>
</tr>
<tr>
<td>PyTorch</td>
<td>Using PyTorch with the SageMaker Python SDK</td>
</tr>
<tr>
<td>Chainer</td>
<td>Using Chainer with the SageMaker Python SDK</td>
</tr>
<tr>
<td>Hugging Face</td>
<td>Using Hugging Face with the SageMaker Python SDK</td>
</tr>
</tbody>
</table>

Extending Prebuilt SageMaker Docker Images

You can customize these prebuilt containers or extend them to handle any additional functional requirements for your algorithm or model that the prebuilt SageMaker Docker image doesn't support. For an example, see Extending Our PyTorch Containers.

You can also use prebuilt containers to deploy your custom models or models that have been trained in a framework other than SageMaker. For an overview of the process of bringing the trained model artifacts into SageMaker and hosting them at an endpoint, see Bring Your Own Pretrained MXNet or TensorFlow Models into Amazon SageMaker.

Prebuilt Amazon SageMaker Docker Images for Scikit-learn and Spark ML

SageMaker provides prebuilt Docker images that install the scikit-learn and Spark ML libraries. These libraries also include the dependencies needed to build Docker images that are compatible with SageMaker using the Amazon SageMaker Python SDK. With the SDK, you can use scikit-learn for machine learning tasks and use Spark ML to create and tune machine learning pipelines. For instructions on installing and using the SDK, see SageMaker Python SDK.

Using the SageMaker Python SDK

The following table contains links to the GitHub repositories with the source code for the scikit-learn and Spark ML containers. The table also contains links to instructions that show how use these containers with Python SDK estimators to run your own training algorithms and hosting your own models.
Amazon SageMaker Developer Guide
Prebuilt Scikit-learn and Spark ML Images

<table>
<thead>
<tr>
<th>Library</th>
<th>Prebuilt Docker Image Source Code</th>
<th>Instructions</th>
</tr>
</thead>
<tbody>
<tr>
<td>scikit-learn</td>
<td>SageMaker Scikit-learn Containers</td>
<td>Using Scikit-learn with the Amazon SageMaker Python SDK</td>
</tr>
<tr>
<td>Spark ML</td>
<td>SageMaker Spark ML Serving Containers</td>
<td>SparkML Python SDK Documentation</td>
</tr>
</tbody>
</table>

### Specifying the Prebuilt Images Manually

If you are not using the SageMaker Python SDK and one of its estimators to manage the container, you have to retrieve the relevant prebuilt container manually. The SageMaker prebuilt Docker images are stored in Amazon Elastic Container Registry (Amazon ECR). You can push or pull them using their fullname registry addresses. SageMaker uses the following Docker Image URL patterns for scikit-learn and Spark ML:

- `<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/sagemaker-scikit-learn:<SCIKIT-LEARN_VERSION>-cpu-py<PYTHON_VERSION>

  For example, `746614075791.dkr.ecr.us-west-1.amazonaws.com/sagemaker-scikit-learn:0.23-1-cpu-py3`

- `<ACCOUNT_ID>.dkr.ecr.<REGION_NAME>.amazonaws.com/sagemaker-sparkml-serving:<SPARK-ML_VERSION>

  For example, `341280168497.dkr.ecr.ca-central-1.amazonaws.com/sagemaker-sparkml-serving:2.4`

The following table lists the supported values for account IDs and corresponding AWS Region names.

<table>
<thead>
<tr>
<th>ACCOUNT_ID</th>
<th>REGION_NAME</th>
</tr>
</thead>
<tbody>
<tr>
<td>746614075791</td>
<td>us-west-1</td>
</tr>
<tr>
<td>246618743249</td>
<td>us-west-2</td>
</tr>
<tr>
<td>683313688378</td>
<td>us-east-1</td>
</tr>
<tr>
<td>257758044811</td>
<td>us-east-2</td>
</tr>
<tr>
<td>354813040037</td>
<td>ap-northeast-1</td>
</tr>
<tr>
<td>366743142698</td>
<td>ap-northeast-2</td>
</tr>
<tr>
<td>121021644041</td>
<td>ap-southeast-1</td>
</tr>
<tr>
<td>783357654285</td>
<td>ap-southeast-2</td>
</tr>
<tr>
<td>720646828776</td>
<td>ap-south-1</td>
</tr>
<tr>
<td>141502667606</td>
<td>eu-west-1</td>
</tr>
<tr>
<td>764974769150</td>
<td>eu-west-2</td>
</tr>
<tr>
<td>492215442770</td>
<td>eu-central-1</td>
</tr>
<tr>
<td>341280168497</td>
<td>ca-central-1</td>
</tr>
</tbody>
</table>
Finding Available Images

Use the following commands to find out which versions of the images are available. For example, use the following to find the available sagemaker-sparkml-serving image in the ca-central-1 Region:

```
aws \
  ecr describe-images \
  --region ca-central-1 \
  --registry-id 341280168497 \
  --repository-name sagemaker-sparkml-serving
```

Train a Deep Graph Network

In this overview, you learn how to get started with a deep graph network by using one of the DGL containers in Amazon Elastic Container Registry (Amazon ECR). You can also see links to practical examples for deep graph networks.

What Is a Deep Graph Network?

Deep graph networks refer to a type of neural network that is trained to solve graph problems. A deep graph network uses an underlying deep learning framework like PyTorch or MXNet. The potential for graph networks in practical AI applications is highlighted in the Amazon SageMaker tutorials for Deep Graph Library (DGL). Examples for training models on graph datasets include social networks, knowledge bases, biology, and chemistry.
Several examples are provided using Amazon SageMaker’s deep learning containers that are preconfigured with DGL. If you have special modules you want to use with DGL, you can also build your own container. The examples involve heterographs, which are graphs that have multiple types of nodes and edges, and draw on a variety of applications across disparate scientific fields, such as bioinformatics and social network analysis. DGL provides a wide array of graph neural network implementations for different types models. Some of the highlights include:

- Graph convolutional network (GCN)
- Relational graph convolutional network (R-GCN)
- Graph attention network (GAT)
- Deep generative models of graphs (DGMG)
- Junction tree neural network (JTNN)

Get Started

DGL is available as a deep learning container in Amazon ECR. You can select deep learning containers when you write your estimator function in an Amazon SageMaker notebook. You can also craft your own custom container with DGL by following the Bring Your Own Container guide. The easiest way to get started with a deep graph network uses one of the DGL containers in Amazon ECR.

Note

Backend framework support is limited to PyTorch and MXNet.

Setup
If you are using Amazon SageMaker Studio, you need to clone the examples repository first. If you are using a notebook instance, you can find the examples by choosing the SageMaker icon at bottom of the left toolbar.

**To clone the Amazon SageMaker SDK and notebook examples repository**

1. From the JupyterLab view in Amazon SageMaker, go to the File Browser at the top of the left toolbar. From the File Browser panel, you can see a new navigation at the top of the panel.
2. Choose the icon on the far right to clone a Git repository.
3. Add the repository URL: https://github.com/awslabs/amazon-sagemaker-examples.git
4. Browse the newly added folder and its contents. The DGL examples are stored in the sagemaker-python-sdk folder.

**Run a Graph Network Training Example**

**To train a deep graph network**

1. From the JupyterLab view in Amazon SageMaker, browse the example notebooks and look for DGL folders. Several files may be included to support an example. Examine the README for any prerequisites.
2. Run the .ipynb notebook example.
3. Find the estimator function, and note the line where it is using an Amazon ECR container for DGL and a specific instance type. You may want to update this to use a container in your preferred Region.
4. Run the function to launch the instance and use the DGL container for training a graph network. Charges are incurred for launching this instance. The instance self-terminates when the training is complete.

**Examples**

An example of knowledge graph embedding (KGE) is provided. It uses the Freebase dataset, a knowledge base of general facts. An example use case would be to graph the relationships of persons and predict their nationality.

An example implementation of a graph convolutional network (GCN) shows how you can train a graph network to predict toxicity. A physiology dataset, Tox21, provides toxicity measurements for how substances affect biological responses.

Another GCN example shows you how to train a graph network on a scientific publications bibliography dataset, known as Cora. You can use it to find relationships between authors, topics, and conferences.

The last example is a recommender system for movie reviews. It uses a graph convolutional matrix completion (GCMC) network trained on the MovieLens datasets. These datasets consist of movie titles, genres, and ratings by users.

**Use a Deep Learning Container with DGL**

The following example uses preconfigured deep learning containers. This is the easiest to try since it works out of the box on Amazon SageMaker.

- Semi-supervised classification of a knowledge base using a GCN
Bring Your Own Container with DGL

The following examples enable you to bring your own container (BYOC). Read the BYOC guide and familiarize yourself with that process before trying these. Configuration is required.

- Molecular property prediction of toxicity using a GCN
- Recommender system for movies using a GCMC implementation

Extend a Prebuilt Container

If a prebuilt SageMaker container doesn't fulfill all of your requirements, you can extend the existing image to accommodate your needs. Even if there is direct support for your environment or framework, you may want to add additional functionality or configure your container environment differently. By extending a prebuilt image, you can leverage the included deep learning libraries and settings without having to create an image from scratch. You can extend the container to add libraries, modify settings, and install additional dependencies.

The following tutorial shows how to extend a prebuilt SageMaker image and publish it to Amazon ECR.

Topics
- Requirements to Extend a Prebuilt Container (p. 3156)
- Extend SageMaker Containers to Run a Python Script (p. 3156)

Requirements to Extend a Prebuilt Container

To extend a pre-built SageMaker image, you need to set the following environment variables within your Dockerfile. For more information on environment variables with SageMaker containers, see the SageMaker Training Toolkit GitHub repo.

- SAGEMAKER_SUBMIT_DIRECTORY: The directory within the container in which the Python script for training is located.
- SAGEMAKER_PROGRAM: The Python script that should be invoked and used as the entry point for training.

You can also install additional libraries by including the following in your Dockerfile:

```
RUN pip install <library>
```

The following tutorial shows how to use these environment variables.

Extend SageMaker Containers to Run a Python Script

In this tutorial, you learn how to extend the SageMaker PyTorch container with a Python file that uses the CIFAR-10 dataset. By extending the SageMaker PyTorch container, you utilize the existing training solution made to work with SageMaker. This tutorial extends a training image, but the same steps can be taken to extend an inference image. For a full list of the available images, see Available Deep Learning Containers Images.

To run your own training model using the SageMaker containers, build a Docker container through a SageMaker Notebook instance.

Step 1: Create an SageMaker Notebook Instance

1. Open the SageMaker console.
2. In the left navigation pane, choose Notebook, choose Notebook instances, and then choose Create notebook instance.

3. On the Create notebook instance page, provide the following information:
   a. For Notebook instance name, enter RunScriptNotebookInstance.
   b. For Notebook Instance type, choose ml.t2.medium.
   c. In the Permissions and encryption section, do the following:
      i. For IAM role, choose Create a new role.
      ii. On the Create an IAM role page, choose Specific S3 buckets, specify an Amazon S3 bucket named sagemaker-run-script, and then choose Create role.
         SageMaker creates an IAM role named AmazonSageMaker-ExecutionRole-YYYYMMDDTHHmmsS, such as AmazonSageMaker-ExecutionRole-20190429T110788. Note that the execution role naming convention uses the date and time when the role was created, separated by a T.
   d. For Root Access, choose Enable.
   e. Choose Create notebook instance.

4. On the Notebook instances page, the Status is Pending. It can take a few minutes for Amazon SageMaker to launch a machine learning compute instance—in this case, it launches a notebook instance—and attach an ML storage volume to it. The notebook instance has a preconfigured Jupyter notebook server and a set of Anaconda libraries. For more information, see CreateNotebookInstance.

5. In the Permissions and encryption section, copy the IAM role ARN number, and paste it into a notepad file to save it temporarily. You use this IAM role ARN number later to configure a local training estimator in the notebook instance. The IAM role ARN number looks like the following: 'arn:aws:iam::111122223333:role/service-role/AmazonSageMaker-ExecutionRole-20190429T110788'

6. After the status of the notebook instance changes to InService, choose Open JupyterLab.

Step 2: Create and Upload the Dockerfile and Python Training Scripts

1. After JupyterLab opens, create a new folder in the home directory of your JupyterLab. In the upper-left corner, choose the New Folder icon, and then enter the folder name docker_test_folder.

2. Create a Dockerfile text file in the docker_test_folder directory.
   a. Choose the New Launcher icon (+) in the upper-left corner.
   b. In the right pane under the Other section, choose Text File.
   c. Paste the following Dockerfile sample code into your text file.

```
# SageMaker PyTorch image
FROM 763104351884.dkr.ecr.us-east-1.amazonaws.com/pytorch-training:1.5.1-cpu-py36-ubuntu16.04

ENV PATH=":opt/ml/code:${PATH}"

# this environment variable is used by the SageMaker PyTorch container to determine our user code directory.
ENV SAGEMAKER_SUBMIT_DIRECTORY /opt/ml/code

# /opt/ml and all subdirectories are utilized by SageMaker, use the /code subdirectory to store your user code.
COPY cifar10.py /opt/ml/code/cifar10.py
```
The Dockerfile script performs the following tasks:

- **FROM 763104351884.dkr.ecr.us-east-1.amazonaws.com/pytorch-training:1.5.1-cpu-py36-ubuntu16.04** – Downloads the SageMaker PyTorch base image. You can replace this with any SageMaker base image you want to bring to build containers.
- **ENV SAGEMAKER_SUBMIT_DIRECTORY /opt/ml/code** – Sets /opt/ml/code as the training script directory.
- **COPY cifar10.py /opt/ml/code/cifar10.py** – Copies the script to the location inside the container that is expected by SageMaker. The script must be located in this folder.
- **ENV SAGEMAKER_PROGRAM cifar10.py** – Sets your cifar10.py training script as the entrypoint script.

On the left directory navigation pane, the text file name might automatically be named untitled.txt. To rename the file, right-click the file, choose Rename, rename the file as Dockerfile without the .txt extension, and then press Ctrl+s or Command+s to save the file.

3. Create or upload a training script cifar10.py in the docker_test_folder. You can use the following example script for this exercise.

```python
import ast
import argparse
import logging
import os
import torch
import torch.distributed as dist
import torch.nn as nn
import torch.nn.parallel
import torch.optim
import torch.utils.data
import torch.utils.data.distributed
import torchvision
import torchvision.models
import torchvision.transforms as transforms
import torch.nn.functional as F

logger=logging.getLogger(__name__)
logger.setLevel(logging.DEBUG)
classes=('plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck')

# https://github.com/pytorch/tutorials/blob/master/beginner_source/blitz/cifar10_tutorial.py#L118
class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1=nn.Conv2d(3, 6, 5)
        self.pool=nn.MaxPool2d(2, 2)
        self.conv2=nn.Conv2d(6, 16, 5)
        self.fc1=nn.Linear(16 * 5 * 5, 120)
        self.fc2=nn.Linear(120, 84)
        self.fc3=nn.Linear(84, 10)
        def forward(self, x):
```
```python
x = self.pool(F.relu(self.conv1(x)))
x = self.pool(F.relu(self.conv2(x)))
x = x.view(-1, 16 * 5 * 5)
x = F.relu(self.fc1(x))
x = F.relu(self.fc2(x))
x = self.fc3(x)
return x

def _train(args):
    is_distributed = len(args.hosts) > 1 and args.dist_backend is not None
    logger.debug("Distributed training - {}".format(is_distributed))

    if is_distributed:
        # Initialize the distributed environment.
        world_size = len(args.hosts)
        os.environ["WORLD_SIZE"] = str(world_size)
        host_rank = args.hosts.index(args.current_host)
        dist.init_process_group(backend=args.dist_backend, rank=host_rank,
                                world_size=world_size)
        logger.info(
            "Initialized the distributed environment: \"{}\" backend on {} nodes.
            Number of gpus: {}\".format(args.dist_backend, dist.get_world_size(),
                                         dist.get_rank(), torch.cuda.is_available(),
                                         args.num_gpus))

        device = "cuda" if torch.cuda.is_available() else "cpu"
        logger.info("Device Type: {}".format(device))

    logger.info("Loading Cifar10 dataset")
    transform = transforms.Compose(
        [transforms.ToTensor(),
         transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
    trainset = torchvision.datasets.CIFAR10(root=args.data_dir, train=True,
                                             download=False, transform=transform)
    train_loader = torch.utils.data.DataLoader(trainset, batch_size=args.batch_size,
                                              shuffle=True, num_workers=args.workers)

    testset = torchvision.datasets.CIFAR10(root=args.data_dir, train=False,
                                            download=False, transform=transform)
    test_loader = torch.utils.data.DataLoader(testset, batch_size=args.batch_size,
                                              shuffle=False, num_workers=args.workers)

    logger.info("Model loaded")
    model = Net()

    if torch.cuda.device_count() > 1:
        logger.info("Gpu count: {}".format(torch.cuda.device_count()))
        model = nn.DataParallel(model)

    model = model.to(device)

    criterion = nn.CrossEntropyLoss().to(device)
    optimizer = torch.optim.SGD(model.parameters(), lr=args.lr, momentum=args.momentum)

    for epoch in range(0, args.epochs):
        running_loss = 0.0
        for i, data in enumerate(train_loader):
            # get the inputs
            inputs, labels = data
            inputs, labels = inputs.to(device), labels.to(device)

            # zero the parameter gradients
```
optimizer.zero_grad()
#
outputs=model(inputs)
loss=criterion(outputs, labels)
loss.backward()
optimizer.step()
#
running_loss += loss.item()
if i % 2000 == 1999:  # print every 2000 mini-batches
    print('[%d, %5d] loss: %.3f' %
          (epoch + 1, i + 1, running_loss / 2000))
running_loss=0.0
print('Finished Training')
return _save_model(model, args.model_dir)

def _save_model(model, model_dir):
    logger.info("Saving the model.")
    path=os.path.join(model_dir, 'model.pth')
    torch.save(model.cpu().state_dict(), path)

def model_fn(model_dir):
    logger.info('model_fn')
    device="cuda" if torch.cuda.is_available() else "cpu"
    model=Net()
    if torch.cuda.device_count() > 1:
        logger.info("Gpu count: {}".format(torch.cuda.device_count()))
        model=nn.DataParallel(model)
    with open(os.path.join(model_dir, 'model.pth'), 'rb') as f:
        model.load_state_dict(torch.load(f))
    return model.to(device)

if __name__ == '__main__':
    parser=argparse.ArgumentParser()
    parser.add_argument('--workers', type=int, default=2, metavar='W',
                        help='number of data loading workers (default: 2)')
    parser.add_argument('--epochs', type=int, default=2, metavar='E',
                        help='number of total epochs to run (default: 2)')
    parser.add_argument('--batch-size', type=int, default=4, metavar='BS',
                        help='batch size (default: 4)')
    parser.add_argument('--lr', type=float, default=0.001, metavar='LR',
                        help='initial learning rate (default: 0.001)')
    parser.add_argument('--momentum', type=float, default=0.9, metavar='M',
                        help='momentum (default: 0.9)')
    parser.add_argument('--dist-backend', type=str, default='gloo', help='distributed
                        backend (default: gloo)')

    # The parameters below retrieve their default values from SageMaker environment
    # variables, which are
    # instantiated by the SageMaker containers framework.
    # https://github.com/aws/sagemaker-containers#how-a-script-is-executed-inside-the-
    # container
    parser.add_argument('--hosts', type=str, default=ast.literal_eval(os.environ['SM_HOSTS']))
    parser.add_argument('--current-host', type=str, default=os.environ['SM_CURRENT_HOST'])
    parser.add_argument('--model-dir', type=str, default=os.environ['SM_MODEL_DIR'])
    parser.add_argument('--data-dir', type=str, default=os.environ['SM_CHANNEL_TRAINING'])
Step 3: Build the Container

1. In the JupyterLab home directory, open a Jupyter notebook. To open a new notebook, choose the New Launch icon and then choose **conda_pytorch_p36** in the Notebook section.

2. Run the following command in the first notebook cell to change to the `docker_test_folder` directory:

   ```bash
   % cd ~/SageMaker/docker_test_folder
   ```

   This returns your current directory as follows:

   ```bash
   ! pwd
   ```

   output: /home/ec2-user/SageMaker/docker_test_folder

3. Log in to Docker to access the base container:

   ```bash
   ! aws ecr get-login-password --region us-east-1 | docker login --username AWS --password-stdin 763104351884.dkr.ecr.us-east-1.amazonaws.com
   ```

4. To build the Docker container, run the following Docker build command, including the space followed by a period at the end:

   ```bash
   ! docker build -t pytorch-extended-container-test .
   ```

   The Docker build command must be run from the Docker directory you created, in this case `docker_test_folder`.

   **Note**

   If you get the following error message that Docker cannot find the Dockerfile, make sure the Dockerfile has the correct name and has been saved to the directory.

   ```bash
   unable to prepare context: unable to evaluate symlinks in Dockerfile path:
lstat /home/ec2-user/SageMaker/docker/Dockerfile: no such file or directory
   ```

   Remember that `docker` looks for a file specifically called Dockerfile without any extension within the current directory. If you named it something else, you can pass in the file name manually with the `-f` flag. For example, if you named your Dockerfile `Dockerfile-text.txt`, run the following command:

   ```bash
   ! docker build -t tf-custom-container-test -f Dockerfile-text.txt .
   ```

Step 4: Test the Container

1. To test the container locally in the notebook instance, open a Jupyter notebook. Choose New Launcher and choose Notebook in **conda_pytorch_p36** framework. The rest of the code snippets must run from the Jupyter notebook instance.

2. Download the CIFAR-10 dataset.
import torch
import torchvision
import torchvision.transforms as transforms

def _get_transform():
    return transforms.Compose([transforms.ToTensor(),
                               transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

def get_train_data_loader(data_dir='/tmp/pytorch/cifar-10-data'):
    transform=_get_transform()
    trainset=torchvision.datasets.CIFAR10(root=data_dir, train=True,
                                          download=True, transform=transform)
    return torch.utils.data.DataLoader(trainset, batch_size=4,
                                        shuffle=True, num_workers=2)

def get_test_data_loader(data_dir='/tmp/pytorch/cifar-10-data'):
    transform=_get_transform()
    testset=torchvision.datasets.CIFAR10(root=data_dir, train=False,
                                          download=True, transform=transform)
    return torch.utils.data.DataLoader(testset, batch_size=4,
                                         shuffle=False, num_workers=2)

trainloader=get_train_data_loader('/tmp/pytorch-example/cifar-10-data')
testloader=get_test_data_loader('/tmp/pytorch-example/cifar-10-data')

3. Set role to the role used to create your Jupyter notebook. This is used to configure your SageMaker Estimator.

   from sagemaker import get_execution_role
   role=get_execution_role()

4. Paste the following example script into the notebook code cell to configure a SageMaker Estimator using your extended container.

   from sagemaker.estimator import Estimator
   hyperparameters={'epochs': 1}
   estimator=Estimator(
       image_uri='pytorch-extended-container-test',
       role=role,
       instance_count=1,
       instance_type='local',
       hyperparameters=hyperparameters
   )
   estimator.fit('file:///tmp/pytorch-example/cifar-10-data')

5. Run the code cell. This test outputs the training environment configuration, the values used for the environmental variables, the source of the data, and the loss and accuracy obtained during training.

   **Step 5: Push the Container to Amazon Elastic Container Registry (Amazon ECR)**

   1. After you successfully run the local mode test, you can push the Docker container to Amazon ECR and use it to run training jobs.
Run the following command lines in a notebook cell.

```
# Specify an algorithm name
algorithm_name=pytorch-extended-container-test
account=$(aws sts get-caller-identity --query Account --output text)
# Get the region defined in the current configuration (default to us-west-2 if none defined)
region=$(aws configure get region)
fullname="${account}.dkr.ecr.${region}.amazonaws.com/${algorithm_name}:latest"
# If the repository doesn’t exist in ECR, create it.
aws ecr describe-repositories --repository-names "$\{algorithm_name\}" > /dev/null 2>&1
if [ $? -ne 0 ]
then
  aws ecr create-repository --repository-name "$\{algorithm_name\}" > /dev/null
fi
# Log into Docker
aws ecr get-login-password --region $\{region\}|docker login --username AWS --password-stdin $\{fullname\}
# Build the docker image locally with the image name and then push it to ECR
# with the full name.
docker build -t $\{algorithm_name\} .
docker tag $\{algorithm_name\} $\{fullname\}
docker push $\{fullname\}
```

2. After you push the container, you can call the Amazon ECR image from anywhere in the SageMaker environment. Run the following code example in the next notebook cell.

If you want to use this training container with SageMaker Studio to use its visualization features, you can also run the following code in a Studio notebook cell to call the Amazon ECR image of your training container.

```
import boto3
client=boto3.client('sts')
account=client.get_caller_identity()['Account']
my_session=boto3.session.Session()
region=my_session.region_name
algorithm_name="pytorch-extended-container-test"
ecr_image='{}.dkr.ecr.{}.amazonaws.com/{}:latest'.format(account, region, algorithm_name)

ecr_image
# This should return something like
# 12-digits-of-your-account.dkr.ecr.us-east-2.amazonaws.com/tf-2.2-test:latest
```

3. Use the ecr_image retrieved from the previous step to configure a SageMaker estimator object. The following code sample configures a SageMaker PyTorch estimator.

```
import sagemaker
```
Step 6: Clean up Resources

To clean up resources when done with the Get Started example

1. Open the SageMaker console, choose the notebook instance RunScriptNotebookInstance, choose Actions, and choose Stop. It can take a few minutes for the instance to stop.
2. After the instance Status changes to Stopped, choose Actions, choose Delete, and then choose Delete in the dialog box. It can take a few minutes for the instance to be deleted. The notebook instance disappears from the table when it has been deleted.
3. Open the Amazon S3 console and delete the bucket that you created for storing model artifacts and the training dataset.
4. Open the IAM console and delete the IAM role. If you created permission policies, you can delete them, too.

Note
The Docker container shuts down automatically after it has run. You don't need to delete it.

Adapting Your Own Docker Container to Work with SageMaker

You can adapt an existing Docker image to work with SageMaker. You may need to use an existing, external Docker image with SageMaker when you have a container that satisfies feature or safety requirements that are not currently supported by a prebuilt SageMaker image. There are two toolkits that allow you to bring your own container and adapt it to work with SageMaker:

- SageMaker Training Toolkit
- SageMaker Inference Toolkit

The following topics show how to adapt your existing image using the SageMaker Training and Inference toolkits:

Topics
- Individual Framework Libraries (p. 3165)
- Using the SageMaker Training and Inference Toolkits (p. 3165)
- Adapting Your Own Training Container (p. 3166)
Individual Framework Libraries

In addition to the SageMaker Training Toolkit and SageMaker Inference Toolkit, SageMaker also provides toolkits specialized for TensorFlow, MXNet, PyTorch, and Chainer. The following table provides links to the GitHub repositories that contain the source code for each framework and their respective serving toolkits. The instructions linked are for using the Python SDK to run training algorithms and host models on SageMaker. The functionality for these individual libraries is included in the SageMaker Training Toolkit and SageMaker Inference Toolkit.

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Using the SageMaker Training and Inference Toolkits

The SageMaker Training and SageMaker Inference toolkits implement the functionality that you need to adapt your containers to run scripts, train algorithms, and deploy models on SageMaker. When installed, the library defines the following for users:

- The locations for storing code and other resources.
- The entry point that contains the code to run when the container is started. Your Dockerfile must copy the code that needs to be run into the location expected by a container that is compatible with SageMaker.
- Other information that a container needs to manage deployments for training and inference.

SageMaker Toolkits Containers Structure

When SageMaker trains a model, it creates the following file folder structure in the container's /opt/ml directory.

```
/opt/ml
### input
#   ### config
#   #   ### hyperparameters.json
#   #   ### resourceConfig.json
#   ### data
#   #   ### <channel_name>
#          ### <input data>
### model
#```

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When you run a model training job, the SageMaker container uses the `/opt/ml/input/` directory, which contains the JSON files that configure the hyperparameters for the algorithm and the network layout used for distributed training. The `/opt/ml/input/` directory also contains files that specify the channels through which SageMaker accesses the data, which is stored in Amazon Simple Storage Service (Amazon S3). The SageMaker containers library places the scripts that the container will run in the `/opt/ml/code/` directory. Your script should write the model generated by your algorithm to the `/opt/ml/model/` directory. For more information, see Use Your Own Training Algorithms (p. 3181).

When you host a trained model on SageMaker to make inferences, you deploy the model to an HTTP endpoint. The model makes real-time predictions in response to inference requests. The container must contain a serving stack to process these requests.

In a hosting or batch transform container, the model files are located in the same folder to which they were written during training.

```
/opt/ml/model
# <model files>
```

For more information, see Use Your Own Inference Code (p. 3191).

**Single Versus Multiple Containers**

You can either provide separate Docker images for the training algorithm and inference code or you can use a single Docker image for both. When creating Docker images for use with SageMaker, consider the following:

- Providing two Docker images can increase storage requirements and cost because common libraries might be duplicated.
- In general, smaller containers start faster for both training and hosting. Models train faster and the hosting service can react to increases in traffic by automatically scaling more quickly.
- You might be able to write an inference container that is significantly smaller than the training container. This is especially common when you use GPUs for training, but your inference code is optimized for CPUs.
- SageMaker requires that Docker containers run without privileged access.
- Both Docker containers that you build and those provided by SageMaker can send messages to the `Stdout` and `Stderr` files. SageMaker sends these messages to Amazon CloudWatch logs in your AWS account.

For more information about how to create SageMaker containers and how scripts are executed inside them, see the SageMaker Training Toolkit and SageMaker Inference Toolkit repositories on GitHub. They also provide lists of important environmental variables and the environmental variables provided by SageMaker containers.

**Adapting Your Own Training Container**

To run your own training model, build a Docker container using the Amazon SageMaker Training Toolkit through an Amazon SageMaker notebook instance.
**Step 1: Create a SageMaker notebook instance**

2. In the left navigation pane, choose **Notebook**, choose **Notebook instances**, and then choose **Create notebook instance**.
3. On the **Create notebook instance** page, provide the following information:
   a. For **Notebook instance name**, enter `RunScriptNotebookInstance`.
   b. For **Notebook Instance type**, choose `ml.t2.medium`.
   c. In the **Permissions and encryption** section, do the following:
      i. For **IAM role**, choose **Create a new role**.
      ii. On the **Create an IAM role** page, choose **Specific S3 buckets**, specify an Amazon S3 bucket named `sagemaker-run-script`, and then choose **Create role**.

   SageMaker creates an IAM role named `AmazonSageMaker-ExecutionRole-YYYYMMDDTHHmmSS`. For example, `AmazonSageMaker-ExecutionRole-20190429T110788`. Note that the execution role naming convention uses the date and time at which the role was created, separated by a T.
   d. For **Root Access**, choose **Enable**.
   e. Choose **Create notebook instance**.
4. On the **Notebook instances** page, the **Status** is **Pending**. It can take a few minutes for Amazon SageMaker to launch a machine learning compute instance—in this case, it launches a notebook instance—and attach an ML storage volume to it. The notebook instance has a preconfigured Jupyter notebook server and a set of Anaconda libraries. For more information, see `CreateNotebookInstance`.

5. In the **Permissions and encryption** section, copy the **IAM role ARN number**, and paste it into a notepad file to save it temporarily. You use this IAM role ARN number later to configure a local training estimator in the notebook instance. The **IAM role ARN number** looks like the following: 
   `arn:aws:iam::111122223333:role/service-role/AmazonSageMaker-ExecutionRole-20190429T110788`

6. After the status of the notebook instance changes to **InService**, choose **Open JupyterLab**.

**Step 2: Create and upload the Dockerfile and Python training scripts**

1. After JupyterLab opens, create a new folder in the home directory of your JupyterLab. In the upper-left corner, choose the **New Folder** icon, and then enter the folder name `docker_test_folder`.
2. Create a **Dockerfile** text file in the `docker_test_folder` directory.
   a. Choose the **New Launcher** icon (+) in the upper-left corner.
   b. In the right pane under the **Other** section, choose **Text File**.
   c. Paste the following **Dockerfile** sample code into your text file.

   ```
   FROM tensorflow/tensorflow:2.2.0rc2-gpu-py3-jupyter
   
   # Install sagemaker-training toolkit that contains the common functionality necessary to create a container compatible with SageMaker and the Python SDK.
   RUN pip3 install sagemaker-training
   
   # Copies the training code inside the container
   COPY train.py /opt/ml/code/train.py
   ```
# Defines train.py as script entrypoint
ENV SAGEMAKER_PROGRAM train.py

The Dockerfile script performs the following tasks:

- **FROM tensorflow/tensorflow:2.2.0rc2-gpu-py3-jupyter** – Downloads the TensorFlow Docker base image. You can replace this with any Docker base image you want to bring to build containers, as well as with AWS pre-built container base images.
- **RUN pip install sagemaker-training** – Installs SageMaker Training Toolkit that contains the common functionality necessary to create a container compatible with SageMaker.
- **COPY train.py /opt/ml/code/train.py** – Copies the script to the location inside the container that is expected by SageMaker. The script must be located in this folder.
- **ENV SAGEMAKER_PROGRAM train.py** – Takes your training script train.py as the entrypoint script copied in the /opt/ml/code folder of the container. This is the only environmental variable that you must specify when you build your own container.

d. On the left directory navigation pane, the text file name might automatically be named untitled.txt. To rename the file, right-click the file, choose Rename, rename the file as Dockerfile without the .txt extension, and then press Ctrl+s or Command+s to save the file.

3. Create or upload a training script train.py in the docker_test_folder. You can use the following example script for this exercise.

```python
import tensorflow as tf

mnist = tf.keras.datasets.mnist
(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0

model = tf.keras.models.Sequential([tf.keras.layers.Flatten(input_shape=(28, 28)),
                                     tf.keras.layers.Dense(128, activation='relu'),
                                     tf.keras.layers.Dropout(0.2),
                                     tf.keras.layers.Dense(10, activation='softmax')])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=1)
model.evaluate(x_test, y_test)
```

## Step 3: Build the container

1. In the JupyterLab home directory, open a Jupyter notebook. To open a new notebook, choose the New Launch icon and then choose conda_tensorflow2_p36 in the Notebook section.
2. Run the following command in the first notebook cell to change to the docker_test_folder directory:

```bash
% cd ~/SageMaker/docker_test_folder
```
This returns your current directory as follows:

```bash
! pwd
```

output: /home/ec2-user/SageMaker/docker_test_folder

3. To build the Docker container, run the following Docker build command, including the space followed by a period at the end:

```bash
! docker build -t tf-custom-container-test .
```

The Docker build command must be run from the Docker directory you created, in this case `docker_test_folder`.

**Note**
If you get the following error message that Docker cannot find the Dockerfile, make sure the Dockerfile has the correct name and has been saved to the directory.

```bash
unable to prepare context: unable to evaluate symlinks in Dockerfile path: lstat /home/ec2-user/SageMaker/docker/Dockerfile: no such file or directory
```

Remember that `docker` looks for a file specifically called `Dockerfile` without any extension within the current directory. If you named it something else, you can pass in the file name manually with the `-f` flag. For example, if you named your Dockerfile as `Dockerfile-text.txt`, run the following command:

```bash
! docker build -t tf-custom-container-test -f Dockerfile-text.txt .
```

**Step 4: Test the container**

1. To test the container locally in the notebook instance, open a Jupyter notebook. Choose **New Launcher** and choose **Notebook** in `conda_tensorflow_p36` framework.
2. Paste the following example script into the notebook code cell to configure a SageMaker Estimator.

**SageMaker Python SDK v1**

```python
from sagemaker.estimator import Estimator

estimator = Estimator(image_name='tf-custom-container-test',
    role='arn:aws:iam::111122223333:role/role-name',
    instance_count=1,
    instance_type='local')

estimator.fit()
```

**SageMaker Python SDK v2**

```python
from sagemaker.estimator import Estimator

estimator = Estimator(image_uri='tf-custom-container-test',
    role='arn:aws:iam::111122223333:role/role-name',
    instance_count=1,
    instance_type='local')
```
estimator.fit()

3. Replace the 'Put_YourARN_Here' value with the IAM role ARN number you copied to a notepad file when you configured the notebook instance. The ARN should look like the following: 'arn:aws:iam::11112223333:role/service-role/AmazonSageMaker-ExecutionRole-20190429T110788'.

4. Run the code cell. This test outputs the training environment configuration, the values used for the environmental variables, the source of the data, and the loss and accuracy obtained during training.

**Step 5: Push the container to Amazon Elastic Container Registry (Amazon ECR)**

1. After you successfully run the local mode test, you can push the Docker container to Amazon ECR and use it to run training jobs.

Run the following command lines in a notebook cell.

```bash
# Specify an algorithm name
algorithm_name=tf-custom-container-test

account=$(aws sts get-caller-identity --query Account --output text)

# Get the region defined in the current configuration (default to us-west-2 if none defined)
region=$(aws configure get region)
region=${region:-us-west-2}

fullname="${account}.dkr.ecr.${region}.amazonaws.com/${algorithm_name}:latest"

# If the repository doesn't exist in ECR, create it.
aws ecr describe-repositories --repository-names "${algorithm_name}" > /dev/null 2>&1
if [ $? -ne 0 ]
then
aws ecr create-repository --repository-name "${algorithm_name}" > /dev/null
fi

# Get the login command from ECR and execute it directly
aws ecr get-login-password --region ${region}|docker login --username AWS --password-stdin ${fullname}

# Build the docker image locally with the image name and then push it to ECR with the full name.
docker build -t ${algorithm_name} .
docker tag ${algorithm_name} ${fullname}
docker push ${fullname}
```

**Note**

This bash shell script may raise a permission issue similar to the following error message:

"denied: User: [ARN] is not authorized to perform: ecr:InitiateLayerUpload on resource: arn:aws:ecr:us-east-1:[id]:repository/tf-custom-container-test"
Adapting Your Own Training Container

If this error occurs, you need to attach the AmazonEC2ContainerRegistryFullAccess policy to your IAM role. Go to the IAM console, choose Roles from the left navigation pane, look up the IAM role you used for the Notebook instance. Under the Permission tab, choose the Attach policies button, and search the AmazonEC2ContainerRegistryFullAccess policy. Mark the check box of the policy, and choose Attach policy to finish.

2. After you push the container, you can call the Amazon ECR image from anywhere in the SageMaker environment. Run the following code example in the next notebook cell.

If you want to use this training container with SageMaker Studio to use its visualization features, you can also run the following code in a Studio notebook cell to call the Amazon ECR image of your training container.

```python
import boto3

account_id = boto3.client('sts').get_caller_identity().get('Account')
ecr_repository = 'tf-custom-container-test'
tag = '::latest'

region = boto3.session.Session().region_name
uri_suffix = 'amazonaws.com'
if region in ['cn-north-1', 'cn-northwest-1']:
    uri_suffix = 'amazonaws.com.cn'

byoc_image_uri = '{}.dkr.ecr.{}.{}/{}'.format(account_id, region, uri_suffix, ecr_repository + tag)

byoc_image_uri
# This should return something like
# 111122223333.dkr.ecr.us-east-2.amazonaws.com/sagemaker-byoc-test:latest
```

3. Use the ecr_image retrieved from the previous step to configure a SageMaker estimator object. The following code sample configures a SageMaker estimator with the byoc_image_uri and initiates a training job on an Amazon EC2 instance.

SageMaker Python SDK v1

```python
import sagemaker
from sagemaker import get_execution_role
from sagemaker.estimator import Estimator

estimator = Estimator(image_uri=byoc_image_uri,
                      role=get_execution_role(),
                      base_job_name='tf-custom-container-test-job',
                      instance_count=1,
                      instance_type='ml.p2.xlarge')

# start training
estimator.fit()

# deploy the trained model
predictor = estimator.deploy(1, instance_type)
```

SageMaker Python SDK v2

```python
import sagemaker
from sagemaker import get_execution_role
from sagemaker.estimator import Estimator

estimator = Estimator(image_uri=byoc_image_uri,
                      role=get_execution_role(),
                      base_job_name='tf-custom-container-test-job',
                      instance_count=1,
                      instance_type='ml.p2.xlarge')
```

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# start training
estimator.fit()

# deploy the trained model
predictor = estimator.deploy(1, instance_type)

For a full example that shows how to test a custom container locally and push it to an Amazon ECR image, see the Building Your Own TensorFlow Container example notebook.

Tip
To profile and debug training jobs to monitor system utilization issues (such as CPU bottlenecks and GPU underutilization) and identify training issues (such as overfitting, overtraining, exploding tensors, and vanishing gradients), use Amazon SageMaker Debugger. For more information, see Amazon SageMaker Debugger is available for any deep learning models that you bring to Amazon SageMaker. The AWS CLI, SageMaker Estimator API, and the Debugger APIs enable you to use any Docker base images to build and customize containers to train your models. To use Debugger with customized containers, you need to make a minimal change to your training script to implement the Debugger hook callback and retrieve tensors from training jobs.

You need the following resources to build a customized container with Debugger.

- Amazon SageMaker Python SDK
- The SMDebug open source client library
- A Docker base image of your choice
- Your training script with a Debugger hook registered – For more information about registering a Debugger hook to your training script, see Register Debugger Hook to Your Training Script (p. 2412).

For an end-to-end example of using Debugger with a custom training container, see the following example notebook.

- Build a Custom Training Container and Debug Training Jobs with Debugger

Tip
This custom container with Debugger guide is an extension of the Adapting Your Own Training Container (p. 3166) guide which walks you thorough how to build and push your custom training container to Amazon ECR.

Prepare to Build a Custom Training Container

To build a docker container, the basic structure of files should look like the following:

```bash
### debugger_custom_container_test_notebook.ipynb  # a notebook to run python snippet codes
```
Register Debugger Hook to Your Training Script

To debug your model training, you need to add a Debugger hook to your training script.

**Note**
This step is required to collect model parameters (output tensors) for debugging your model training. If you only want to monitor and profile, you can skip this hook registration step and exclude the **debugger_hook_config** parameter when constructing an estimator.

The following example code shows the structure of a training script using the Keras ResNet50 model and how to pass the Debugger hook as a Keras callback for debugging. To find a complete training script, see TensorFlow training script with SageMaker Debugger hook.

```python
# An example of training script (your-training-script.py)
import tensorflow.compat.v2 as tf
from tensorflow.keras.applications.resnet50 import ResNet50
import smdebug.tensorflow as smd

def train(batch_size, epoch, model, hook):

    ...

    model.fit(X_train, Y_train,
              batch_size=batch_size,
              epochs=epoch,
              validation_data=(X_valid, Y_valid),
              shuffle=True,

    # smdebug modification: Pass the Debugger hook in
    # the main() as a KerasCallback
    callbacks=[hook])
```
For more information about registering the Debugger hook for the supported frameworks and algorithm, see the following links in the SMDebug client library:

- SMDebug TensorFlow hook
- SMDebug PyTorch hook
- SMDebug MXNet hook
- SMDebug XGBoost hook

In the following example notebooks' training scripts, you can find more examples about how to add the Debugger hooks to training scripts and collect output tensors in detail:

- Debugger in script mode with the TensorFlow 2.1 framework
  To see the difference between using Debugger in a Deep Learning Container and in script mode, open this notebook and put it and the previous Debugger in a Deep Learning Container TensorFlow v2.1 notebook example side by side.
  In script mode, the hook configuration part is removed from the script in which you set the estimator. Instead, the Debugger hook feature is merged into the training script, TensorFlow Keras ResNet training script in script mode. The training script imports the smdebug library in the required TensorFlow Keras environment to communicate with the TensorFlow ResNet50 algorithm. It also manually implements the smdebug hook functionality by adding the `callbacks=[hook]` argument inside the `train` function (in line 49), and by adding the manual hook configuration (in line 89) provided through SageMaker Python SDK.
  This script mode example runs the training job in the TF 2.1 framework for direct comparison with the zero script change in the TF 2.1 example. The benefit of setting up Debugger in script mode is the flexibility to choose framework versions not covered by AWS Deep Learning Containers.

- Using Amazon SageMaker Debugger in a PyTorch Container in Script Mode
  This notebook enables Debugger in script mode in PyTorch v1.3.1 framework. PyTorch v1.3.1 is supported by SageMaker containers, and this example shows details of how to modify a training script. The SageMaker PyTorch estimator is already in script mode by default. In the notebook, the line to activate `script_mode` is not included in the estimator configuration.
  This notebook shows detailed steps to change an original PyTorch training script to a modified version with Debugger enabled. Additionally, this example shows how you can use Debugger built-in rules to detect training issues such as the vanishing gradients problem, and the Debugger trial features to call and analyze the saved tensors.
Create and Configure a Dockerfile

Open your SageMaker JupyterLab and create a new folder, debugger_custom_container_test_folder in this example, to save your training script and Dockerfile. The following code example is a Dockerfile that includes essential docker build commends. Paste the following code into the Dockerfile text file and save it. Upload your training script to the same folder.

```bash
# Specify a docker base image
FROM tensorflow/tensorflow:2.2.0rc2-gpu-py3
RUN /usr/bin/python3 -m pip install --upgrade pip
RUN pip install --upgrade protobuf

# Install required packages to enable the SageMaker Python SDK and the smdebug library
RUN pip install sagemaker-training
RUN pip install smdebug

CMD ["bin/bash"]
```

If you want to use a pre-built AWS Deep Learning Container image, see Available AWS Deep Learning Containers Images.

Build and Push the Custom Training Container to Amazon ECR

Create a test notebook, debugger_custom_container_test_notebook.ipynb, and run the following code in the notebook cell. This will access the debugger_byoc_test_docker directory, build the docker with the specified algorithm_name, and push the docker container to your Amazon ECR.

```python
import boto3

account_id = boto3.client('sts').get_caller_identity().get('Account')
ecr_repository = 'sagemaker-debugger-mnist-byoc-tf2'
tag = ':latest'
region = boto3.session.Session().region_name
uri_suffix = 'amazonaws.com'

if region in ['cn-north-1', 'cn-northwest-1']:
    uri_suffix = 'amazonaws.com.cn'

byoc_image_uri = '{}.dkr.ecr.{}.{}/{}'.format(account_id, region, uri_suffix, ecr_repository + tag)

!docker build -t $ecr_repository docker
!$(aws ecr get-login --region $region --registry-ids $account_id --no-include-email)
!aws ecr create-repository --repository-name $ecr_repository
!docker tag {ecr_repository + tag} $byoc_image_uri
!docker push $byoc_image_uri
```

Tip
If you use one of the AWS Deep Learning Container base images, run the following code to log in to Amazon ECR and access to the Deep Learning Container image repository.
Run and Debug Training Jobs Using the Custom Training Container

After you build and push your docker container to Amazon ECR, configure a SageMaker estimator with your training script and the Debugger-specific parameters. After you execute the estimator.fit(), Debugger will collect output tensors, monitor them, and detect training issues. Using the saved tensors, you can further analyze the training job by using the smdebug core features and tools. Configuring a workflow of Debugger rule monitoring process with Amazon CloudWatch Events and AWS Lambda, you can automate a stopping training job process whenever the Debugger rules spots training issues.

```python
import sagemaker

from sagemaker.estimator import Estimator
from sagemaker.debugger import Rule, DebuggerHookConfig, CollectionConfig, rule_configs

profiler_config = ProfilerConfig(...)  
debugger_hook_config = DebuggerHookConfig(...)  
rules = [
    Rule.sagemaker(rule_configs.built_in_rule()),
    ProfilerRule.sagemaker(rule_configs.BuiltInRule())
]

estimator = Estimator(
    image_uri=byoc_image_uri,
    entry_point="./debugger_custom_container_test_folder/your-training-script.py",
    role=sagemaker.get_execution_role(),
    base_job_name='debugger-custom-container-test',
    instance_count=1,
    instance_type='ml.p3.2xlarge',
)  
```

Step 6: Clean up resources

1. Open the SageMaker console, choose the notebook instance RunScriptNotebookInstance, choose Actions, and choose Stop. It can take a few minutes for the instance to stop.

2. After the instance Status changes to Stopped, choose Actions, choose Delete, and then choose Delete in the dialog box. It can take a few minutes for the instance to be deleted. The notebook instance disappears from the table when it has been deleted.
3. Open the Amazon S3 console and delete the bucket that you created for storing model artifacts and the training dataset.

4. Open the IAM console and delete the IAM role. If you created permission policies, you can delete them, too.

   **Note**
   The Docker container shuts down automatically after it has run. You don’t need to delete it.

### Adapting Your Own Inference Container

If none of the Amazon SageMaker prebuilt inference containers suffice for your situation, and you want to use your own Docker container, use the SageMaker Inference Toolkit to adapt your container to work with SageMaker hosting. To adapt your container to work with SageMaker hosting, create the inference code in one or more Python script files and a Dockerfile that imports the inference toolkit.

The inference code includes an inference handler, a handler service, and an entrypoint. In this example, they are stored as three separate Python files. All three of these Python files must be in the same directory as your Dockerfile.

For an example Jupyter notebook that shows a complete example of extending a container by using the SageMaker inference toolkit, see [Amazon SageMaker Multi-Model Endpoints using your own algorithm container](#).

### Step 1: Create an Inference Handler

The SageMaker inference toolkit is built on the multi-model server (MMS). MMS expects a Python script that implements functions to load the model, pre-process input data, get predictions from the model, and process the output data in a model handler.

#### The model_fn Function

There are default implementations for the model_fn function, named default_model_fn, on the SageMaker PyTorch and MXNet Inference toolkits. The default implementation loads models saved using torchscript, of the form .pt or .pth. If your model requires custom methods to load, or you want to perform extra steps when loading your model, you must implement the model_fn function.

The following simple example shows an implementation of a model_fn function that loads a PyTorch model:

```python
def model_fn(self, model_dir):
    import torch

    logger.info('model_fn')
    device = "cuda" if torch.cuda.is_available() else "cpu"
    with open(os.path.join(model_dir, 'model.pth'), 'rb') as f:
        model = torch.jit.load(f)
    return model.to(device)
```

#### The input_fn Function

The input_fn function is responsible for deserializing your input data so that it can be passed to your model. It takes input data and content type as parameters, and returns deserialized data. The SageMaker inference toolkit provides a default implementation that deserializes the following content types:

- JSON
- CSV
- Numpy array
• NPZ

If your model requires a different content type, or you want to preprocess your input data before sending it to the model, you must implement the `input_fn` function. The following example shows a simple implementation of the `input_fn` function.

```python
from sagemaker_inference import content_types, decoder
def input_fn(self, input_data, content_type):
    """A default input_fn that can handle JSON, CSV and NPZ formats.
    Args:
        input_data: the request payload serialized in the content_type format
        content_type: the request content_type
    Returns: input_data deserialized into torch.FloatTensor or torch.cuda.FloatTensor depending if cuda is available.
    """
    return decoder.decode(input_data, content_type)
```

The `predict_fn` Function

The `predict_fn` function is responsible for getting predictions from the model. It takes the model and the data returned from `input_fn` as parameters, and returns the prediction. There is no default implementation for the `predict_fn`. You must implement it yourself. The following is a simple implementation of the `predict_fn` function for a PyTorch model.

```python
def predict_fn(self, data, model):
    """A default predict_fn for PyTorch. Calls a model on data deserialized in input_fn.
    Runs prediction on GPU if cuda is available.
    Args:
        data: input data (torch.Tensor) for prediction deserialized by input_fn
        model: PyTorch model loaded in memory by model_fn
    Returns: a prediction
    """
    return model(data)
```

The `output_fn` Function

The `output_fn` function is responsible for serializing the data that the `predict_fn` function returns as a prediction. The SageMaker inference toolkit implements a default `output_fn` function that serializes Numpy arrays, JSON, and CSV. If your model outputs any other content type, or you want to perform other post-processing of your data before sending it to the user, you must implement your own `output_fn` function. The following shows a simple `output_fn` function for a PyTorch model.

```python
from sagemaker_inference import encoder
def output_fn(self, prediction, accept):
    """A default output_fn for PyTorch. Serializes predictions from predict_fn to JSON, CSV or NPY format.
    Args:
        prediction: a prediction result from predict_fn
        accept: type which the output data needs to be serialized
    Returns: output data serialized
    """
    return encoder.encode(prediction, accept)
```
Step 2: Implement a Handler Service

The handler service is executed by the model server. The handler service implements initialize and handle methods. The initialize method is invoked when the model server starts, and the handle method is invoked for all incoming inference requests to the model server. For more information, see Custom Service in the Multi-model server documentation. The following is an example of a handler service for a PyTorch model server.

```python
from sagemaker_inference.default_handler_service import DefaultHandlerService
from sagemaker_inference.transformer import Transformer
from sagemaker_pytorch_serving_container.default_inference_handler import DefaultPytorchInferenceHandler

class HandlerService(DefaultHandlerService):
    '''Handler service that is executed by the model server.
    Determines specific default inference handlers to use based on model being used.
    This class extends `DefaultHandlerService`, which define the following:
    - The `handle` method is invoked for all incoming inference requests to the model server.
    - The `initialize` method is invoked at model server start up.
    Based on: https://github.com/awslabs/mxnet-model-server/blob/master/docs/custom_service.md
    '''

    def __init__(self):
        transformer = Transformer(default_inference_handler=DefaultPytorchInferenceHandler())
        super(HandlerService, self).__init__(transformer=transformer)
```

Step 3: Implement an Entrypoint

The entrypoint starts the model server by invoking the handler service. You specify the location of the entrypoint in your Dockerfile. The following is an example of an entrypoint.

```python
from sagemaker_inference import model_server
model_server.start_model_server(handler_service=HANDLER_SERVICE)
```

Step 4: Write a Dockerfile

In your Dockerfile, copy the model handler from step 2 and specify the Python file from the previous step as the entrypoint in your Dockerfile. The following is an example of the lines you can add to your Dockerfile to copy the model handler and specify the entrypoint. For a full example of a Dockerfile for an inference container, see Dockerfile.

```bash
# Copy the default custom service file to handle incoming data and inference requests
COPY model_handler.py /home/model-server/model_handler.py

# Define an entrypoint script for the docker image
ENTRYPOINT ["python", "/usr/local/bin/entrypoint.py"]
```

Step 5: Build and Register Your Container

Now you can build your container and register it in Amazon Elastic Container Registry (Amazon ECR). The following shell script from the sample notebook builds the container and uploads it to an Amazon ECR repository in your AWS account.
Create a container with your own algorithms and models

If none of the existing SageMaker containers meet your needs and you don’t have an existing container of your own, you may need to create a new Docker container. The following sections show how to create Docker containers with your training and inference algorithms for use with SageMaker.

**Topics**

- Use Your Own Training Algorithms (p. 3181)
- Use Your Own Inference Code (p. 3191)
Use Your Own Training Algorithms

This section explains how Amazon SageMaker interacts with a Docker container that runs your custom training algorithm. Use this information to write training code and create a Docker image for your training algorithms.

Topics
- How Amazon SageMaker Runs Your Training Image (p. 3181)
- How Amazon SageMaker Provides Training Information (p. 3185)
- Run Training with EFA (p. 3188)
- How Amazon SageMaker Signals Algorithm Success and Failure (p. 3190)
- How Amazon SageMaker Processes Training Output (p. 3191)

How Amazon SageMaker Runs Your Training Image

Amazon SageMaker processes your training image using a Docker container entrypoint script. By default, SageMaker looks for a script called train inside your container. You can also provide your own custom entrypoint by using the ContainerArguments and ContainerEntrypoint parameters of the AlgorithmSpecification API. If you use your own custom entrypoint, you have the added flexibility to run it as a standalone script without rebuilding your images.

This section shows how to run a training image without using the SageMaker training toolkit library. If you're unfamiliar with manually configuring a Docker container, we recommend that you use the toolkit instead. For more information about how to use the training toolkit, see Adapting Your Own Training Container (p. 3166).

You have two options to manually configure your Docker container to run your image. You can use the CreateTrainingJob API and a Docker container with an entrypoint instruction contained inside of it. Alternatively, you can use the CreateTrainingJob API, and pass your training script from outside of your Docker container.

Run a training job with an entrypoint script bundled inside the Docker container

SageMaker can run an entrypoint script bundled inside your Docker container.

- By default, Amazon SageMaker runs the following container.

```bash
docker run image train
```

- SageMaker overrides any default CMD statements in a container by specifying the train argument after the image name. In your Docker container, use the following exec form of the ENTRYPONT instruction.

```bash
ENTRYPOINT ["executable", "param1", "param2", ...]
```

The following example shows how to specify a python entrypoint instruction called k-means-algorithm.py.

```bash
ENTRYPOINT ["python", "k-means-algorithm.py"]
```

The exec form of the ENTRYPONT instruction starts the executable directly, not as a child of /bin/sh. This enables it to receive signals like SIGTERM and SIGKILL from SageMaker APIs. The following conditions apply when using the SageMaker APIs.
The `CreateTrainingJob` API has a stopping condition that directs SageMaker to stop model training after a specific time.

The following shows the `StopTrainingJob` API. This API issues the equivalent of the `docker stop`, with a 2-minute timeout command to gracefully stop the specified container.

```
docker stop -t 120
```

The command attempts to stop the running container by sending a SIGTERM signal. After the 2-minute timeout, the API sends SIGKILL and forcibly stops the containers. If the container handles the SIGTERM gracefully and exits within 120 seconds from receiving it, no SIGKILL is sent.

If you want access to the intermediate model artifacts after SageMaker stops the training, add code to handle saving artifacts in your SIGTERM handler.

- If you plan to use GPU devices for model training, make sure that your containers are `nvidia-docker` compatible. Include only the CUDA toolkit on containers; don't bundle NVIDIA drivers with the image. For more information about `nvidia-docker`, see NVIDIA/nvidia-docker.
- You can't use the `tini` initializer as your entrypoint script in SageMaker containers because it gets confused by the `train` and `serve` arguments.
- `/opt/ml` and all subdirectories are reserved by SageMaker training. When building your algorithm's Docker image, make sure that you don't place any data that's required by your algorithm in this directory. Because if you do, the data may no longer be visible during training.

### Run a training job with an entrypoint script outside the Docker container

You can use your own Docker container for training and pass in an entrypoint script from outside the Docker container. There are some benefits to structuring your entrypoint script outside the container. If you update your entrypoint script, you don't need to rebuild the Docker container. You can also use several different scripts to run in the same container.

Specify the location of your training script using the `ContainerEntrypoint` and `ContainerArguments` parameters of the `AlgorithmSpecification` API. These entrypoints and arguments behave in the same manner as Docker entrypoints and arguments. The values in these parameters override the corresponding `ENTRYPOINT` or `CMD` provided as part of the Docker container.

When you pass your custom entrypoint script to your Docker training container, the inputs that you provide determine the behavior of the container.

- For example, if you provide only `ContainerEntrypoint`, the request syntax using the `CreateTrainingJob` API is as follows.

```
{
   "AlgorithmSpecification": {
      "ContainerEntrypoint": ["string"],
      ...
   }
}
```

Then, the SageMaker training backend runs your custom entrypoint as follows.

```
docker run --entrypoint <ContainerEntrypoint> image
```
To bundle your shell or Python scripts inside your Docker image, or to provide the script in an Amazon S3 bucket or by using the AWS Command Line Interface (CLI), continue to the following section.

**Bundle your shell script in a Docker container**

If you want to bundle your custom shell script inside your Docker image, use the following steps.

1. Bundle your shell script inside your Docker container. The following code snippet copies a custom entrypoint script `custom_entrypoint.sh` from the current working directory to a Docker container located in `mydir`. The following example assumes that the base Docker image has Python installed.

   ```
   FROM <base-docker-image>:<tag>
   
   # Copy custom entrypoint from current dir to /mydir on container
   COPY ./custom_entrypoint.sh /mydir/
   
   2. Build and push a Docker container to the Amazon Elastic Container Registry (Amazon ECR) by following the instructions at [Pushing a Docker image](https://docs.aws.amazon.com/AmazonElasticContainerRegistry/latest/userguide/creating-docker-images.html) in the Amazon ECR User Guide.

   3. Launch the training job by running the following AWS CLI command.

Note

If `ContainerEntrypoint` is provided, the SageMaker training backend runs the image with the given entrypoint and overrides the default `ENTRYPOINT` in the image.

- If you provide only `ContainerArguments`, SageMaker assumes that the Docker container contains an entrypoint script. The request syntax using the `CreateTrainingJob` API is as follows.

```json
{
   "AlgorithmSpecification": {
      "ContainerArguments": ["arg1", "arg2"],
      ...
   }
}
```

The SageMaker training backend runs your custom entrypoint as follows.

```bash
docker run image <ContainerArguments>
```

- If you provide both the `ContainerEntrypoint` and `ContainerArguments`, then the request syntax using the `CreateTrainingJob` API is as follows.

```json
{
   "AlgorithmSpecification": {
      "ContainerEntrypoint": ["string"],
      "ContainerArguments": ["arg1", "arg2"],
      ...
   }
}
```

The SageMaker training backend runs your custom entrypoint as follows.

```bash
docker run --entrypoint <ContainerEntrypoint> image <ContainerArguments>
```

You can use any supported `InputDataConfig` source in the `CreateTrainingJob` API to provide an entrypoint script to run your training image.
Bundle your Python script in a Docker container

To bundle your custom Python script inside your Docker image, use the following steps.

1. Bundle your Python script in your Dockerfile. The following code snippet copies a custom entrypoint script `custom_entrypoint.py` from the current working directory to a Docker container located in `mydir`.

```bash
FROM <base-docker-image>:<tag>
# Copy custom entrypoint from current dir to /mydir on container
COPY ./custom_entrypoint.py /mydir/
```

2. Launch the training job by running the following AWS CLI command.

```bash
aws --region <your-region> sagemaker create-training-job
--training-job-name <your-training-job-name>
--role-arn <your-execution-role-arn>
--algorithm-specification '{
  "TrainingInputMode": "File", 
  "TrainingImage": "<your-ecr-image>", 
  "ContainerEntrypoint": ["/bin/sh"], 
  "ContainerArguments": ["/mydir/custom_entrypoint.sh"]}
--output-data-config '{"S3OutputPath": "s3://custom-entrypoint-output-bucket/"}'
--resource-config
{"VolumeSizeInGB":10,"InstanceCount":1,"InstanceType":"ml.m5.2xlarge"}
--stopping-condition '{"MaxRuntimeInSeconds": 180}'
```

Provide your entrypoint script in an Amazon S3 bucket

To provide a custom entrypoint script using an S3 bucket, use the `S3DataSource` parameter of the `DataSource` API to specify the location of the script. If you use the `S3DataSource` parameter, the following are required.

- The `InputMode` must be of the type `File`.
- The `S3DataDistributionType` must be `FullyReplicated`.

The following example has a script called `custom_entrypoint.sh` placed in a path to an S3 bucket `s3://<bucket-name>/<bucket prefix>/custom_entrypoint.sh`.

```bash
#!/bin/bash
echo "Running custom_entrypoint.sh"
echo "Hello you have provided the following arguments: "$@"
```

Next, you must set the configuration of the input data channel to run a training job. Do this either by using the AWS CLI directly or with a JSON file.
Using AWS CLI with a JSON file

To use AWS CLI with a JSON file, ensure that all of the following fields use the request syntax defined in the CreateTrainingJob API.

```json
// run-my-training-job.json
{
    "AlgorithmSpecification": {
        "ContainerEntrypoint": ["/bin/sh"],
        "ContainerArguments": ["/opt/ml/input/data/<your_channel_name>/custom_entrypoint.sh"],
        ...
    },
    "InputDataConfig": [
        {
            "ChannelName": "<your_channel_name>",
            "DataSource": {
                "S3DataSource": {
                    "S3DataDistributionType": "FullyReplicated",
                    "S3DataType": "S3Prefix",
                    "S3Uri": "s3://<bucket-name>/<bucket_prefix>",
                }},
            "InputMode": "File",
            ...
        }
    }
}
```

Next, run the AWS CLI command to launch the training job from the JSON file as follows.

```bash
aws sagemaker create-training-job --cli-input-json file://run-my-training-job.json
```

Using AWS CLI directly

To use AWS CLI directly without a JSON file, use the following code structure.

```bash
aws --region <your-region> sagemaker create-training-job \
    --training-job-name <your-training-job-name> \
    --role-arn <your-execution-role-arn> \
    --algorithm-specification '{ 
        "TrainingInputMode": "File", 
        "TrainingImage": "<your-ecr-image>", 
        "ContainerEntrypoint": ["/bin/sh"], 
        "ContainerArguments": ["/opt/ml/input/data/<your_channel_name>/custom_entrypoint.sh"]}
    --input-data-config '{
        "ChannelName": ",
        "DataSource": {
            "S3DataSource": {
                "S3DataDistributionType": "FullyReplicated",
                "S3DataType": "S3Prefix",
                "S3Uri": "s3://<bucket-name>/<bucket_prefix>",
            }
        }},
    --output-data-config '{"S3OutputPath": "s3://custom-entrypoint-output-bucket/"}'}
    --resource-config '{"VolumeSizeInGB": 10,"InstanceCount":1,"InstanceType":"ml.m5.2xlarge"}'}
    --stopping-condition '{"MaxRuntimeInSeconds": 180}'}
```

How Amazon SageMaker Provides Training Information

This section explains how SageMaker makes training information, such as training data, hyperparameters, and other configuration information, available to your Docker container.
When you send a `CreateTrainingJob` request to SageMaker to start model training, you specify the Amazon Elastic Container Registry (Amazon ECR) path of the Docker image that contains the training algorithm. You also specify the Amazon Simple Storage Service (Amazon S3) location where training data is stored and algorithm-specific parameters. SageMaker makes this information available to the Docker container so that your training algorithm can use it. This section explains how we make this information available to your Docker container. For information about creating a training job, see `CreateTrainingJob`. For more information on the way that SageMaker containers organize information, see *Using the SageMaker Training and Inference Toolkits* (p. 3165).

**Topics**

- Hyperparameters (p. 3186)
- Environment Variables (p. 3186)
- Input Data Configuration (p. 3186)
- Training Data (p. 3187)
- Distributed Training Configuration (p. 3188)

### Hyperparameters

SageMaker makes the hyperparameters in a `CreateTrainingJob` request available in the Docker container in the `/opt/ml/input/config/hyperparameters.json` file.

### Environment Variables

The following environment variables are set in the container:

- `TRAINING_JOB_NAME` – Specified in the `TrainingJobName` parameter of the `CreateTrainingJob` request.
- `TRAINING_JOB_ARN` – The Amazon Resource Name (ARN) of the training job returned as the `TrainingJobArn` in the `CreateTrainingJob` response.
- All environment variables specified in the `Environment` parameter in the `CreateTrainingJob` request.

### Input Data Configuration

You specify data channel information in the `InputDataConfig` parameter in a `CreateTrainingJob` request. SageMaker makes this information available in the `/opt/ml/input/config/inputdataconfig.json` file in the Docker container.

For example, suppose that you specify three data channels (train, evaluation, and validation) in your request. SageMaker provides the following JSON:

```json
{
  "train" : {
    "ContentType": "trainingContentType",
    "TrainingInputMode": "File",
    "S3DistributionType": "FullyReplicated",
    "RecordWrapperType": "None"},
  "evaluation" : {
    "ContentType": "evalContentType",
    "TrainingInputMode": "File",
    "S3DistributionType": "FullyReplicated",
    "RecordWrapperType": "None"},
  "validation" : {
    "TrainingInputMode": "File",
    "S3DistributionType": "FullyReplicated",
    "RecordWrapperType": "None"}
}
```
Note
SageMaker provides only relevant information about each data channel (for example, the channel name and the content type) to the container, as shown. S3DistributionType will be set as FullyReplicated if specify EFS or FSxLustre as input data sources.

Training Data
The TrainingInputMode parameter in the AlgorithmSpecification of the CreateTrainingJob request specifies how the training dataset is made available. The following input modes are available:

- **File mode**
  - TrainingInputMode parameter written to inputdataconfig.json: "File"
  - Data channel directory in the Docker container: /opt/ml/input/data/channel_name
  - Supported data sources: Amazon Simple Storage Service (Amazon S3), Amazon Elastic File System (Amazon EFS), and Amazon FSx for Lustre

  A directory is created for each channel. For example, if you have three channels named training, validation, and testing, SageMaker makes three directories in the Docker container:
  - /opt/ml/input/data/training
  - /opt/ml/input/data/validation
  - /opt/ml/input/data/testing

  **Note**
  Channels that use file system data sources such as Amazon EFS and Amazon FSx must use File mode. If a file system is specified, the directory path provided in the channel is mounted at /opt/ml/input/data/channel_name.

- **FastFile mode**
  - TrainingInputMode parameter written to inputdataconfig.json: "FastFile"
  - Data channel directory in the Docker container: /opt/ml/input/data/channel_name
  - Supported data sources: Amazon S3

  The channel directory is mounted as read-only.

  Algorithms that support File mode can seamlessly work with FastFile mode with no code changes.

  **Note**
  Channels that use FastFile mode must use a S3DataType of "S3Prefix".

  FastFile mode presents a folder view that uses the forward slash (/) as the delimiter for grouping Amazon S3 objects into folders. S3Uri prefixes must not correspond to a partial folder name. For example, if an Amazon S3 dataset contains s3://my-bucket/train-01/data.csv, then neither s3://my-bucket/train nor s3://my-bucket/train-01 are allowed as S3Uri prefixes.

  A trailing forward slash is recommended to define a channel corresponding to a folder. For example, the s3://my-bucket/train-01/ channel for the train-01 folder. Without the trailing forward slash, the channel would be ambiguous if there existed another folder s3://my-bucket/train-011/ or file s3://my-bucket/train-01.txt/.

- **Pipe mode**
  - TrainingInputMode parameter written to inputdataconfig.json: "Pipe"
  - Data channel directory in the Docker container: /opt/ml/input/data/channel_name_epoch_number
  - Supported data sources: Amazon S3

  You need to read from a separate pipe for each channel. For example, if you have three channels named training, validation, and testing, you need to read from the following pipes:
  - /opt/ml/input/data/training_0, /opt/ml/input/data/training_1, ...
• /opt/ml/input/data/validation_0, /opt/ml/input/data/validation_1, ...
• /opt/ml/input/data/testing_0, /opt/ml/input/data/testing_1, ...

Read the pipes sequentially. For example, if you have a channel called training, read the pipes in this sequence:

1. Open /opt/ml/input/data/training_0 in read mode and read it to end-of-file (EOF) or, if you are done with the first epoch, close the pipe file early.
2. After closing the first pipe file, look for /opt/ml/input/data/training_1 and read it until you have completed the second epoch, and so on.

If the file for a given epoch doesn't exist yet, your code may need to retry until the pipe is created. There is no sequencing restriction across channel types. For example, you can read multiple epochs for the training channel and only start reading the validation channel when you are ready. Or, you can read them simultaneously if your algorithm requires that.

For an example of a Jupyter notebook that shows how to use Pipe mode when bringing your own container, see Bring your own pipe-mode algorithm to Amazon SageMaker.

Distributed Training Configuration

If you're performing distributed training with multiple containers, SageMaker makes information about all containers available in the /opt/ml/input/config/resourceconfig.json file.

To enable inter-container communication, this JSON file contains information for all containers. SageMaker makes this file available for both File and Pipe mode algorithms. The file provides the following information:

- current_host—The name of the current container on the container network. For example, algo-1. Host values can change at any time. Don't write code with specific values for this variable.
- hosts—The list of names of all containers on the container network, sorted lexicographically. For example, ["algo-1", "algo-2", "algo-3"] for a three-node cluster. Containers can use these names to address other containers on the container network. Host values can change at any time. Don't write code with specific values for these variables.
- network_interface_name—The name of the network interface that is exposed to your container. For example, containers running the Message Passing Interface (MPI) can use this information to set the network interface name.
- Do not use the information in /etc/hostname or /etc/hosts because it might be inaccurate.
- Hostname information may not be immediately available to the algorithm container. We recommend adding a retry policy on hostname resolution operations as nodes become available in the cluster.

The following is an example file on node 1 in a three-node cluster:

```json
{
    "current_host": "algo-1",
    "hosts": ["algo-1","algo-2","algo-3"],
    "network_interface_name": "eth1"
}
```

Run Training with EFA

SageMaker provides integration with EFA devices to accelerate High Performance Computing (HPC) and machine learning applications. This integration allows you to leverage an EFA device when running your distributed training jobs. You can add EFA integration to an existing Docker container that you bring
to SageMaker. The following information outlines how to configure your own container to use an EFA device for your distributed training jobs.

Prerequisites

Your container must satisfy the SageMaker Training container specification.

Install EFA and required packages

Your container must download and install the EFA software. This allows your container to recognize the EFA device, and provides compatible versions of Libfabric and Open MPI.

Any tools like MPI and NCCL must be installed and managed inside the container to be used as part of your EFA-enabled training job. The following example shows how to modify the Dockerfile of your EFA-enabled container to install EFA, MPI, OFI, NCCL, and NCCL-TEST.

Note

When using PyTorch with EFA on your container, the NCCL version of your container should match the NCCL version of your PyTorch installation. To verify the PyTorch NCCL version, use the following command:

```
torch.cuda.nccl.version()
```

ARG OPEN_MPI_PATH=/opt/amazon/openmpi/
ENV NCCL_VERSION=2.7.8
ENV EFA_VERSION=1.11.2
ENV BRANCH_OFI=1.1.1

#################################################
## EFA and MPI SETUP
RUN cd $HOME 
   && curl -O https://s3-us-west-2.amazonaws.com/aws-efa-installer/aws-efa-installer-
   ${EFA_VERSION}.tar.gz 
   && tar -xf aws-efa-installer-$EFA_VERSION.tar.gz 
   && cd aws-efa-installer 
   && ./efa_installer.sh -y --skip-kmod -g 
   ENV PATH="$OPEN_MPI_PATH/bin:$PATH"
   ENV LD_LIBRARY_PATH="$OPEN_MPI_PATH/lib/:$LD_LIBRARY_PATH"

#################################################
## NCCL, OFI, NCCL-TEST SETUP
RUN cd $HOME 
   && git clone https://github.com/NVIDIA/nccl.git -b v${NCCL_VERSION}-1 
   && cd nccl 
   && make -j64 src.build BUILDDIR=/usr/local 

RUN apt-get update && apt-get install -y autoconf
RUN cd $HOME 
   && git clone https://github.com/aws/aws-ofi-nccl.git -b v${BRANCH_OFI} 
   && cd aws-ofi-nccl 
   && ./autogen.sh 
   && ./configure --with-libfabric=/opt/amazon/efa 
   && make & make install 

RUN cd $HOME 
   && git clone https://github.com/NVIDIA/nccl-tests 
   && cd nccl-tests 
   && make MPI=1 MPI_HOME=/opt/amazon/openmpi CUDA_HOME=/usr/local/cuda NCCL_HOME=/usr/local

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Considerations when creating your container

The EFA device is mounted to the container as /dev/infiniband/uverbs0 under the list of devices accessible to the container. On P4d instances, the container has access to 4 EFA devices. The EFA devices can be found in the list of devices accessible to the container as:

- /dev/infiniband/uverbs0
- /dev/infiniband/uverbs1
- /dev/infiniband/uverbs2
- /dev/infiniband/uverbs3

To get information about hostname, peer hostnames, and network interface (for MPI) from the resourceconfig.json file provided to each container instances, see Distributed Training Configuration. Your container handles regular TCP traffic among peers through the default Elastic Network Interfaces (ENI), while handling OFI (kernel bypass) traffic through the EFA device.

Verify that your EFA device is recognized

To verify that the EFA device is recognized, run the following command from within your container.

```
/opt/amazon/efa/bin/fi_info -p efa
```

Your output should look similar to the following.

```
provider: efa
  fabric: EFA-fe80::e5:56ff:fe34:56a8
  domain: efa_0-rdm
  version: 2.0
  type: FI_EP_RDM
  protocol: FI_PROTO_EFA
provider: efa
  fabric: EFA-fe80::e5:56ff:fe34:56a8
  domain: efa_0-dgrm
  version: 2.0
  type: FI_EP_DGRAM
  protocol: FI_PROTO_EFA
provider: efa;ofi_rxd
  fabric: EFA-fe80::e5:56ff:fe34:56a8
  domain: efa_0-drgm
  version: 1.0
  type: FI_EP_RDM
  protocol: FI_PROTO_RXD
```

Running a training job with EFA

Once you've created an EFA-enabled container, you can run a training job with EFA using a SageMaker Estimator the same way as you would with any other Docker image. For more information on registering your container and using it for training, see Adapting Your Own Training Container.

How Amazon SageMaker Signals Algorithm Success and Failure

A training algorithm indicates whether it succeeded or failed using the exit code of its process.

A successful training execution should exit with an exit code of 0 and an unsuccessful training execution should exit with a non-zero exit code. These will be converted to Completed and Failed in the TrainingJobStatus returned by DescribeTrainingJob. This exit code convention is standard and is easily implemented in all languages. For example, in Python, you can use `sys.exit(1)` to signal a failure exit, and simply running to the end of the main routine will cause Python to exit with code 0.
In the case of failure, the algorithm can write a description of the failure to the failure file. See next section for details.

**How Amazon SageMaker Processes Training Output**

As your algorithm runs in a container, it generates output including the status of the training job and model and output artifacts. Your algorithm should write this information to the following files, which are located in the container's `/output` directory. Amazon SageMaker processes the information contained in this directory as follows:

- `/opt/ml/model` – Your algorithm should write all final model artifacts to this directory. SageMaker copies this data as a single object in compressed tar format to the S3 location that you specified in the `CreateTrainingJob` request. If multiple containers in a single training job write to this directory they should ensure no file/directory names clash. SageMaker aggregates the result in a tar file and uploads to S3. SageMaker aggregates the result in a TAR file and uploads to S3 at the end of the training job.

- `/opt/ml/output` – Your algorithm should write artifacts you want to store other than the final model to this directory. SageMaker copies this data as a single object in compressed tar format to the S3 location that you specified in the `CreateTrainingJob` request. If multiple containers in a single training job write to this directory they should ensure no file/directory names clash. SageMaker aggregates the result in a TAR file and uploads to S3 at the end of the training job.

- `/opt/ml/output/failure` – If training fails, after all algorithm output (for example, logging) completes, your algorithm should write the failure description to this file. In a `DescribeTrainingJob` response, SageMaker returns the first 1024 characters from this file as `FailureReason`.

**Use Your Own Inference Code**

You can use Amazon SageMaker to interact with Docker containers and run your own inference code in one of two ways:

- To use your own inference code with a persistent endpoint to get one prediction at a time, use SageMaker hosting services.
- To use your own inference code to get predictions for an entire dataset, use SageMaker batch transform.

**Topics**
- Use Your Own Inference Code with Hosting Services (p. 3191)
- Use Your Own Inference Code with Batch Transform (p. 3197)

**Use Your Own Inference Code with Hosting Services**

This section explains how Amazon SageMaker interacts with a Docker container that runs your own inference code for hosting services. Use this information to write inference code and create a Docker image.

**Topics**
- How SageMaker Runs Your Inference Image (p. 3192)
- How SageMaker Loads Your Model Artifacts (p. 3193)
- How Containers Serve Requests (p. 3193)
- How Your Container Should Respond to Inference Requests (p. 3193)
- How Your Container Should Respond to Health Check (Ping) Requests (p. 3193)
• Use a Private Docker Registry for Real-Time Inference Containers (p. 3194)

How SageMaker Runs Your Inference Image

To configure a container to run as an executable, use an ENTRYPOINT instruction in a Dockerfile. Note the following:

• For model inference, SageMaker runs the container as:

  ```bash
docker run image serve
  ```

  SageMaker overrides default CMD statements in a container by specifying the `serve` argument after the image name. The `serve` argument overrides arguments that you provide with the CMD command in the Dockerfile.

• We recommend that you use the `exec` form of the ENTRYPOINT instruction:

  ```python
  ENTRYPOINT ["executable", "param1", "param2"]
  ```

  For example:

  ```python
  ENTRYPOINT ["python", "k_means_inference.py"]
  ```

  The `exec` form of the ENTRYPOINT instruction starts the executable directly, not as a child of `/bin/sh`. This enables it to receive signals like `SIGTERM` and `SIGKILL` from the SageMaker API operations, which is a requirement.

  For example, when you use the `CreateEndpoint` API to create an endpoint, SageMaker provisions the number of ML compute instances required by the endpoint configuration, which you specify in the request. SageMaker runs the Docker container on those instances.

  If you reduce the number of instances backing the endpoint (by calling the `UpdateEndpointWeightsAndCapacities` API), SageMaker runs a command to stop the Docker container on the instances that are being terminated. The command sends the `SIGTERM` signal, then it sends the `SIGKILL` signal thirty seconds later.

  If you update the endpoint (by calling the `UpdateEndpoint` API), SageMaker launches another set of ML compute instances and runs the Docker containers that contain your inference code on them. Then it runs a command to stop the previous Docker containers. To stop a Docker container, command sends the `SIGTERM` signal, then it sends the `SIGKILL` signal 30 seconds later.

• SageMaker uses the container definition that you provided in your `CreateModel` request to set environment variables and the DNS hostname for the container as follows:

  • It sets environment variables using the `ContainerDefinition.Environment string-to-string map`. 
• It sets the DNS hostname using the `ContainerDefinition.ContainerHostname`.

• If you plan to use GPU devices for model inferences (by specifying GPU-based ML compute instances in your `CreateEndpointConfig` request), make sure that your containers are `nvidia-docker` compatible. Don't bundle NVIDIA drivers with the image. For more information about `nvidia-docker`, see `NVIDIA/nvidia-docker`.

• You can't use the `tini` initializer as your entry point in SageMaker containers because it gets confused by the `train` and `serve` arguments.

How SageMaker Loads Your Model Artifacts

In your `CreateModel` request, the container definition includes the `ModelDataUrl` parameter, which identifies the S3 location where model artifacts are stored. SageMaker uses this information to determine from where to copy the model artifacts. It copies the artifacts to the `/opt/ml/model` directory for use by your inference code.

The `ModelDataUrl` must point to a tar.gz file. Otherwise, SageMaker won't download the file.

If you trained your model in SageMaker, the model artifacts are saved as a single compressed tar file in Amazon S3. If you trained your model outside SageMaker, you need to create this single compressed tar file and save it in a S3 location. SageMaker decompresses this tar file into `/opt/ml/model` directory before your container starts.

How Containers Serve Requests

Containers need to implement a web server that responds to `/invocations` and `/ping` on port 8080.

How Your Container Should Respond to Inference Requests

To obtain inferences, the client application sends a POST request to the SageMaker endpoint. For more information, see the `InvokeEndpoint` API. SageMaker passes the request to the container, and returns the inference result from the container to the client. Note the following:

• SageMaker strips all POST headers except those supported by `InvokeEndpoint`. SageMaker might add additional headers. Inference containers must be able to safely ignore these additional headers.

• To receive inference requests, the container must have a web server listening on port 8080 and must accept POST requests to the `/invocations` endpoint.

• A customer's model containers must accept socket connection requests within 250 ms.

• A customer's model containers must respond to requests within 60 seconds. The model itself can have a maximum processing time of 60 seconds before responding to the `/invocations`. If your model is going to take 50-60 seconds of processing time, the SDK socket timeout should be set to be 70 seconds.

How Your Container Should Respond to Health Check (Ping) Requests

The `CreateEndpoint` and `UpdateEndpoint` API calls result in SageMaker starting new inference containers. Soon after container startup, SageMaker starts sending periodic GET requests to the `/ping` endpoint.

The simplest requirement on the container is to respond with an HTTP 200 status code and an empty body. This indicates to SageMaker that the container is ready to accept inference requests at the `/invocations` endpoint.
If the container does not begin to pass health checks, by consistently responding with 200s, during the 4 minutes after startup, `CreateEndPoint` will fail, leaving the endpoint in a failed state, and the update requested by `UpdateEndpoint` will not be completed.

While the minimum bar is for the container to return a static 200, a container developer can use this functionality to perform deeper checks. The request timeout on `/ping` attempts is 2 seconds.

**Use a Private Docker Registry for Real-Time Inference Containers**

Amazon SageMaker hosting enables you to use images stored in Amazon ECR to build your containers for real-time inference by default. Optionally, you can build containers for real-time inference from images in a private Docker registry. The private registry must be accessible from an Amazon VPC in your account. Models that you create based on the images stored in your private Docker registry must be configured to connect to the same VPC where the private Docker registry is accessible. For information about connecting your model to a VPC, see *Give SageMaker Hosted Endpoints Access to Resources in Your Amazon VPC* (p. 3650).

Your Docker registry must be secured with a TLS certificate from a known public certificate authority (CA).

**Note**

Your private Docker registry must allow inbound traffic from the security groups you specify in the VPC configuration for your model, so that SageMaker hosting is able to pull model images from your registry.

SageMaker can pull model images from DockerHub if there's a path to the open internet inside your VPC.

**Topics**

- *Store Images in a Private Docker Registry other than Amazon Elastic Container Registry* (p. 3194)
- *Use an Image from a Private Docker Registry for Real-time Inference* (p. 3194)
- *Allow SageMaker to authenticate to a private Docker registry* (p. 3196)
- *Create the Lambda function* (p. 3196)
- *Give your execution role permission to Lambda* (p. 3197)
- *Create an interface VPC endpoint for Lambda* (p. 3197)

**Store Images in a Private Docker Registry other than Amazon Elastic Container Registry**

To use a private Docker registry to store your images for SageMaker real-time inference, create a private registry that is accessible from your Amazon VPC. For information about creating a Docker registry, see *Deploy a registry server* in the Docker documentation. The Docker registry must comply with the following:

- The registry must be a *Docker Registry HTTP API V2* registry.
- The Docker registry must be accessible from the same VPC that you specify in the `VpcConfig` parameter that you specify when you create your model.

**Use an Image from a Private Docker Registry for Real-time Inference**

When you create a model and deploy it to SageMaker hosting, you can specify that it use an image from your private Docker registry to build the inference container. Specify this in the `ImageConfig` object in the `PrimaryContainer` parameter that you pass to a call to the `create_model` function.

**To use an image stored in your private Docker registry for your inference container**

1. Create the image configuration object and specify a value of `Vpc` for the `RepositoryAccessMode` field.
2. If your private Docker registry requires authentication, add a RepositoryAuthConfig object to the image configuration object. For the RepositoryCredentialsProviderArn field of the RepositoryAuthConfig object, specify the Amazon Resource Name (ARN) of an AWS Lambda function that provides credentials that allows SageMaker to authenticate to your private Docker Registry. For information about how to create the Lambda function to provide authentication, see Allow SageMaker to authenticate to a private Docker registry (p. 3196).

```python
image_config = {
    'RepositoryAccessMode': 'Vpc',
    'RepositoryAuthConfig': {
        'RepositoryCredentialsProviderArn':
            'arn:aws:lambda:Region:Acct:function:FunctionName'
    }
}
```

3. Create the primary container object that you want to pass to create_model, using the image configuration object that you created in the previous step.

Provide your image in digest form. If you provide your image using the :latest tag, there is a risk that SageMaker pulls a newer version of the image than intended. Using the digest form ensures that SageMaker pulls the intended image version.

```python
primary_container = {
    'ContainerHostname': 'ModelContainer',
    'Image': 'myteam.myorg.com/docker-local/my-inference-image:<IMAGE-TAG>',
    'ImageConfig': image_config
}
```

4. Specify the model name and the execution role that you want to pass to create_model.

```python
model_name = 'vpc-model'
execution_role_arn = 'arn:aws:iam::123456789012:role/SageMakerExecutionRole'
```

5. Specify one or more security groups and subnets for the VPC configuration for your model. Your private Docker registry must allow inbound traffic from the security groups that you specify. The subnets that you specify must be in the same VPC as your private Docker registry.

```python
vpc_config = {
    'SecurityGroupIds': ['sg-0123456789abcdef0'],
    'Subnets': ['subnet-0123456789abcdef0','subnet-0123456789abcdef1']
}
```


```python
import boto3
sm = boto3.client('sagemaker')
```

7. Create the model by calling create_model, using the values you specified in the previous steps for the PrimaryContainer and VpcConfig parameters.

```python
try:
    resp = sm.create_model(
        ModelName=model_name,
        PrimaryContainer=primary_container,
        ExecutionRoleArn=execution_role_arn,
        VpcConfig=vpc_config,
    )
```
8. Finally, call `create_endpoint_config` and `create_endpoint` to create the hosting endpoint, using the model that you created in the previous step.

```python
endpoint_config_name = 'my-endpoint-config'
sm.create_endpoint_config(
    EndpointConfigName=endpoint_config_name,
    ProductionVariants=[
        {'VariantName': 'MyVariant',
         'ModelName': model_name,
         'InitialInstanceCount': 1,
         'InstanceType': 'ml.t2.medium'},
    ],
)
endpoint_name = 'my-endpoint'
sm.create_endpoint(
    EndpointName=endpoint_name,
    EndpointConfigName=endpoint_config_name,
)
sm.describe_endpoint(EndpointName=endpoint_name)
```

**Allow SageMaker to authenticate to a private Docker registry**

To pull an inference image from a private Docker registry that requires authentication, create an AWS Lambda function that provides credentials, and provide the Amazon Resource Name (ARN) of the Lambda function when you call `create_model`. When SageMaker runs `create_model`, it calls the Lambda function that you specified to get credentials to authenticate to your Docker registry.

**Create the Lambda function**

Create an AWS Lambda function that returns a response with the following form:

```python
def handler(event, context):
    response = {
        "Credentials": {"Username": "username", "Password": "password"}
    }
    return response
```

Depending on how you set up authentication for your private Docker registry, the credentials that your Lambda function returns can mean either of the following:

- If you set up your private Docker registry to use basic authentication, this is the `username` and `password` to authenticate to the registry.
- If you set up your private Docker registry to use bearer token authentication, the `username` and `password` are sent to your authorization server, which returns a Bearer token that can then be used to authenticate to the private Docker registry.
Give your execution role permission to Lambda

The execution role that you use to call create_model must have permissions to call AWS Lambda functions. Add the following to the permissions policy of your execution role.

```
{
    "Effect": "Allow",
    "Action": [
        "lambda:InvokeFunction"
    ],
    "Resource": [
        "arn:aws:lambda:*:*:function:*myLambdaFunction*"
    ]
}
```

Where `myLambdaFunction` is the name of your Lambda function. For information about editing a role permissions policy, see Modifying a role permissions policy (console) in the AWS Identity and Access Management User Guide.

**Note**

An execution role with the AmazonSageMakerFullAccess managed policy attached to it has permission to call any Lambda function with SageMaker in its name.

Create an interface VPC endpoint for Lambda

Create an interface endpoint so that your Amazon VPC can communicate with your AWS Lambda function without sending traffic over the internet. For information about how to do this, see Configuring interface VPC endpoints for Lambda in the AWS Lambda Developer Guide.

SageMaker hosting sends a request through your VPC to `lambda.region.amazonaws.com`, to call your Lambda function. If you choose Private DNS Name when you create your interface endpoint, Amazon Route 53 routes the call to the Lambda interface endpoint. If you use a different DNS provider, make sure to map `lambda.region.amazonaws.com` to your Lambda interface endpoint.

Use Your Own Inference Code with Batch Transform

This section explains how Amazon SageMaker interacts with a Docker container that runs your own inference code for batch transform. Use this information to write inference code and create a Docker image.

**Topics**
- How SageMaker Runs Your Inference Image (p. 3197)
- How SageMaker Loads Your Model Artifacts (p. 3198)
- How Containers Serve Requests (p. 3199)
- How Your Container Should Respond to Inference Requests (p. 3199)
- How Your Container Should Respond to Health Check (Ping) Requests (p. 3200)

**How SageMaker Runs Your Inference Image**

To configure a container to run as an executable, use an ENTRYPOINT instruction in a Dockerfile. Note the following:

- For batch transforms, SageMaker runs the container as:

```
docker run image serve
```
SageMaker overrides default CMD statements in a container by specifying the `serve` argument after the image name. The `serve` argument overrides arguments that you provide with the CMD command in the Dockerfile.

- We recommend that you use the exec form of the ENTRYPOINT instruction:

  ```
  ENTRYPOINT ["executable", "param1", "param2"]
  ```

  For example:

  ```
  ENTRYPOINT ["python", "k_means_inference.py"]
  ```

- SageMaker sets environment variables specified in `CreateModel` and `CreateTransformJob` on your container. Additionally, the following environment variables are populated:
  - `SAGEMAKER_BATCH` is always set to `true` when the container runs in Batch Transform.
  - `SAGEMAKER_MAX_PAYLOAD_IN_MB` is set to the largest size payload that is sent to the container via HTTP.
  - `SAGEMAKER_BATCH_STRATEGY` is set to `SINGLE_RECORD` when the container is sent a single record per call to invocations and `MULTI_RECORD` when the container gets as many records as will fit in the payload.
  - `SAGEMAKER_MAX_CONCURRENT_TRANSFORMS` is set to the maximum number of /invocations requests that can be opened simultaneously.

  **Note**
  The last three environment variables come from the API call made by the user. If the user doesn't set values for them, they aren't passed. In that case, either the default values or the values requested by the algorithm (in response to the /execution-parameters) are used.

- If you plan to use GPU devices for model inferences (by specifying GPU-based ML compute instances in your `CreateTransformJob` request), make sure that your containers are nvidia-docker compatible. Don't bundle NVIDIA drivers with the image. For more information about nvidia-docker, see [NVIDIA/nvidia-docker](https://github.com/NVIDIA/nvidia-docker).

- You can't use the `init` initializer as your entry point in SageMaker containers because it gets confused by the train and serve arguments.

### How SageMaker Loads Your Model Artifacts

In a `CreateModel` request, container definitions include the `ModelDataUrl` parameter, which identifies the location in Amazon S3 where model artifacts are stored. When you use SageMaker to run inferences, it uses this information to determine from where to copy the model artifacts. It copies the artifacts to the `/opt/ml/model` directory in the Docker container for use by your inference code.

The `ModelDataUrl` parameter must point to a tar.gz file. Otherwise, SageMaker can't download the file. If you train a model in SageMaker, it saves the artifacts as a single compressed tar file in Amazon S3. If you train a model in another framework, you need to store the model artifacts in Amazon S3 as a compressed tar file. SageMaker decompresses this tar file and saves it in the `/opt/ml/model` directory in the container before the batch transform job starts.
How Containers Serve Requests

Containers must implement a web server that responds to invocations and ping requests on port 8080. For batch transforms, you have the option to set algorithms to implement execution-parameters requests to provide a dynamic runtime configuration to SageMaker. SageMaker uses the following endpoints:

- ping—Used to periodically check the health of the container. SageMaker waits for an HTTP 200 status code and an empty body for a successful ping request before sending an invocations request. You might use a ping request to load a model into memory to generate inference when invocations requests are sent.
- (Optional) execution-parameters—Allows the algorithm to provide the optimal tuning parameters for a job during runtime. Based on the memory and CPUs available for a container, the algorithm chooses the appropriate MaxConcurrentTransforms, BatchStrategy, and MaxPayloadInMB values for the job.

Before calling the invocations request, SageMaker attempts to invoke the execution-parameters request. When you create a batch transform job, you can provide values for the MaxConcurrentTransforms, BatchStrategy, and MaxPayloadInMB parameters. SageMaker determines the values for these parameters using this order of precedence:

1. The parameter values that you provide when you create the CreateTransformJob request.
2. The values that the model container returns when SageMaker invokes the execution-parameters endpoint.
3. The default parameter values, listed in the following table.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Default Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>MaxConcurrentTransforms</td>
<td>1</td>
</tr>
<tr>
<td>BatchStrategy</td>
<td>MULTI_RECORD</td>
</tr>
<tr>
<td>MaxPayloadInMB</td>
<td>6</td>
</tr>
</tbody>
</table>

The response for a GET execution-parameters request is a JSON object with keys for MaxConcurrentTransforms, BatchStrategy, and MaxPayloadInMB parameters. This is an example of a valid response:

```json
{
    "MaxConcurrentTransforms": 8,
    "BatchStrategy": "MULTI_RECORD",
    "MaxPayloadInMB": 6
}
```

How Your Container Should Respond to Inference Requests

To obtain inferences, Amazon SageMaker sends a POST request to the inference container. The POST request body contains data from Amazon S3. Amazon SageMaker passes the request to the container, and returns the inference result from the container, saving the data from the response to Amazon S3.

To receive inference requests, the container must have a web server listening on port 8080 and must accept POST requests to the /invocations endpoint. The inference request timeout and max retries can be configured through ModelClientConfig.
How Your Container Should Respond to Health Check (Ping) Requests

The simplest requirement on the container is to respond with an HTTP 200 status code and an empty body. This indicates to SageMaker that the container is ready to accept inference requests at the /invocations endpoint.

While the minimum bar is for the container to return a static 200, a container developer can use this functionality to perform deeper checks. The request timeout on /ping attempts is 2 seconds.

Example Notebooks: Use Your Own Algorithm or Model

The following Jupyter notebooks show how to use your own algorithms or pretrained models from an Amazon SageMaker notebook instance. For links to the GitHub repositories with the prebuilt Dockerfiles for the TensorFlow, MXNet, Chainer, and PyTorch frameworks and instructions on using the AWS SDK for Python (Boto3) estimators to run your own training algorithms on SageMaker Learner and your own models on SageMaker hosting, see Prebuilt SageMaker Docker Images for Deep Learning (p. 3151)

Setup

1. Create a SageMaker notebook instance. For instructions on how to create and access Jupyter notebook instances, see Use Amazon SageMaker Notebook Instances (p. 291).
2. Open the notebook instance you created.
3. Choose the SageMaker Examples tab for a list of all SageMaker example notebooks.
4. Open the sample notebooks from the Advanced Functionality section in your notebook instance or from GitHub using the provided links. To open a notebook, choose its Use tab, then choose Create copy.

Host Models Trained in Scikit-learn

To learn how to host models trained in Scikit-learn for making predictions in SageMaker by injecting them into first-party k-means and XGBoost containers, see the following sample notebooks.

• kmeans_bring_your_own_model
• xgboost_bring_your_own_model

Package TensorFlow and Scikit-learn Models for Use in SageMaker

To learn how to package algorithms that you have developed in TensorFlow and scikit-learn frameworks for training and deployment in the SageMaker environment, see the following notebooks. They show you how to build, register, and deploy your own Docker containers using Dockerfiles.

• tensorflow_bring_your_own
• scikit_bring_your_own
Train and Deploy a Neural Network on SageMaker

To learn how to train a neural network locally using MXNet or TensorFlow, and then create an endpoint from the trained model and deploy it on SageMaker, see the following notebooks. The MXNet model is trained to recognize handwritten numbers from the MNIST dataset. The TensorFlow model is trained to classify irises.

- `mxnet_mnist_byom`
- `tensorflow_iris_byom`

Training Using Pipe Mode

To learn how to use a Dockerfile to build a container that calls the `train.py` script and uses pipe mode to custom train an algorithm, see the following notebook. In pipe mode, the input data is transferred to the algorithm while it is training. This can decrease training time compared to using file mode.

- `pipe_bring_your_own`

Bring Your Own R Model

To learn how to use an R container to train and host a model with the R kernel installed in a notebook, see the following notebook. To take advantage of the AWS SDK for Python (Boto3), we use Python within the notebook. You can achieve the same results in R by invoking command line arguments.

- `r_bring_your_own`

Extend a Prebuilt PyTorch Container Image

To learn how to extend a prebuilt SageMaker PyTorch container image when you have additional functional requirements for your algorithm or model that the prebuilt Docker image doesn't support, see the following notebook.

- `pytorch_extending_our_containers`

Train and Debug Training Jobs on a Custom Container

To learn how to train and debug training jobs using SageMaker Debugger, see the following notebook. A training script provided through this example uses the TensorFlow Keras ResNet 50 model and the CIFAR10 dataset. A Docker custom container is built with the training script and pushed to Amazon ECR. While the training job is running, Debugger collects tensor outputs and identifies debugging problems. With `smdebug` client library tools, you can set a `smdebug` trial object that calls the training job and debugging information, check the training and Debugger rule status, and retrieve tensors saved in an Amazon S3 bucket to analyze training issues.

- `build_your_own_container_with_debugger`
Troubleshooting your Docker containers

The following are common errors that you might run into when using Docker containers with SageMaker. Each error is followed by a solution to the error.

- **Error: SageMaker has lost the Docker daemon.**
  To fix this error, restart Docker using the following command.

  ```
  sudo service docker restart
  ```

- **Error: The /tmp directory of your Docker container has run out of space.**
  Docker containers use the / and /tmp partitions to store code. These partitions can fill up easily when using large code modules in local mode. The SageMaker Python SDK supports specifying a custom temp directory for your local mode root directory to avoid this issue.

  To specify the custom temp directory in the EBS volume storage, create a file at the following path `~/.sagemaker/config.yaml` and add the following configuration. The directory that you specify as `container_root` must already exist. The SageMaker Python SDK will not try to create it.

  ```
  local:
    container_root: /home/ec2-user/SageMaker/temp
  ```

  With this configuration, local mode uses the /temp directory and not the default /tmp directory.
SageMaker Workflows

You can manage your Amazon SageMaker training and inference workflows using Amazon SageMaker Studio and the Amazon SageMaker Python SDK. With the available tools, you can simplify your SageMaker process and integrate it into your existing project.

The following workflow technologies are supported.

- **Amazon SageMaker Model Building Pipelines** (p. 3203): SageMaker’s tool for building and managing end-to-end ML pipelines.
- **Airflow Workflows**: SageMaker APIs to export configurations for creating and managing Airflow workflows.
- **Kubernetes Orchestration** (p. 3327): SageMaker custom operators for your Kubernetes cluster, as well as custom components for Kubeflow Pipelines.
- **AWS Step Functions**: Create multi-step machine learning workflows in Python that orchestrate SageMaker infrastructure without having to provision your resources separately.

For more information on managing SageMaker training and inference, see Amazon SageMaker Python SDK Workflows.

Topics

- Amazon SageMaker Model Building Pipelines (p. 3203)
- Automate MLOps with SageMaker Projects (p. 3281)
- Amazon SageMaker ML Lineage Tracking (p. 3309)
- Kubernetes Orchestration (p. 3327)
- Amazon SageMaker Workflows FAQ (p. 3385)

Amazon SageMaker Model Building Pipelines

Amazon SageMaker Model Building Pipelines is a tool for building machine learning pipelines that take advantage of direct SageMaker integration. Because of this integration, you can create a pipeline and set up SageMaker Projects for orchestration using a tool that handles much of the step creation and management for you. SageMaker Pipelines provides the following advantages over other AWS workflow offerings:

**SageMaker Integration**

SageMaker Pipelines is integrated directly with SageMaker, so you don't need to interact with any other AWS services. You also don't need to manage any resources because SageMaker Pipelines is a fully managed service, which means that it creates and manages resources for you.

**SageMaker Python SDK Integration**

Because SageMaker Pipelines is integrated with the SageMaker Python SDK, you can create your pipelines programmatically using a high-level Python interface that you might already be familiar
with. To view the SageMaker Python SDK API reference, see Pipelines. For SageMaker Python SDK code examples, see Amazon SageMaker Model Building Pipelines.

SageMaker Studio Integration

SageMaker Studio offers an environment to manage the end-to-end SageMaker Pipelines experience. Using Studio, you can bypass the AWS console for your entire workflow management. For more information on managing SageMaker Pipelines from SageMaker Studio, see View, Track, and Execute SageMaker Pipelines in SageMaker Studio (p. 3266).

Data Lineage Tracking

With SageMaker Pipelines you can track the history of your data within the pipeline execution. Amazon SageMaker ML Lineage Tracking lets you analyze where the data came from, where it was used as an input, and the outputs that were generated from it. For example, you can view the models created from an individual dataset, and you can view the datasets that went into creating an individual model. For more information, see Amazon SageMaker ML Lineage Tracking (p. 3309).

Step Reuse

With SageMaker Pipelines, you can designate steps for caching. When a step is cached, it is indexed for reuse later if the same step is executed again. As a result, you can reuse the output from previous step executions of the same step in the same pipeline without having to run the step again. For more information on step caching, see Caching Pipeline Steps (p. 3230).

Topics

- SageMaker Pipelines Overview (p. 3204)
- Create and Manage SageMaker Pipelines (p. 3250)

SageMaker Pipelines Overview

An Amazon SageMaker Model Building Pipelines pipeline is a series of interconnected steps that are defined using the Pipelines SDK. This pipeline definition encodes a pipeline using a directed acyclic graph (DAG) that can be exported as a JSON definition. This DAG gives information on the requirements for and relationships between each step of your pipeline. The structure of a pipeline's DAG is determined by the data dependencies between steps. These data dependencies are created when the properties of a step's output are passed as the input to another step. The following image is an example of a pipeline DAG:
The following topics describe fundamental SageMaker Pipelines concepts. For a tutorial describing the implementation of these concepts, see Create and Manage SageMaker Pipelines (p. 3250).

**Topics**
- Pipeline Structure and Execution (p. 3205)
- IAM Access Management (p. 3206)
- Cross-Account Support for SageMaker Pipelines (p. 3208)
- Pipeline Parameters (p. 3209)
- Pipeline Steps (p. 3211)
- Property Files and JsonGet (p. 3229)
- Caching Pipeline Steps (p. 3230)
- Retry Policy for Pipeline Steps (p. 3235)
- Baseline calculation, drift detection and lifecycle with ClarifyCheck and QualityCheck steps in Amazon SageMaker Model Building Pipelines (p. 3238)
- Amazon EventBridge Integration (p. 3243)
- Amazon SageMaker Experiments Integration (p. 3245)
- Local Mode (p. 3248)
- Troubleshooting Amazon SageMaker Model Building Pipelines (p. 3249)

**Pipeline Structure and Execution**

**Topics**
Pipeline Structure

An Amazon SageMaker Model Building Pipelines instance is composed of a name, parameters, and steps. Pipeline names must be unique within an (account, region) pair. All parameters used in step definitions must be defined in the pipeline. Pipeline steps listed automatically determine their order of execution by their data dependencies on one another. The SageMaker Pipelines service resolves the relationships between steps in the data dependency DAG to create a series of steps that the execution completes. The following is an example of a pipeline structure.

```python
from sagemaker.workflow.pipeline import Pipeline

pipeline_name = f"AbalonePipeline"
pipeline = Pipeline(
    name=pipeline_name,
    parameters=[
        processing_instance_type,
        processing_instance_count,
        training_instance_type,
        model_approval_status,
        input_data,
        batch_data,
    ],
    steps=[step_process, step_train, step_eval, step_cond],
)
```

Pipeline Execution using Parallelism Configuration

By default, a pipeline performs all steps that are available to run in parallel. You can control this behavior by using the `ParallelismConfiguration` property when creating or updating a pipeline, as well as when starting or retrying a pipeline execution.

Parallelism configurations are applied per execution. For example, if two executions are started they can each run a maximum of 50 steps concurrently, for a total of 100 concurrently running steps. Also, `ParallelismConfiguration(s)` specified when starting, retrying or updating an execution take precedence over parallelism configurations defined in the pipeline.

Example Creating a pipeline execution with `ParallelismConfiguration`

```python
pipeline = Pipeline(
    name="myPipeline",
    steps=[step_process, step_train]
)

pipeline.create(role, parallelism_config={"MaxParallelExecutionSteps": 50})
```

IAM Access Management

The following sections describe the AWS Identity and Access Management (IAM) requirements for Amazon SageMaker Model Building Pipelines. For an example of how you can implement these permissions, see Prerequisites (p. 3251).

Topics

- Pipeline Role Permissions (p. 3207)
- Pipeline Step Permissions (p. 3207)
- Service Control Policies with Pipelines (p. 3207)

### Pipeline Role Permissions

Your pipeline requires an IAM pipeline execution role that is passed to SageMaker Pipelines when you create a pipeline. The role for the SageMaker instance that is creating the pipeline must have the `iam:PassRole` permission for the pipeline execution role in order to pass it. For more information on IAM roles, see [IAM Roles](#).

Your pipeline execution role requires the following permissions:

- To pass any role to a SageMaker job within a pipeline, the `iam:PassRole` permission for the role that is being passed.
- Create and Describe permissions for each of the job types in the pipeline.
- Amazon S3 permissions to use the `JsonGet` function. You control access to your Amazon S3 resources using resource-based policies and identity-based policies. A resource-based policy is applied to your Amazon S3 bucket and grants SageMaker Pipelines access to the bucket. An identity-based policy gives your pipeline the ability to make Amazon S3 calls from your account. For more information on resource-based policies and identity-based policies, see [Identity-based policies and resource-based policies](#).

```json
{
    "Action": ["s3:GetObject"],
    "Resource": "arn:aws:s3:::<your-bucket-name>/*",
    "Effect": "Allow"
}
```

### Pipeline Step Permissions

SageMaker Pipelines include steps that run SageMaker jobs. In order for the pipeline steps to run these jobs, they require an IAM role in your account that provides access for the needed resource. This role is passed to the SageMaker service principal by your pipeline. For more information on IAM roles, see [IAM Roles](#).

By default, each step takes on the pipeline execution role. You can optionally pass a different role to any of the steps in your pipeline. This ensures that the code in each step does not have the ability to impact resources used in other steps unless there is a direct relationship between the two steps specified in the pipeline definition. You pass these roles when defining the processor or estimator for your step. For examples of how to include these roles in these definitions, see the [SageMaker Python SDK documentation](#).

### Service Control Policies with Pipelines

Service control policies (SCPs) are a type of organization policy that you can use to manage permissions in your organization. SCPs offer central control over the maximum available permissions for all accounts in your organization. By using SageMaker Pipelines within your organization, you can ensure that data scientists manage your pipeline executions without having to interact with the AWS console.

If you're using a VPC with your SCP that restricts access to Amazon S3, you need to take steps to allow your pipeline to access other Amazon S3 resources.

To allow SageMaker Pipelines to access Amazon S3 outside of your VPC with the `JsonGet` function, update your organization's SCP to ensure that the role using SageMaker Pipelines can access Amazon S3. To do this, create an exception for roles that are being used by the SageMaker Pipelines executor via the pipeline execution role using a principal tag and condition key.
To allow SageMaker Pipelines to access Amazon S3 outside of your VPC

1. Create a unique tag for your pipeline execution role following the steps in Tagging IAM users and roles.
2. Grant an exception in your SCP using the Aws:PrincipalTag IAM condition key for the tag you created. For more information, see Creating, updating, and deleting service control policies.

Cross-Account Support for SageMaker Pipelines

You can use cross-account support for Amazon SageMaker Model Building Pipelines to share pipeline entities across AWS accounts and access shared pipelines through direct API calls.

Set up cross-account pipeline sharing

SageMaker uses AWS Resource Access Manager (AWS RAM) to help you securely share your pipeline entities across accounts.

Create a resource share

1. Select Create a resource share through the AWS RAM console.
2. When specifying resource share details, choose the SageMaker Pipelines resource type and select one or more pipelines that you want to share. When you share a pipeline with any other account, all of its executions are also shared implicitly.
3. Associate permissions with your resource share. Choose either the default read-only permission policy or the extended pipeline execution permission policy. For more detailed information, see Permission policies for SageMaker Pipelines resources (p. 3208).

   Note
   If you select the extended pipeline execution policy, note that any start, stop, and retry commands called by shared accounts use resources in the AWS account that shared the pipeline.
4. Use AWS account IDs to specify the accounts to which you want to grant access to your shared resources.
5. Review your resource share configuration and select Create resource share. It may take a few minutes for the resource share and principal associations to complete.

For more information, see Sharing your AWS resources in the AWS Resource Access Manager User Guide.

Get responses to your resource share invitation

Once the resource share and principal associations are set, the specified AWS accounts receive an invitation to join the resource share. The AWS accounts must accept the invite to gain access to any shared resources.

For more information on accepting a resource share invite through AWS RAM, see Using shared AWS resources in the AWS Resource Access Manager User Guide.

Permission policies for SageMaker Pipelines resources

When creating your resource share, choose one of two supported permission policies to associate with the SageMaker pipeline resource type. Both policies grant access to any selected pipeline and all of its executions.

Default read-only permissions

The AWSRAMDefaultPermissionSageMakerPipeline policy allows the following read-only actions:
Extended pipeline execution permissions

The AWSRAMPermissionSageMakerPipelineAllowExecution policy includes all of the read-only permissions from the default policy and also allows shared accounts to start, stop, and retry pipeline executions.

**Note**

Be mindful of AWS resource usage when using the extended pipeline execution permission policy. With this policy, shared accounts are allowed to start, stop, and retry pipeline executions. Any resources used for shared pipeline executions are consumed by the owner account.

The extended pipeline execution permission policy allows the following actions:

- `sagemaker:DescribePipeline`
- `sagemaker:DescribePipelineDefinitionForExecution`
- `sagemaker:DescribePipelineExecution`
- `sagemaker:ListPipelineExecutions`
- `sagemaker:ListPipelineExecutionSteps`
- `sagemaker:ListPipelineParametersForExecution`
- `sagemaker:StartPipelineExecution`
- `sagemaker:StopPipelineExecution`
- `sagemaker:RetryPipelineExecution`
- `sagemaker:Search`

Access shared pipeline entities through direct API calls

Once cross-account pipeline sharing is set up, you can call the following SageMaker API actions using a pipeline ARN:

**Note**

You can only call API commands if they are included in the permissions associated with your resource share. If you select the AWSRAMPermissionSageMakerPipelineAllowExecution policy, then the start, stop, and retry commands use resources in the AWS account that shared the pipeline.

- `DescribePipeline`
- `DescribePipelineDefinitionForExecution`
- `DescribePipelineExecution`
- `ListPipelineExecutions`
- `ListPipelineExecutionSteps`
- `ListPipelineParametersForExecution`
- `StartPipelineExecution`
- `StopPipelineExecution`
- `RetryPipelineExecution`

Pipeline Parameters

You can introduce variables into your pipeline definition using parameters. You can reference parameters that you define throughout your pipeline definition. Parameters have a default value, which you can
override by specifying parameter values when starting a pipeline execution. The default value must be an instance matching the parameter type. All parameters used in step definitions must be defined in your pipeline definition. Amazon SageMaker Model Building Pipelines supports the following parameter types:

- **ParameterString** – Representing a string parameter.
- **ParameterInteger** – Representing an integer parameter.
- **ParameterFloat** – Representing a float parameter.
- **ParameterBoolean** – Representing a Boolean Python type.

Parameters take the following format:

```python
<parameter> = <parameter_type>(
    name="<parameter_name>",
    default_value=<default_value>
)
```

The following example shows a sample parameter implementation.

```python
from sagemaker.workflow.parameters import (ParameterInteger,
                                          ParameterString,
                                          ParameterFloat,
                                          ParameterBoolean)

processing_instance_count = ParameterInteger(
    name="ProcessingInstanceCount",
    default_value=1
)
```

You pass the parameter when creating your pipeline as shown in the following example.

```python
pipeline = Pipeline(
    name=pipeline_name,
    parameters=[
        processing_instance_count
    ],
    steps=[step_process]
)
```

You can also pass a parameter value that differs from the default value to a pipeline execution, as shown in the following example.

```python
execution = pipeline.start(
    parameters=dict(
        ProcessingInstanceType="ml.c5.xlarge",
        ModelApprovalStatus="Approved"
    )
)
```

You can manipulate parameters with SageMaker Python SDK functions like `sagemaker.workflow.functions.Join`. For more information on parameters, see [SageMaker Pipelines Parameters](#). For known limitations of SageMaker Pipelines Parameters, see [Limitations - Parameterization](#) in the Amazon SageMaker Python SDK.
Pipeline Steps

SageMaker Pipelines are composed of steps. These steps define the actions that the pipeline takes and the relationships between steps using properties.

Topics

- Step Types (p. 3211)
- Step Properties (p. 3227)
- Step Parallelism (p. 3227)
- Data Dependency Between Steps (p. 3227)
- Custom Dependency Between Steps (p. 3228)
- Use a Custom Image in a Step (p. 3229)

Step Types

The following describes the requirements of each step type and provides an example implementation of the step. These are not functional implementations because they don't provide the resource and inputs needed. For a tutorial that implements these steps, see Create and Manage SageMaker Pipelines (p. 3250).

Amazon SageMaker Model Building Pipelines support the following step types:

- Processing (p. 3211)
- Training (p. 3213)
- Tuning (p. 3213)
- Model (p. 3214)
- CreateModel (p. 3216)
- RegisterModel (p. 3216)
- Transform (p. 3217)
- Condition (p. 3218)
- Callback (p. 3218)
- Lambda (p. 3220)
- ClarifyCheck (p. 3222)
- QualityCheck (p. 3224)
- EMR (p. 3225)
- Fail (p. 3226)

Processing Step

Use a processing step to create a processing job for data processing. For more information on processing jobs, see Process Data and Evaluate Models.

A processing step requires a processor, a Python script that defines the processing code, outputs for processing, and job arguments. The following example shows how to create a ProcessingStep definition.

```python
from sagemaker.sklearn.processing import SKLearnProcessor
sklearn_processor = SKLearnProcessor(framework_version='1.0-1',
```
Pass runtime parameters

The following example shows how to pass runtime parameters from a PySpark processor to a ProcessingStep.

```python
from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.spark.processing import PySparkProcessor
from sagemaker.processing import ProcessingInput, ProcessingOutput
from sagemaker.workflow.steps import ProcessingStep

pipeline_session = PipelineSession()

pyspark_processor = PySparkProcessor(  
    framework_version='2.4',  
    role=<role>,  
    instance_type='ml.m5.xlarge',  
    instance_count=1,  
    sagemaker_session=pipeline_session,
)

step_args = pyspark_processor.run(  
    inputs=[ProcessingInput(source=<input_data>, destination="/opt/ml/processing/input"),],  
    outputs=[  
        ProcessingOutput(output_name="train", source="/opt/ml/processing/train"),  
        ProcessingOutput(output_name="validation", source="/opt/ml/processing/validation"),  
        ProcessingOutput(output_name="test", source="/opt/ml/processing/test"),  
    ],  
    code="preprocess.py",  
    arguments=None,
)

step_process = ProcessingStep(  
    name="AbaloneProcess",  
    step_args=step_args,
)
```

For more information on processing step requirements, see the `sagemaker.workflow.steps.ProcessingStep` documentation. For an in-depth example, see Define a
**Processing Step for Feature Engineering** in the Orchestrate Jobs to Train and Evaluate Models with Amazon SageMaker Pipelines example notebook.

**Training Step**

You use a training step to create a training job to train a model. For more information on training jobs, see Train a Model with Amazon SageMaker.

A training step requires an estimator, as well as training and validation data inputs. The following example shows how to create a TrainingStep definition. For more information on training step requirements, see the sagemaker.workflow.steps.TrainingStep documentation.

```python
from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.inputs import TrainingInput
from sagemaker.workflow.steps import TrainingStep
from sagemaker.xgboost.estimator import XGBoost
pipeline_session = PipelineSession()
xgb_estimator = XGBoost(..., sagemaker_session=pipeline_session)
step_args = xgb_estimator.fit(
    inputs={
        "train": TrainingInput(
            s3_data=step_process.properties.ProcessingOutputConfig.Outputs["train"].S3Output.S3Uri,
            content_type="text/csv"
        ),
        "validation": TrainingInput(
            s3_data=step_process.properties.ProcessingOutputConfig.Outputs["validation"].S3Output.S3Uri,
            content_type="text/csv"
        )
    }
)
step_train = TrainingStep(
    name="TrainAbaloneModel",
    step_args=step_args,
)
```

**Tuning Step**

You use a tuning step to create a hyperparameter tuning job, also known as hyperparameter optimization (HPO). A hyperparameter tuning job runs multiple training jobs, each one producing a model version. For more information on hyperparameter tuning, see Perform Automatic Model Tuning with SageMaker (p. 2436).

The tuning job is associated with the SageMaker experiment for the pipeline, with the training jobs created as trials. For more information, see Experiments Integration (p. 3245).

A tuning step requires a HyperparameterTuner and training inputs. You can retrain previous tuning jobs by specifying the warm_start_config parameter of the HyperparameterTuner. For more information on hyperparameter tuning and warm start, see Run a Warm Start Hyperparameter Tuning Job (p. 2459).

You use the get_top_model_s3_uri method of the sagemaker.workflow.steps.TuningStep class to get the model artifact from one of the top-performing model versions. For a notebook that shows how to use a tuning step in a SageMaker pipeline, see sagemaker-pipelines-tuning-step.ipynb.
Important
Tuning steps were introduced in Amazon SageMaker Python SDK v2.48.0 and Amazon SageMaker Studio v3.8.0. You must update Studio before you use a tuning step or the pipeline DAG doesn't display. To update Studio, see Shut down and Update SageMaker Studio (p. 179).

The following example shows how to create a TuningStep definition.

```python
from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.tuner import HyperparameterTuner
from sagemaker.inputs import TrainingInput
from sagemaker.workflow.steps import TuningStep
tuner = HyperparameterTuner(..., sagemaker_session=PipelineSession())
step_tuning = TuningStep(
    name = "HPTuning",
    step_args = tuner.fit(inputs=TrainingInput(s3_data="s3://my-bucket/my-data"))
)
```

Get the best model version

The following example shows how to get the best model version from the tuning job using the `get_top_model_s3_uri` method. At most, the top 50 performing versions are available ranked according to `HyperParameterTuningJobObjective`. The top_k argument is an index into the versions, where top_k=0 is the best-performing version and top_k=49 is the worst-performing version.

```python
best_model = Model(
    image_uri=image_uri,
    model_data=step_tuning.get_top_model_s3_uri(
        top_k=0,
        s3_bucket=sagemaker_session.default_bucket()
    ),
    ...)
```

For more information on tuning step requirements, see the `sagemaker.workflow.steps.TuningStep` documentation.

Model Step

Use a ModelStep to create or register a SageMaker model. For more information on ModelStep requirements, see the `sagemaker.workflow.model_step.ModelStep` documentation.

Create a model

You can use a ModelStep to create a SageMaker model. A ModelStep requires model artifacts and information about the SageMaker instance type that you need to use to create the model. For more information on SageMaker models, see Train a Model with Amazon SageMaker.

The following example shows how to create a ModelStep definition.

```python
from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.model import Model
from sagemaker.workflow.model_step import ModelStep
step_train = TrainingStep(...) model = Model(
    image_uri=pytorch Estimator.training_image_uri(),
    model_data=step_train.properties.ModelArtifacts.S3ModelArtifacts,
    sagemaker_session=PipelineSession(),
)```
role=role,
)

step_model_create = ModelStep(
    name="MyModelCreationStep",
    step_args=model.create(instance_type="ml.m5.xlarge"),
)

Register a model

You can use a ModelStep to register a sagemaker.model.Model or a sagemaker.pipeline.PipelineModel with the Amazon SageMaker model registry. A PipelineModel represents an inference pipeline, which is a model composed of a linear sequence of containers that process inference requests. For more information about how to register a model, see Register and Deploy Models with Model Registry (p. 2982).

The following example shows how to create a ModelStep that registers a PipelineModel.

```python
import time
from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.sklearn import SKLearnModel
from sagemaker.xgboost import XGBoostModel

pipeline_session = PipelineSession()

code_location = 's3://[0]/[1]/code'.format(bucket_name, prefix)

sklearn_model = SKLearnModel(
    model_data=processing_step.properties.ProcessingOutputConfig.Outputs['model'].S3Output.S3Uri,
    entry_point='inference.py',
    source_dir='sklearn_source_dir/',
    code_location=code_location,
    framework_version='1.0-1',
    role=role,
    sagemaker_session=pipeline_session,
    py_version='py3'
)

xgboost_model = XGBoostModel(
    model_data=training_step.properties.ModelArtifacts.S3ModelArtifacts,
    entry_point='inference.py',
    source_dir='xgboost_source_dir/',
    code_location=code_location,
    framework_version='0.90-2',
    py_version='py3',
    sagemaker_session=pipeline_session,
    role=role
)

from sagemaker.workflow.pipeline_step import PipelineStep
from sagemaker import PipelineModel

pipeline_model = PipelineModel(
    models=[sklearn_model, xgboost_model],
    role=role,sagemaker_session=pipeline_session,
)

register_model_step_args = pipeline_model.register(
    content_types=['application/json'],
    response_types=['application/json'],
    inference_instances=['ml.t2.medium', "ml.m5.xlarge"],
    transform_instances=['ml.m5.xlarge'],
)
CreateModel Step

**Important**

We recommend using Model Step (p. 3214) to create models as of v2.90.0 of the SageMaker Python SDK. CreateModelStep will continue to work in previous versions of the SageMaker Python SDK, but is no longer actively supported.

You use a CreateModel step to create a SageMaker model. For more information on SageMaker models, see Train a Model with Amazon SageMaker.

A create model step requires model artifacts and information about the SageMaker instance type that you need to use to create the model. The following example shows how to create a CreateModel step definition. For more information on CreateModel step requirements, see the sagemaker.workflow.steps.CreateModelStep documentation.

```python
from sagemaker.workflow.steps import CreateModelStep

step_create_model = CreateModelStep(
    name="AbaloneCreateModel",
    model=best_model,
    inputs=inputs
)
```

RegisterModel Step

**Important**

We recommend using Model Step (p. 3214) to register models as of v2.90.0 of the SageMaker Python SDK. RegisterModel will continue to work in previous versions of the SageMaker Python SDK, but is no longer actively supported.

You use a RegisterModel step to register a sagemaker.model.Model or a sagemaker.pipeline.PipelineModel with the Amazon SageMaker model registry. A PipelineModel represents an inference pipeline, which is a model composed of a linear sequence of containers that process inference requests.

For more information about how to register a model, see Register and Deploy Models with Model Registry (p. 2982). For more information on RegisterModel step requirements, see the sagemaker.workflow.step_collections.RegisterModel documentation.

The following example shows how to create a RegisterModel step that registers a PipelineModel.

```python
import time
from sagemaker.sklearn import SKLearnModel
from sagemaker.xgboost import XGBoostModel

code_location = 's3://{0}/{1}/code'.format(bucket_name, prefix)

sklearn_model = SKLearnModel(model_data=processing_step.properties.ProcessingOutputConfig.Outputs['model'].S3Output.S3Uri,
    entry_point='inference.py',
    source_dir='sklearn_source_dir/',
    code_location=code_location,
    framework_version='1.0-1',
    )
```
role=role,
sagemaker_session=sagemaker_session,
py_version='py3')

xgboost_model =
XGBoostModel(model_data=training_step.properties.ModelArtifacts.S3ModelArtifacts,
entry_point='inference.py',
source_dir='xgboost_source_dir/',
code_location=code_location,
framework_version='0.90-2',
py_version='py3',
sagemaker_session=sagemaker_session,
role=role)

from sagemaker.workflow.step_collections import RegisterModel
from sagemaker import PipelineModel
pipeline_model =
PipelineModel(models=[sklearn_model, xgboost_model], role=role, sagemaker_session=sagemaker_session)

step_register = RegisterModel(
    name="AbaloneRegisterModel",
    model=pipeline_model,
    content_types=['application/json'],
    response_types=['application/json'],
    inference_instances=['ml.t2.medium', 'ml.m5.xlarge'],
    transform_instances=['ml.m5.xlarge'],
    model_package_group_name='sipgroup',
    approval_status=model_approval_status,
    model_metrics=model_metrics
)

if model isn’t provided, the register model step requires an estimator as shown in the following example.

from sagemaker.workflow.step_collections import RegisterModel

step_register = RegisterModel(
    name="AbaloneRegisterModel",
    estimator=xgb_train,
    model_data=step_train.properties.ModelArtifacts.S3ModelArtifacts,
    content_types=['text/csv'],
    response_types=['text/csv'],
    inference_instances=['ml.t2.medium', 'ml.m5.xlarge'],
    transform_instances=['ml.m5.xlarge'],
    model_package_group_name=model_package_group_name,
    approval_status=model_approval_status,
    model_metrics=model_metrics
)

Transform Step

You use a transform step for batch transformation to run inference on an entire dataset. For more information about batch transformation, see Run Batch Transforms with Inference Pipelines (p. 2795).

A transform step requires a transformer and the data on which to run batch transformation. The following example shows how to create a Transform step definition. For more information on Transform step requirements, see the sagemaker.workflow.steps.TransformStep documentation.

from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.transformer import Transformer
from sagemaker.inputs import TransformInput
from sagemaker.workflow.steps import TransformStep
transformer = Transformer(...)
Condition Step

You use a condition step to evaluate the condition of step properties to assess which action should be taken next in the pipeline.

A condition step requires a list of conditions, a list of steps to run if the condition evaluates to `true`, and a list of steps to run if the condition evaluates to `false`. The following example shows how to create a `ConditionStep` definition.

```python
from sagemaker.workflow.conditions import ConditionLessThanOrEqualTo
from sagemaker.workflow.condition_step import (ConditionStep,
                                           JsonGet)

cond_lte = ConditionLessThanOrEqualTo(
    left=JsonGet(
        step_name=step_eval.name,
        property_file=evaluation_report,
        json_path="regression_metrics.mse.value"),
    right=6.0)

step_cond = ConditionStep(
    name="AbaloneMSECond",
    conditions=[cond_lte],
    if_steps=[step_register, step_create_model, step_transform],
    else_steps=[])
```

For more information on `ConditionStep` requirements, see the `sagemaker.workflow.condition_step.ConditionStep` API reference. For more information on supported conditions, see `Amazon SageMaker Model Building Pipelines - Conditions` in the SageMaker Python SDK documentation.

Callback Step

You use a Callback step to incorporate additional processes and AWS services into your workflow that aren't directly provided by Amazon SageMaker Model Building Pipelines. When a Callback step runs, the following procedure occurs:

- SageMaker Pipelines sends a message to a customer-specified Amazon Simple Queue Service (Amazon SQS) queue. The message contains a SageMaker Pipelines–generated token and a customer-supplied list of input parameters. After sending the message, SageMaker Pipelines waits for a response from the customer.
- The customer retrieves the message from the Amazon SQS queue and starts their custom process.
When the process finishes, the customer calls one of the following APIs and submits the SageMaker Pipelines-generated token:
- `SendPipelineExecutionStepSuccess`, along with a list of output parameters
- `SendPipelineExecutionStepFailure`, along with a failure reason
The API call causes SageMaker Pipelines to either continue the pipeline process or fail the process.

For more information on Callback step requirements, see the `sagemaker.workflow.callback_step.CallbackStep` documentation. For a complete solution, see Extend SageMaker Pipelines to include custom steps using callback steps.

**Important**
Callback steps were introduced in Amazon SageMaker Python SDK v2.45.0 and Amazon SageMaker Studio v3.6.2. You must update Studio before you use a Callback step or the pipeline DAG doesn't display. To update Studio, see Shut down and Update SageMaker Studio (p. 179).

The following sample demonstrates an implementation of the preceding procedure.

```python
from sagemaker.workflow.callback_step import CallbackStep

step_callback = CallbackStep(
    name="MyCallbackStep",
    sqs_queue_url="https://sqs.us-east-2.amazonaws.com/012345678901/MyCallbackQueue",
    inputs={...},
    outputs=[...]
)

callback_handler_code = ''
    import boto3
    import json
    def handler(event, context):
        sagemaker_client=boto3.client("sagemaker")
        for record in event['Records']:
            payload=json.loads(record['body'])
            token=payload['token']
            # Custom processing
            # Call SageMaker to complete the step
            sagemaker_client.send_pipeline_execution_step_success(
                CallbackToken=token,
                OutputParameters={...}
            )
    

**Note**
Output parameters for CallbackStep should not be nested. For example, if you use a nested dictionary as your output parameter, then the dictionary is treated as a single string (ex. `{"output1": "{\"nested_output1\": "my-output\"\"}"}`). If you provide a nested value, then when you try to refer to a particular output parameter, a non-retryable client error is thrown.

**Stopping behavior**
A pipeline process doesn't stop while a Callback step is running.

When you call `StopPipelineExecution` on a pipeline process with a running Callback step, SageMaker Pipelines sends an additional Amazon SQS message to the specified SQS queue. The body of the SQS
message contains a **Status** field, which is set to Stopping. The following shows an example SQS message body.

```json
{
    "token": "26vcYbeWsZ",
    "pipelineExecutionArn": "arn:aws:sagemaker:us-east-2:012345678901:pipeline/callback-pipeline/execution/7pinimwddh3a",
    "arguments": {
        "number": 5,
        "stringArg": "some-arg",
        "inputData": "s3://sagemaker-us-west-2-012345678901/abalone/abalone-dataset.csv"
    },
    "status": "Stopping"
}
```

You should add logic to your Amazon SQS message consumer to take any needed action (for example, resource cleanup) upon receipt of the message, followed by a call to `SendPipelineExecutionStepSuccess` or `SendPipelineExecutionStepFailure`. Only when SageMaker Pipelines receives one of these calls does it stop the pipeline process.

**Lambda Step**

You use a Lambda step to run an AWS Lambda function. You can run an existing Lambda function, or SageMaker can create and run a new Lambda function. For a notebook that shows how to use a Lambda step in a SageMaker pipeline, see `sagemaker-pipelines-lambda-step.ipynb`.

**Important**

Lambda steps were introduced in Amazon SageMaker Python SDK v2.51.0 and Amazon SageMaker Studio v3.9.1. You must update Studio before you use a Lambda step or the pipeline DAG doesn't display. To update Studio, see *Shut down and Update SageMaker Studio* (p. 179).

SageMaker provides the `sagemaker.lambda_helper.Lambda` class to create, update, invoke, and delete Lambda functions. Lambda has the following signature.

```
Lambda(
    function_arn,       # Only required argument to invoke an existing Lambda function
    # The following arguments are required to create a Lambda function:
    function_name,
    execution_role_arn,
    zipped_code_dir,    # Specify either zipped_code_dir and s3_bucket, OR script
    s3_bucket,          # S3 bucket where zipped_code_dir is uploaded
    script,             # Path of Lambda function script
    handler,            # Lambda handler specified as "lambda_script.lambda_handler"
    timeout,            # Maximum time the Lambda function can run before the lambda step fails
    ...
)
```

The `sagemaker.workflow.lambda_step.LambdaStep` class has a `lambda_func` argument of type Lambda. To invoke an existing Lambda function, the only requirement is to supply the Amazon Resource Name (ARN) of the function to `function_arn`. If you don't supply a value for `function_arn`, you must specify `handler` and one of the following:

- **zipped_code_dir** – The path of the zipped Lambda function
- **s3_bucket** – Amazon S3 bucket where `zipped_code_dir` is to be uploaded
- **script** – The path of the Lambda function script file
The following example shows how to create a Lambda step definition that invokes an existing Lambda function.

```python
from sagemaker.workflow.lambda_step import LambdaStep
from sagemaker.lambda_helper import Lambda

step_lambda = LambdaStep(
    name="ProcessingLambda",
    lambda_func=Lambda(
    ),
    inputs={
        s3_bucket = s3_bucket,
        data_file = data_file
    },
    outputs=[
        "train_file", "test_file"
    ]
)
```

The following example shows how to create a Lambda step definition that creates and invokes a Lambda function using a Lambda function script.

```python
from sagemaker.workflow.lambda_step import LambdaStep
from sagemaker.lambda_helper import Lambda

step_lambda = LambdaStep(
    name="ProcessingLambda",
    lambda_func=Lambda(
        function_name="split-dataset-lambda",
        execution_role_arn=execution_role_arn,
        script="lambda_script.py",
        handler="lambda_script.lambda_handler",
    ),
    inputs={
        s3_bucket = s3_bucket,
        data_file = data_file
    },
    outputs=[
        "train_file", "test_file"
    ]
)
```

**Inputs and outputs**

If your Lambda function has inputs or outputs, these must also be defined in your Lambda step.

**Note**

Input and output parameters should not be nested. For example, if you use a nested dictionary as your output parameter, then the dictionary is treated as a single string (ex. `{"output1": 
  "}`). If you provide a nested value and try to refer to it later, a non-retryable client error is thrown.

When defining the Lambda step, inputs must be a dictionary of key-value pairs. Each value of the inputs dictionary must be a primitive type (string, integer, or float). Nested objects are not supported. If left undefined, the inputs value defaults to None.

The outputs value must be a list of keys. These keys refer to a dictionary defined in the output of the Lambda function. Like inputs, these keys must be primitive types, and nested objects are not supported.
Timeout and stopping behavior

The Lambda class has a timeout argument that specifies the maximum time that the Lambda function can run. The default value is 120 seconds with a maximum value of 10 minutes. If the Lambda function is running when the timeout is met, the Lambda step fails; however, the Lambda function continues to run.

A pipeline process can't be stopped while a Lambda step is running because the Lambda function invoked by the Lambda step can't be stopped. If you attempt to stop the process while the Lambda function is running, the pipeline waits for the Lambda function to finish or until the timeout is hit, whichever occurs first, and then stops. If the Lambda function finishes, the pipeline process status is Stopped. If the timeout is hit the pipeline process status is Failed.

ClarifyCheck Step

You can use the ClarifyCheck step to conduct baseline drift checks against previous baselines for bias analysis and model explainability. You can then generate and register your baselines with the model.register() method and pass the output of that method to Model Step (p. 3214) using step_args. These baselines for drift check can be used by Amazon SageMaker Model Monitor for your model endpoints so that you don't need to do a baseline suggestion separately. The ClarifyCheck step can also pull baselines for drift check from the model registry. The ClarifyCheck step leverages the Amazon SageMaker Clarify prebuilt container that provides a range of model monitoring capabilities, including constraint suggestion and constraint validation against a given baseline. For more information, see Getting Started with a SageMaker Clarify Container.

Configuring the ClarifyCheck step

You can configure the ClarifyCheck step to conduct only one of the following check types each time it's used in a pipeline.

- Data bias check
- Model bias check
- Model explainability check

You do this by setting the clarify_check_config parameter with one of the following check type values:

- DataBiasCheckConfig
- ModelBiasCheckConfig
- ModelExplainabilityCheckConfig

The ClarifyCheck step launches a processing job that runs the SageMaker Clarify prebuilt container and requires dedicated configurations for the check and the processing job. ClarifyCheckConfig and CheckJobConfig are helper functions for these configurations that are aligned with how the SageMaker Clarify processing job computes for checking model bias, data bias, or model explainability. For more information, see Run SageMaker Clarify Processing Jobs for Bias Analysis and Explainability (p. 2627).

Controlling step behaviors for drift check

The ClarifyCheck step requires the following two boolean flags to control its behavior:

- skip_check: This parameter indicates if the drift check against the previous baseline is skipped or not. If it is set to False, the previous baseline of the configured check type must be available.
- register_new_baseline: This parameter indicates if a newly calculated baseline can be accessed through step property BaselineUsedForDriftCheckConstraints. If it is set to False, the
previous baseline of the configured check type also must be available. This can be accessed through the `BaselineUsedForDriftCheckConstraints` property.

For more information, see Baseline calculation, drift detection and lifecycle with ClarifyCheck and QualityCheck steps in Amazon SageMaker Model Building Pipelines (p. 3238).

**Working with baselines**

You can optionally specify the `model_package_group_name` to locate the existing baseline and the ClarifyCheck step pulls the `DriftCheckBaselines` on the latest approved model package in the model package group. Or, you can provide a previous baseline through the `supplied_baseline_constraints` parameter. If you specify both the `model_package_group_name` and the `supplied_baseline_constraints`, the ClarifyCheck step uses the baseline specified by the `supplied_baseline_constraints` parameter.

For more information on using the ClarifyCheck step requirements, see the `sagemaker.workflow.steps.ClarifyCheckStep` in the Amazon SageMaker SageMaker SDK for Python. For an Amazon SageMaker Studio notebook that shows how to use ClarifyCheck step in SageMaker Pipelines, see sagemaker-pipeline-model-monitor-clarify-steps.ipynb.

**Example: Create a ClarifyCheck step for data bias check**

```python
from sagemaker.workflow.check_job_config import CheckJobConfig
from sagemaker.workflow.clarify_check_step import DataBiasCheckConfig, ClarifyCheckStep
from sagemaker.workflow.execution_variables import ExecutionVariables

check_job_config = CheckJobConfig(
    role=role,
    instance_count=1,
    instance_type="ml.c5.xlarge",
    volume_size_in_gb=120,
    sagemaker_session=sagemaker_session,
)

data_bias_data_config = DataConfig(
    s3_data_input_path=step_process.properties.ProcessingOutputConfig.Outputs["train"].S3Output.S3Uri,
    s3_output_path=Join(on='/', values=['s3://', your_bucket, base_job_prefix, ExecutionVariables.PIPELINE_EXECUTION_ID, 'databiascheckstep']),
    label=0,
    dataset_type="text/csv",
    s3_analysis_config_output_path=data_bias_analysis_cfg_output_path,
)

data_bias_config = BiasConfig(
    label_values_or_threshold=[15.0],
    facet_name=[8],
    facet_values_or_threshold=[[0.5]]
)

data_bias_check_config = DataBiasCheckConfig(
    data_config=data_bias_data_config,
    data_bias_config=data_bias_config,
)

data_bias_check_step = ClarifyCheckStep(
    name="DataBiasCheckStep",
    clarify_check_config=data_bias_check_config,
    check_job_config=check_job_config,
    skip_check=False,
    register_new_baseline=False,
    supplied_baseline_constraints="s3://sagemaker-us-west-2-111122223333/baseline/analysis.json",
    model_package_group_name="MyModelPackageGroup"
)
QualityCheck Step

You can use the QualityCheck step to conduct baseline suggestions and drift checks against a previous baseline for data quality or model quality in a pipeline. You can then generate and register your baselines with the `model.register()` method and pass the output of that method to `Model Step` (p. 3214) using `step_args`. Model Monitor can use these baselines for drift check for your model endpoints so that you don’t need to do a baseline suggestion separately. The QualityCheck step can also pull baselines for drift check from the model registry. The QualityCheck step leverages the Amazon SageMaker Model Monitor prebuilt container, which has a range of model monitoring capabilities including constraint suggestion, statistics generation, and constraint validation against a baseline. For more information, see Amazon SageMaker Model Monitor prebuilt container (p. 2899).

Configuring the QualityCheck step

You can configure the QualityCheck step to conduct only one of the following check types each time it’s used in a pipeline.

- Data quality check
- Model quality check

You do this by setting the `quality_check_config` parameter with one of the following check type values:

- `DataQualityCheckConfig`
- `ModelQualityCheckConfig`

The QualityCheck step launches a processing job that runs the Model Monitor prebuilt container and requires dedicated configurations for the check and the processing job. The `QualityCheckConfig` and `CheckJobConfig` are helper functions for these configurations that are aligned with how Model Monitor creates a baseline for the model quality or data quality monitoring. For more information on the Model Monitor baseline suggestions, see Create a Baseline (p. 2865) and Create a Model Quality Baseline (p. 2871).

Controlling step behaviors for drift check

The QualityCheck step requires the following two Boolean flags to control its behavior:

- `skip_check`: This parameter indicates if the drift check against the previous baseline is skipped or not. If it is set to `False`, the previous baseline of the configured check type must be available.
- `register_new_baseline`: This parameter indicates if a newly calculated baseline can be accessed through step properties `BaselineUsedForDriftCheckConstraints` and `BaselineUsedForDriftCheckStatistics`. If it is set to `False`, the previous baseline of the configured check type must also be available. These can be accessed through the `BaselineUsedForDriftCheckConstraints` and `BaselineUsedForDriftCheckStatistics` properties.

For more information, see Baseline calculation, drift detection and lifecycle with ClarifyCheck and QualityCheck steps in Amazon SageMaker Model Building Pipelines (p. 3238).

Working with baselines

You can specify a previous baseline directly through the `supplied_baseline_statistics` and `supplied_baseline_constraints` parameters, or you can simply specify the
model_package_group_name and the QualityCheck step pulls the DriftCheckBaselines on the latest approved model package in the model package group. When you specify the model_package_group_name, the supplied_baseline_constraints, and supplied_baseline_statistics, the QualityCheck step uses the baseline specified by supplied_baseline_constraints and supplied_baseline_statistics on the check type of the QualityCheck step you are running.

For more information on using the QualityCheck step requirements, see the sagemaker.workflow.steps.QualityCheckStep in the Amazon SageMaker SageMaker SDK for Python. For an Amazon SageMaker Studio notebook that shows how to use QualityCheck step in SageMaker Pipelines, see sagemaker-pipeline-model-monitor-clarify-steps.ipynb.

Example Create a QualityCheck step for data quality check

```python
from sagemaker.workflow.check_job_config import CheckJobConfig
from sagemaker.workflow.quality_check_step import DataQualityCheckConfig, QualityCheckStep
from sagemaker.workflow.execution_variables import ExecutionVariables

check_job_config = CheckJobConfig(
    role=role,
    instance_count=1,
    instance_type="ml.c5.xlarge",
    volume_size_in_gb=120,
    sagemaker_session=sagemaker_session,
)

data_quality_check_config = DataQualityCheckConfig(
    baseline_dataset=step_process.properties.ProcessingOutputConfig.Outputs["train"].S3Output.S3Uri,
    dataset_format=DatasetFormat.csv(header=False, output_columns_position="START"),
    output_s3_uri=Join(on='/', values=['s3://', your_bucket, base_job_prefix, ExecutionVariables.PIPELINE_EXECUTION_ID, 'dataqualitycheckstep'])
)

data_quality_check_step = QualityCheckStep(
    name="DataQualityCheckStep",
    skip_check=False,
    register_new_baseline=False,
    quality_check_config=data_quality_check_config,
    check_job_config=check_job_config,
    supplied_baseline_statistics="s3://sagemaker-us-west-2-555555555555/baseline/statistics.json",
    supplied_baseline_constraints="s3://sagemaker-us-west-2-555555555555/baseline/constraints.json",
    model_package_group_name="MyModelPackageGroup"
)
```

Amazon EMR Step

You can use the Amazon SageMaker Model Building Pipelines Amazon EMR step to process EMR steps to a running Amazon EMR cluster. For more information, see Getting started with Amazon EMR.

The Amazon EMR step requires an EMRStepConfig having the Amazon S3 location of the JAR to be used by the Amazon EMR cluster and any arguments to be passed, as well as the Amazon EMR cluster ID.

**Note**

- Amazon EMR steps require that the role passed to your pipeline has additional permissions. You should attach the AWS managed policy: AmazonSageMakerPipelinesIntegrations to your pipeline role, or ensure that the role includes the permissions in that policy.
- Amazon EMR on EKS is not supported.
- You can only run an EMR step on a cluster that is in one of the following states: STARTING, BOOTSTRAPPING, RUNNING, or WAITING.
- You can have at most 256 EMR steps in PENDING on an EMR cluster; EMR steps submitted beyond that limit result in the pipeline execution failing. You may consider using Retry Policy for Pipeline Steps (p. 3235).

**Example Create an Amazon EMR step definition that launches a new job on an EMR cluster.**

```python
from sagemaker.workflow.emr_step import EMRStep, EMRStepConfig

emr_config = EMRStepConfig(
    jar="s3://path/to/jar/MyJar.jar",  # required, S3 path to jar
    args=['--verbose', '--force'],  # optional list of arguments to pass to the jar
    main_class="com.my.Main1",  # optional main class, this can be omitted if jar above has
    properties=[  # optional list of Java properties that are set when the step runs
        
        "key": "mapred.tasktracker.map.tasks.maximum",
        "value": "2"
    ],
    
    "key": "mapreduce.map.sort.spill.percent",
    "value": "0.90"
    
    "key": "mapreduce.tasktracker.reduce.tasks.maximum",
    "value": "5"
    
)

step_emr = EMRStep (  # required
    name="EMRSampleStep",  # required
    cluster_id="j-1YONHTCP3YZK",  # required
    step_config=emr_config,  # required
    display_name="My EMR Step",
    description="Pipeline step to execute EMR job"
)
```

**Fail Step**

You use a FailStep to stop an Amazon SageMaker Model Building Pipelines execution when a desired condition or state is not achieved and to mark that pipeline's execution as failed. The FailStep also allows you to enter a custom error message, indicating the cause of the pipeline's execution failure.

**Note**

When a FailStep and other pipeline steps execute concurrently, the pipeline does not terminate until all concurrent steps are completed.

**Limitations for using FailStep**

- You cannot add a FailStep to the DependsOn list of other steps. For more information, see Custom Dependency Between Steps (p. 3228).
- Other steps cannot reference the FailStep. It is always the last step in a pipeline's execution.
- You cannot retry a pipeline execution ending with a FailStep.

You can create the FailStep ErrorMessage in the form of a static text string. Alternatively, you can also use Pipeline Parameters a Join operation, or other step properties to create a more informative error message.
Example

The following example code snippet uses a FailStep with an ErrorMessage configured with Pipeline Parameters and a Join operation.

```python
from sagemaker.workflow.fail_step import FailStep
from sagemaker.workflow.functions import Join
from sagemaker.workflow.parameters import ParameterInteger

mse_threshold_param = ParameterInteger(name="MseThreshold", default_value=5)
step_fail = FailStep(
    name="AbaloneMSEFail",
    error_message=Join(
        on=" ", values=["Execution failed due to MSE >", mse_threshold_param]
    ),
)
```

Step Properties

The properties attribute is used to add data dependencies between steps in the pipeline. These data dependencies are then used by SageMaker Pipelines to construct the DAG from the pipeline definition. These properties can be referenced as placeholder values and are resolved at runtime.

The properties attribute of a SageMaker Pipelines step matches the object returned by a Describe call for the corresponding SageMaker job type. For each job type, the Describe call returns the following response object:

- ProcessingStep – DescribeProcessingJob
- TrainingStep – DescribeTrainingJob
- TransformStep – DescribeTransformJob

To check which properties are referrable for each step type during data dependency creation, see Data Dependency - Property Reference in the Amazon SageMaker Python SDK.

Step Parallelism

When a step does not depend on any other step, it is run immediately upon pipeline execution. However, executing too many pipeline steps in parallel can quickly exhaust available resources. Control the number of concurrent steps for a pipeline execution with ParallelismConfiguration.

The following example uses ParallelismConfiguration to set the concurrent step limit to five.

```python
pipeline.create(
    parallelism_config=ParallelismConfiguration(5),
)
```

Data Dependency Between Steps

You define the structure of your DAG by specifying the data relationships between steps. To create data dependencies between steps, pass the properties of one step as the input to another step in the pipeline. The step receiving the input isn’t started until after the step providing the input finishes running.

A data dependency uses JsonPath notation in the following format. This format traverses the JSON property file, which means you can append as many `<property>` instances as needed to reach the desired nested property in the file. For more information on JsonPath notation, see the JsonPath repo.
The following shows how to specify an Amazon S3 bucket using the ProcessingOutputConfig property of a processing step.

```
step_process.properties.ProcessingOutputConfig.Outputs["train_data"].S3Output.S3Uri
```

To create the data dependency, pass the bucket to a training step as follows.

```
from sagemaker.workflow.pipeline_context import PipelineSession
sklearn_train = SKLearn(..., sagemaker_session=PipelineSession())
step_train = TrainingStep(
  name="CensusTrain",
  step_args=sklearn_train.fit(inputs=TrainingInput(
    s3_data=step_process.properties.ProcessingOutputConfig.Outputs["train_data"].S3Output.S3Uri
  ))
)
```

To check which properties are referrable for each step type during data dependency creation, see Data Dependency - Property Reference in the Amazon SageMaker Python SDK.

**Custom Dependency Between Steps**

When you specify a data dependency, SageMaker Pipelines provides the data connection between the steps. Alternatively, one step can access the data from a previous step without directly using SageMaker Pipelines. In this case, you can create a custom dependency that tells SageMaker Pipelines not to start a step until after another step has finished running. You create a custom dependency by specifying a step's DependsOn attribute.

As an example, the following defines a step C that starts only after both step A and step B finish running.

```
{
    'Steps': [
        {'Name': 'A', ...},
        {'Name': 'B', ...},
        {'Name': 'C', 'DependsOn': ['A', 'B']}
    ]
}
```

SageMaker Pipelines throws a validation exception if the dependency would create a cyclic dependency.

The following example creates a training step that starts after a processing step finishes running.

```
processing_step = ProcessingStep(...)  
training_step = TrainingStep(...)  
training_step.add_depends_on([processing_step])
```

The following example creates a training step that doesn't start until two different processing steps finish running.

```
processing_step_1 = ProcessingStep(...)  
processing_step_2 = ProcessingStep(...)  
```
training_step = TrainingStep(...)
training_step.add_depends_on([processing_step_1, processing_step_2])

The following provides an alternate way to create the custom dependency.

training_step.add_depends_on([processing_step_1])
training_step.add_depends_on([processing_step_2])

The following example creates a training step that receives input from one processing step and waits for a different processing step to finish running.

processing_step_1 = ProcessingStep(...)
processing_step_2 = ProcessingStep(...)

training_step = TrainingStep(
    inputs=TrainingInput(
        s3_data=processing_step_1.properties.ProcessingOutputConfig.Outputs["train_data"].S3Output.S3Uri
    ),
    training_step.add_depends_on([processing_step_2])

The following example shows how to retrieve a string list of the custom dependencies of a step.

custom_dependencies = training_step.depends_on

Use a Custom Image in a Step

You can use any of the available SageMaker Deep Learning Container images when you create a step in your pipeline.

You can also use your own container with pipeline steps. Because you can't create an image from within Amazon SageMaker Studio, you must create your image using another method before using it with Amazon SageMaker Model Building Pipelines.

To use your own container when creating the steps for your pipeline, include the image URI in the estimator definition. For more information on using your own container with SageMaker, see Using Docker Containers with SageMaker.

Property Files and JsonGet

Use property files to store information from the output of a processing step. This is particularly useful when analyzing the results of a processing step to decide how a conditional step should be executed. The JsonGet function processes a property file and enables you to use JsonPath notation to query the property JSON file. For more information on JsonPath notation, see the JsonPath repo.

To store a property file for later use, you must first create a PropertyFile instance with the following format. The path parameter is the name of the JSON file to which the property file is saved. Any output_name must match the output_name of the ProcessingOutput that you define in your processing step. This enables the property file to capture the ProcessingOutput in the step.

from sagemaker.workflow.properties import PropertyFile
When you create your ProcessingStep instance, add the property_files parameter to list all of the parameter files that the Amazon SageMaker Model Building Pipelines service must index. This saves the property file for later use.

```
property_files=[<property_file_instance>]
```

To use your property file in a condition step, add the property_file to the condition that you pass to your condition step as shown in the following example to query the JSON file for your desired property using the json_path parameter.

```
cond_lte = ConditionLessThanOrEqualTo(
    left=JsonGet(
        step_name=step_eval.name,
        property_file=<property_file_instance>,
        json_path="mse"
    ),
    right=6.0
)
```

For more in-depth examples, see Property File in the Amazon SageMaker Python SDK.

### Caching Pipeline Steps

When you use step signature caching, SageMaker Pipelines tries to find a previous run of your current pipeline step with the same values for certain attributes. If found, SageMaker Pipelines propagates the outputs from the previous run rather than recomputing the step. The attributes checked are specific to the step type, and are listed in Default cache key attributes by pipeline step type (p. 3233).

You must opt in to step caching — it is off by default. When you turn on step caching, you must also define a timeout. This timeout defines how old a previous run can be to remain a candidate for reuse.

Step caching only considers successful runs — it never reuses failed runs. A previous run of a pipeline step is considered successful when the run itself and the entire pipeline are both successful. When multiple successful runs exist within the timeout period, SageMaker Pipelines uses the result for the most recent successful run. If no successful runs match in the timeout period, SageMaker Pipelines reruns the step. If the executor finds a previous run that meets the criteria but is still in progress, both steps continue running and update the cache if they're successful.

Step caching is only scoped for individual pipelines, so you can't reuse a step from another pipeline even if there is a step signature match.

Step caching is available for the following step types:

- Processing (p. 3211)
- Training (p. 3213)
- Tuning (p. 3213)
- Transform (p. 3217)
- ClarifyCheck (p. 3222)
- QualityCheck (p. 3224)
### Turn on step caching

To turn on step caching, you must add a `CacheConfig` property to the step definition.

CacheConfig properties use the following format in the pipeline definition file:

```json
{
   "CacheConfig": {
      "Enabled": false,
      "ExpireAfter": "<time>"
   }
}
```

The `Enabled` field indicates whether caching is turned on for the particular step. You can set the field to `true`, which tells SageMaker to try to find a previous run of the step with the same attributes. Or, you can set the field to `false`, which tells SageMaker to run the step every time the pipeline runs. `ExpireAfter` is a string in ISO 8601 duration format that defines the timeout period. The `ExpireAfter` duration can be a year, month, week, day, hour, or minute value. Each value consists of a number followed by a letter indicating the unit of duration. For example:

- "30d" = 30 days
- "5y" = 5 years
- "T16m" = 16 minutes
- "30dT5h" = 30 days and 5 hours.

The following discussion describes the procedure to turn on caching for new or pre-existing pipelines using the Amazon SageMaker Python SDK.

#### Turn on caching for new pipelines

For new pipelines, initialize a `CacheConfig` instance with `enable_caching=True` and provide it as an input to your pipeline step. The following example turns on caching with a 1-hour timeout period for a training step:

```python
from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.workflow.steps import CacheConfig

cache_config = CacheConfig(enable_caching=True, expire_after="PT1H")
estimator = Estimator(..., sagemaker_session=PipelineSession())

step_train = TrainingStep(
   name="TrainAbaloneModel",
   step_args=estimator.fit(inputs=inputs),
   cache_config=cache_config
)
```

#### Turn on caching for pre-existing pipelines
To turn on caching for pre-existing, already-defined pipelines, turn on the `enable_caching` property for the step, and set `expire_after` to a timeout value. Lastly, update the pipeline with `pipeline.upsert()` or `pipeline.update()`. Once you run it again, the following code example turns on caching with a 1-hour timeout period for a training step:

```python
from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.workflow.steps import CacheConfig
from sagemaker.workflow.pipeline import Pipeline

cache_config = CacheConfig(enable_caching=True, expire_after="PT1H")
estimator = Estimator(..., sagemaker_session=PipelineSession())

step_train = TrainingStep(
    name="TrainAbaloneModel",
    step_args=estimator.fit(inputs=inputs),
    cache_config=cache_config
)

# define pipeline
pipeline = Pipeline(
    steps=[step_train]
)

# additional step for existing pipelines
pipeline.update()
# or, call upsert() to update the pipeline
# pipeline.upsert()
```

Alternatively, update the cache config after you have already defined the (pre-existing) pipeline, allowing one continuous code run. The following code sample demonstrates this method:

```python
# turn on caching with timeout period of one hour
pipeline.steps[0].cache_config.enable_caching = True
pipeline.steps[0].cache_config.expire_after = "PT1H"

# additional step for existing pipelines
pipeline.update()
# or, call upsert() to update the pipeline
# pipeline.upsert()
```

For more detailed code examples and a discussion about how Python SDK parameters affect caching, see Caching Configuration in the Amazon SageMaker Python SDK documentation.

**Turn off step caching**

A pipeline step does not rerun if you change any attributes that are not listed in Default cache key attributes by pipeline step type (p. 3233) for its step type. However, you may decide that you want the pipeline step to rerun anyway. In this case, you need to turn off step caching.

To turn off step caching, set the `Enabled` attribute in the step definition's `CacheConfig` property in the step definition to `false`, as shown in the following code snippet:

```json
{
    "CacheConfig": {
        "Enabled": false,
        "ExpireAfter": "<time>"
    }
}
```

Note that the `ExpireAfter` attribute is ignored when `Enabled` is `false`.

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To turn off caching for a pipeline step using the Amazon SageMaker Python SDK, define the pipeline of your pipeline step, turn off the enable_caching property, and update the pipeline.

Once you run it again, the following code example turns off caching for a training step:

```python
from sagemaker.workflow.pipeline_context import PipelineSession
from sagemaker.workflow.steps import CacheConfig
from sagemaker.workflow.pipeline import Pipeline

cache_config = CacheConfig(enable_caching=False, expire_after="PT1H")
estimator = Estimator(..., sagemaker_session=PipelineSession())

step_train = TrainingStep(
    name="TrainAbaloneModel",
    step_args=estimator.fit(inputs=inputs),
    cache_config=cache_config
)

# define pipeline
pipeline = Pipeline(
    steps=[step_train]
)

# update the pipeline
pipeline.update()
# or, call upsert() to update the pipeline
# pipeline.upsert()

Alternatively, turn off the enable_caching property after you have already defined the pipeline, allowing one continuous code run. The following code sample demonstrates this solution:

```python
# turn off caching for the training step
pipeline.steps[0].cache_config.enable_caching = False

# update the pipeline
pipeline.update()
# or, call upsert() to update the pipeline
# pipeline.upsert()

For more detailed code examples and a discussion about how Python SDK parameters affect caching, see Caching Configuration in the Amazon SageMaker Python SDK documentation.

**Default cache key attributes by pipeline step type**

When deciding whether to reuse a previous pipeline step or rerun the step, SageMaker Pipelines checks to see if certain attributes have changed. If the set of attributes is different from all previous runs within the timeout period, the step runs again. These attributes include input artifacts, app or algorithm specification, and environment variables.

The following list shows each pipeline step type and the attributes that, if changed, initiate a rerun of the step. For more information about which Python SDK parameters are used to create the following attributes, see Caching Configuration in the Amazon SageMaker Python SDK documentation.

**Processing step**

- AppSpecification
- Environment
- ProcessingInputs. This attribute contains information about the preprocessing script. If the contents of the preprocessing script change, the processing step is rerun.
Training step

- AlgorithmSpecification
- CheckpointConfig
- DebugHookConfig
- DebugRuleConfigurations
- Environment
- HyperParameters
- InputDataConfig. This attribute contains information about the training script. If the contents of the training script change, the training step is rerun.

Tuning step

- HyperParameterTuningJobConfig
- TrainingJobDefinition. This attribute is composed of multiple child attributes, not all of which cause the step to rerun. The child attributes that could incur a rerun (if changed) are:
  - AlgorithmSpecification
  - HyperParameterRanges
  - InputDataConfig
  - StaticHyperParameters
  - TuningObjective
  - TrainingJobDefinitions

Transform step

- DataProcessing
- Environment
- ModelName
- TransformInput

ClarifyCheck Step (p. 3222)

- ClarifyCheckConfig
- CheckJobConfig
- SkipCheck
- RegisterNewBaseline
- ModelPackageGroupName
- SuppliedBaselineConstraints

QualityCheck Step (p. 3224)

- QualityCheckConfig
- CheckJobConfig
- SkipCheck
- RegisterNewBaseline
• ModelPackageGroupName
• SuppliedBaselineConstraints
• SuppliedBaselineStatistics

EMR Step
• ClusterId
• StepConfig

Cached data access control

When a SageMaker pipeline runs, it caches the parameters and metadata associated with the SageMaker jobs launched by the pipeline and saves them for reuse in subsequent runs. This metadata is accessible through a variety of sources in addition to cached pipeline steps, and includes the following types:

• Describe*Job requests
• CloudWatch Logs
• CloudWatch Events
• CloudWatch Metrics
• SageMaker Search

Note that access to each data source in the list is controlled by its own set of IAM permissions. Removing a particular role’s access to one data source does not affect the level of access to the others. For example, an account admin might remove IAM permissions for Describe*Job requests from a caller’s role. While the caller can no longer make Describe*Job requests, they can still retrieve the metadata from a pipeline run with cached steps as long as they have permission to run the pipeline. If an account admin wants to remove access to the metadata from a particular SageMaker job completely, they need to remove permissions for each of the relevant services that provide access to the data.

Retry Policy for Pipeline Steps

Retry policies help you automatically retry your SageMaker Pipelines steps after an error occurs. Any pipeline step can encounter exceptions, and exceptions happen for various reasons. In some cases, a retry can resolve these issues. With a retry policy for pipeline steps, you can choose whether to retry a particular pipeline step or not.

The retry policy only supports the following pipeline steps:

• Processing Step (p. 3211)
• Training Step (p. 3213)
• Tuning Step (p. 3213)

Note
The SageMaker hyperparameter tuning job already conducts retries internally so it does not retry the SageMaker.JOB_INTERNAL_ERROR exception type, even if a retry policy is configured. If you really want to retry, you can program your own Retry Strategy using the SageMaker API.

• CreateModel Step (p. 3216)
• RegisterModel Step (p. 3216)
• Transform Step (p. 3217)
Supported exception types for the retry policy

The retry policy for pipeline steps supports the following exception types:

- **Step.SERVICE_FAULT**: These exceptions occur when an internal server error or transient error happens when calling downstream services. SageMaker Pipelines retries on this type of error automatically. With a retry policy, you can override the default retry operation for this exception type.

- **Step.THROTTLING**: Throttling exceptions can occur while calling the downstream services. SageMaker Pipelines retries on this type of error automatically. With a retry policy, you can override the default retry operation for this exception type.

- **SageMaker.JOB_INTERNAL_ERROR**: These exceptions occur when the SageMaker job returns InternalServerError. In this case, starting a new job may fix a transient issue.

- **SageMaker.CAPACITY_ERROR**: The SageMaker job may encounter Amazon EC2 InsufficientCapacityErrors, which leads to the SageMaker job's failure. You can retry by starting a new SageMaker job to avoid the issue.

- **SageMaker.RESOURCE_LIMIT**: You can exceed the resource limit quota when running a SageMaker job. You can wait and retry running the SageMaker job after a short period and see if resources are released.

The JSON schema for the retry policy

The retry policy for Pipelines has the following JSON schema:

```json
"RetryPolicy": {
  "ExceptionType": [String],
  "IntervalSeconds": Integer,
  "BackoffRate": Double,
  "MaxAttempts": Integer,
  "ExpireAfterMin": Integer
}
```

- **ExceptionType**: This field requires the following exception types in a string array format.
  - Step.SERVICE_FAULT
  - Step.THROTTLING
  - SageMaker.JOB_INTERNAL_ERROR
  - SageMaker.CAPACITY_ERROR
  - SageMaker.RESOURCE_LIMIT

- **IntervalSeconds** (optional): The number of seconds before the first retry attempt (1 by default). IntervalSeconds has a maximum value of 43200 seconds (12 hours).

- **BackoffRate** (optional): The multiplier by which the retry interval increases during each attempt (2.0 by default).

- **MaxAttempts** (optional): A positive integer that represents the maximum number of retry attempts (5 by default). If the error recurs more times than MaxAttempts specifies, retries cease and normal error handling resumes. A value of 0 specifies that errors are never retried. MaxAttempts has a maximum value of 20.

- **ExpireAfterMin** (optional): A positive integer that represents the maximum timespan of retry. If the error recurs after ExpireAfterMin minutes counting from the step gets executed, retries cease and normal error handling resumes. A value of 0 specifies that errors are never retried. ExpireAfterMin has a maximum value of 14,400 minutes (10 days).

**Note**

Only one of MaxAttempts or ExpireAfterMin can be given, but not both; if both are not specified, MaxAttempts becomes the default. If both properties are identified within one policy, then the retry policy generates a validation error.
Configuring a retry policy

The following is an example of a training step with a retry policy.

```json
{
    "Steps": [
        {
            "Name": "MyTrainingStep",
            "Type": "Training",
            "RetryPolicies": [
                {
                    "ExceptionType": [
                        "SageMaker.JOB_INTERNAL_ERROR",
                        "SageMaker.CAPACITY_ERROR"
                    ],
                    "IntervalSeconds": 1,
                    "BackoffRate": 2,
                    "MaxAttempts": 5
                }
            ]
        }
    ]
}
```

The following is an example of how to build a `TrainingStep` in SDK for Python (Boto3) with a retry policy.

```python
from sagemaker.workflow.retry import (StepRetryPolicy,
                                      StepExceptionTypeEnum,
                                      SageMakerJobExceptionTypeEnum,
                                      SageMakerJobStepRetryPolicy)

step_train = TrainingStep(
    name="MyTrainingStep",
    xxx,
    retry_policies=[
        // override the default
        StepRetryPolicy(
            exception_types=[
                StepExceptionTypeEnum.SERVICE_FAULT,
                StepExceptionTypeEnum.THROTTLING
            ],
            expire_after_mins=5,
            interval_seconds=10,
            backoff_rate=2.0
        ),
        // retry when resource limit quota gets exceeded
        SageMakerJobStepRetryPolicy(
            exception_types=[SageMakerJobExceptionTypeEnum.RESOURCE_LIMIT],
            expire_after_mins=120,
            interval_seconds=60,
            backoff_rate=2.0
        ),
        // retry when job failed due to transient error or EC2 ICE.
        SageMakerJobStepRetryPolicy(
            failure_reason_types=[
                SageMakerJobExceptionTypeEnum.INTERNAL_ERROR,
                SageMakerJobExceptionTypeEnum.CAPACITY_ERROR,
            ]
        ),
        max_attempts=10,
        interval_seconds=30,
    ]
)
```
Baseline calculation, drift detection and lifecycle with ClarifyCheck and QualityCheck steps in Amazon SageMaker Model Building Pipelines

The following topic discusses how baselines and model versions evolve in the Amazon SageMaker Model Building Pipelines when using the ClarifyCheck (p. 3222) and QualityCheck (p. 3224) steps.

For the ClarifyCheck step, a baseline is a single file that resides in the step properties with the suffix constraints. For the QualityCheck step, a baseline is a combination of two files that resides in the step properties: one with the suffix statistics and the other with the suffix constraints. In the following topics we discuss these properties with a prefix that describes how they are used, impacting baseline behavior and lifecycle in these two pipeline steps. For example, the ClarifyCheck step always calculates and assigns the new baselines in the CalculatedBaselineConstraints property and the QualityCheck step does the same in the CalculatedBaselineConstraints and CalculatedBaselineStatistics properties.

Baseline calculation and registration for ClarifyCheck and QualityCheck steps

Both the ClarifyCheck and QualityCheck steps always calculate new baselines based on step inputs through the underlying processing job run. These newly calculated baselines are accessed through the properties with the prefix CalculatedBaseline. You can record these properties as the ModelMetrics of your model package in the Model Step (p. 3214). This model package can be registered with 5 different baselines. You can register it with one for each check type: data bias, model bias, and model explainability from running the ClarifyCheck step and model quality, and data quality from running the QualityCheck step. The register_new_baseline parameter dictates the value set in the properties with the prefix BaselineUsedForDriftCheck after a step runs.

The following table of potential use cases shows different behaviors resulting from the step parameters you can set for the ClarifyCheck and QualityCheck steps:

<table>
<thead>
<tr>
<th>Possible use case that you may consider for selecting this configuration</th>
<th>skip_check / register_new_base</th>
<th>Does step do a drift check?</th>
<th>Value of step property CalculatedBaselineConstraints</th>
<th>Value of step property BaselineUsedForDriftCheck</th>
</tr>
</thead>
<tbody>
<tr>
<td>You are doing regular retraining with checks enabled to get a new model version, but you want to carry over the previous baselines as the DriftCheckBaselines in the model registry for</td>
<td>False/False</td>
<td>Drift check runs against existing baselines</td>
<td>New baselines calculated by running the step</td>
<td>Baseline from the latest approved model in Model Registry or the baseline supplied as step parameter</td>
</tr>
<tr>
<td>Possible use case that you may consider for selecting this configuration</td>
<td>skip_check/register_new_baselines</td>
<td>Does step do a drift check?</td>
<td>Value of step property CalculatedBaseline</td>
<td>Value of step property BaselineUsedForDriftCheck</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Your new model version.</td>
<td></td>
<td>False/ True</td>
<td>Drift check runs against existing baselines</td>
<td>New baselines calculated by running the step (value of property CalculatedBaseline)</td>
</tr>
<tr>
<td>You are doing regular retraining with checks enabled to get a new model version, but you want to refresh the DriftCheckBaselines in the model registry with the newly calculated baselines for your new model version.</td>
<td></td>
<td>False/ True</td>
<td>No drift check</td>
<td>New baselines calculated by running Baseline from the latest approved model in the model registry or the baseline supplied as step parameter</td>
</tr>
</tbody>
</table>
### Possible use case that you may consider for selecting this configuration

<table>
<thead>
<tr>
<th>skip_check / register_new_baseline</th>
<th>Does step do a drift check?</th>
<th>Value of step property CalculatedBaseline</th>
<th>Value of step property BaselineUsedForDriftCheck</th>
</tr>
</thead>
<tbody>
<tr>
<td>True/ True</td>
<td>No drift check</td>
<td>New baselines calculated by running the step (value of property CalculatedBaseline)</td>
<td>Newly calculated baseline by running the step (value of property CalculatedBaseline)</td>
</tr>
</tbody>
</table>

This happens in the following cases:

- You are starting the initial run of the pipeline, building your first model version, and generating the initial baselines.
- You are initiating the pipeline to retrain a new model version because there is a violation detected by Model Monitor on the endpoint for a particular type of check. If you want to skip the check against the previous baseline and refresh the DriftCheckBaselines with the newly calculated baseline in the model registry directly.

When you register a model with Model Step (p. 3214), you can register the BaselineUsedForDriftCheck property as DriftCheckBaselines. These baseline files can then be used by Model Monitor for model and data quality checks. In addition, these baselines can also be used in the ClarifyCheckStep and QualityCheck step to compare newly trained models against the existing models that are registered in the model registry for future pipeline runs.

**Drift Detection against Previous Baselines in SageMaker Pipelines**

In the case of the QualityCheck step, when you initiate the pipeline for regular retraining to get a new model version, you may want to run the training step if the data quality and the data bias has issues (p. 2869) on the baselines of your previous approved model version. You also may not want to register the newly trained model version if the model quality, model bias, or model explainability violates the registered baseline of your previous approved model version when running the ClarifyCheck step. In these cases, you can enable the checks you want by setting the
skip_check property of the corresponding check step set to False, resulting in the ClarifyCheck and QualityCheck step failing if violation is detected against previous baselines. The pipeline process then does not proceed so that the model drifted from the baseline isn't registered. ClarifyCheck and QualityCheck steps are able to get DriftCheckBaselines of the latest approved model version of a given model package group against which to compare. Previous baselines can also be supplied directly through supplied_baseline_constraints (in addition to supplied_baseline_statistics if it is a QualityCheck step) and are always prioritized over any baselines pulled from the model package group.

**Baseline and model version lifecycle and evolution with SageMaker Pipelines**

By setting register_new_baseline of your ClarifyCheck and QualityCheck step to False, your previous baseline is accessible through the step property prefix BaselineUsedForDriftCheck. You can then register these baselines as the DriftCheckBaselines in the new model version when you register a model with Model Step (p. 3214). Once you approve this new model version in the model registry, the DriftCheckBaseline in this model version becomes available for the ClarifyCheck and QualityCheck steps in the next pipeline process. If you want to refresh the baseline of a certain check type for future model versions, you can set register_new_baseline to True so that the properties with prefix BaselineUsedForDriftCheck become the newly calculated baseline. In these ways, you can preserve your preferred baselines for a model trained in the future, or refresh the baselines for drift checks when needed, managing your baseline evolution and lifecycle throughout your model training iterations.

The following diagram illustrates a model-version-centric view of the baseline evolution and lifecycle.
Pipeline Run 1: initial run

Pipeline Run 2: Scheduled retraining new model version (Check Succeeded)

Pipeline Run 3: Scheduled retraining new model version (Check Succeeded)

Pipeline Run 4: Drift detected on endpoint, suggest and register new baselines

Pipeline Run 5: Scheduled retraining new model version (Check Succeeded)
Amazon EventBridge Integration

You can schedule your Amazon SageMaker Model Building Pipelines executions using Amazon EventBridge. Amazon SageMaker Model Building Pipelines is supported as a target in Amazon EventBridge. This allows you to initiate the execution of your model building pipeline based on any event in your event bus. With EventBridge, you can automate your pipeline executions and respond automatically to events such as training job or endpoint status changes. Events include a new file being uploaded to your Amazon S3 bucket, a change in status of your Amazon SageMaker endpoint due to drift, and Amazon Simple Notification Service (SNS) topics.

The following SageMaker Pipelines actions can be automatically initiated:

- StartPipelineExecution

For more information on scheduling SageMaker jobs, see Automating SageMaker with Amazon EventBridge.

Schedule a Pipeline with Amazon EventBridge

To start a pipeline execution with Amazon CloudWatch Events, you must create an EventBridge rule. When you create a rule for events, you specify a target action to take when EventBridge receives an event that matches the rule. When an event matches the rule, EventBridge sends the event to the specified target and initiates the action defined in the rule.

The following tutorials show how to schedule a pipeline execution with EventBridge using the EventBridge console or the AWS CLI.

Prerequisites

- A role that EventBridge can assume with the SageMaker::StartPipelineExecution permission. This role can be created automatically if you create a rule from the EventBridge console; otherwise, you need to create this role yourself. For information on creating a SageMaker role, see SageMaker Roles.
- An Amazon SageMaker Pipeline to schedule. To create an Amazon SageMaker Pipeline, see Define a Pipeline.

Create an EventBridge rule using the EventBridge console

The following procedure shows how to create an EventBridge rule using the EventBridge console.

1. Navigate to the EventBridge console.
2. Select Rules on the left hand side.
3. Select Create Rule.
4. Enter a name and description for your rule.
5. Select how you want to initiate this rule. You have the following choices for your rule:
   - Event pattern: Your rule is initiated when an event matching the pattern occurs. You can choose a predefined pattern that matches a certain type of event, or you can create a custom pattern. If you select a predefined pattern, you can edit the pattern to customize it. For more information on Event patterns, see Event Patterns in CloudWatch Events.
   - Schedule: Your rule is initiated regularly on a specified schedule. You can use a fixed-rate schedule that initiates regularly for a specified number of minutes, hour, or weeks. You can also use a cron expression to create a more fine-grained schedule, such as “the first Monday of each month at 8am.” Schedule is not supported on a custom or partner event bus.
6. Select your desired Event bus.
7. Select the target(s) to invoke when an event matches your event pattern or when the schedule is initiated. You can add up to 5 targets per rule. Select SageMaker Pipeline in the target dropdown list.

8. Select the pipeline you want to initiate from the pipeline dropdown list.

9. Add parameters to pass to your pipeline execution using a name and value pair. Parameter values can be static or dynamic. For more information on Amazon SageMaker Pipeline parameters, see AWS::Events::Rule SagemakerPipelineParameters.

   • Static values are passed to the pipeline execution every time the pipeline is initiated. For example, if 
     "Name": "Instance_type", "Value": "ml.4xlarge" is specified in the parameter list, then it is passed as a parameter in StartPipelineExecutionRequest every time EventBridge initiates the pipeline.

   • Dynamic values are specified using a JSON path. EventBridge parses the value from an event payload, then passes it to the pipeline execution. For example: $.detail.param.value

10. Select the role to use for this rule. You can either use an existing role or create a new one.

11. (Optional) Add tags.

12. Select Create to finalize your rule.

Your rule is now in effect and ready to initiate your pipeline executions.

Create an EventBridge rule using the AWS CLI

The following procedure shows how to create an EventBridge rule using the AWS CLI.

1. Create a rule to be initiated. When creating an EventBridge rule using the AWS CLI, you have two options for how your rule is initiated, event pattern and schedule.

   • **Event pattern**: Your rule is initiated when an event matching the pattern occurs. You can choose a predefined pattern that matches a certain type of event, or you can create a custom pattern. If you select a predefined pattern, you can edit the pattern to customize it. You can create a rule with event pattern using the following command:

     
     ```
     aws events put-rule --name <RULE_NAME> --event-pattern <YOUR_EVENT_PATTERN> --description <RULE_DESCRIPTION> --role-arn <ROLE_TO_EXECUTE_PIPELINE> --tags <TAGS>
     ```

   • **Schedule**: Your rule is initiated regularly on a specified schedule. You can use a fixed-rate schedule that initiates regularly for a specified number of minutes, hour, or weeks. You can also use a cron expression to create a more fine-grained schedule, such as "the first Monday of each month at 8am." Schedule is not supported on a custom or partner event bus. You can create a rule with schedule using the following command:

     ```
     aws events put-rule --name <RULE_NAME> --schedule-expression <YOUR_CRON_EXPRESSION> --description <RULE_DESCRIPTION> --role-arn <ROLE_TO_EXECUTE_PIPELINE> --tags <TAGS>
     ```

2. Add target(s) to invoke when an event matches your event pattern or when the schedule is initiated. You can add up to 5 targets per rule. For each target, you must specify:

   • ARN: The resource ARN of your pipeline.

   • Role ARN: The ARN of the role EventBridge should assume to execute the pipeline.

   • Parameters: Amazon SageMaker pipeline parameters to pass.

3. Run the following command to pass a Amazon SageMaker pipeline as a target to your rule using put-targets:

     ```
     aws events put-targets --rule <RULE_NAME> --event-bus-name <EVENT_BUS_NAME> --targets "["
     ```
Amazon SageMaker Experiments Integration

Amazon SageMaker Model Building Pipelines is closely integrated with Amazon SageMaker Experiments. By default, when SageMaker Pipelines creates and executes a pipeline, the following SageMaker Experiments entities are created if they don't exist:

- An experiment for the pipeline
- A trial for every execution of the pipeline
- A trial component that's added to the trial for each SageMaker job created in a pipeline execution step

You can compare metrics such as model training accuracy across multiple pipeline executions just as you can compare such metrics across multiple trials of a SageMaker model training experiment.

The following sample shows the relevant parameters of the `Pipeline` class in the Amazon SageMaker Python SDK.

```python
Pipeline(
  name="MyPipeline",
  parameters=[],
  pipeline_experiment_config=PipelineExperimentConfig(
    ExecutionVariables.PIPELINE_NAME,
    ExecutionVariables.PIPELINE_EXECUTION_ID
  ),
  steps=[...]
)
```

If you don't want an experiment and trial created for the pipeline, set `pipeline_experiment_config` to `None`.

**Note**
Experiments integration was introduced in the Amazon SageMaker Python SDK v2.41.0.

The following naming rules apply based on what you specify for the `ExperimentName` and `TrialName` parameters of `pipeline_experiment_config`:

- If you don't specify `ExperimentName`, the pipeline name is used for the experiment name.

  If you do specify `ExperimentName`, it's used for the experiment name. If an experiment with that name exists, the pipeline-created trials are added to the existing experiment. If an experiment with that name doesn't exist, a new experiment is created.

- If you don't specify `TrialName`, the pipeline execution ID is used for the trial name.

  If you do specify `TrialName`, it's used for the trial name. If a trial with that name exists, the pipeline-created trial components are added to the existing trial. If a trial with that name doesn't exist, a new trial is created.

**Note**
The experiment entities aren't deleted when the pipeline that created the entities is deleted. You can use the SageMaker Experiments API to delete the entities. For more information, see Clean Up Amazon SageMaker Experiment Resources (p. 2251).
For information about how to view the SageMaker Experiment entities associated with a pipeline, see View Experiment Entities Created by SageMaker Pipelines (p. 3273). For more information on SageMaker Experiments, see Manage Machine Learning with Amazon SageMaker Experiments (p. 2231).

The following sections show examples of the previous rules and how they are represented in the pipeline definition file. For more information on pipeline definition files, see SageMaker Pipelines Overview (p. 3204).

Topics
- Default Behavior (p. 3246)
- Disable Experiments Integration (p. 3246)
- Specify a Custom Experiment Name (p. 3247)
- Specify a Custom Trial Name (p. 3247)

Default Behavior

Create a pipeline

The pipeline_experiment_config is omitted. ExperimentName defaults to the pipeline name. TrialName defaults to the execution ID.

```python
pipeline_name = f"MyPipeline"
pipeline = Pipeline(
    name=pipeline_name,
    parameters=[],
    steps=[step_train]
)
```

Pipeline definition file

```json
{
    "Version": "2020-12-01",
    "Parameters": [
        {
            "Name": "InputDataSource"        
        },
        {
            "Name": "InstanceCount",
            "Type": "Integer",
            "DefaultValue": 1
        }
    ],
    "PipelineExperimentConfig": {
        "ExperimentName": {"Get": "Execution.PipelineName"},
        "TrialName": {"Get": "Execution.PipelineExecutionId"}
    },
    "Steps": [...]
}
```

Disable Experiments Integration

Create a pipeline

The pipeline_experiment_config is set to None.

```python
pipeline_name = f"MyPipeline"
pipeline = Pipeline(
    name=pipeline_name,
    parameters=[],
)```
pipeline_experiment_config=None,
    steps=[step_train]
)

Pipeline definition file

This is the same as the preceding default example, without the PipelineExperimentConfig.

Specify a Custom Experiment Name

A custom experiment name is used. The trial name is set to the execution ID, as with the default behavior.

Create a pipeline

```python
pipeline_name = f"MyPipeline"
pipeline = Pipeline(    name=pipeline_name,
    parameters=[...],
    pipeline_experiment_config=PipelineExperimentConfig(        "CustomExperimentName",
        ExecutionVariables.PIPELINE_EXECUTION_ID
    ),
    steps=[step_train]
)
```

Pipeline definition file

```json
{
    "PipelineExperimentConfig": {
        "ExperimentName": "CustomExperimentName",
        "TrialName": {"Get": "Execution.PipelineExecutionId"}
    },
    "Steps": [...]
}
```

Specify a Custom Trial Name

A custom trial name is used and appended with the execution ID. The experiment name is set to the pipeline name, as with the default behavior.

Create a pipeline

```python
pipeline_name = f"MyPipeline"
pipeline = Pipeline(    name=pipeline_name,
    parameters=[...],
    pipeline_experiment_config=PipelineExperimentConfig(        ExecutionVariables.PIPELINE_NAME,
        Join(on="-", values=["CustomTrialName", ExecutionVariables.PIPELINE_EXECUTION_ID])
    ),
    steps=[step_train]
)
```

Pipeline definition file

```json
{
    "PipelineExperimentConfig": {
        "ExperimentName": {"Get": "Execution.PipelineName"},
        "TrialName": {"Get": "Execution.PipelineExecutionId"}
    },
    "Steps": [...]
}
```
Local Mode

SageMaker Pipelines local mode is an easy way to test your training, processing and inference scripts, as well as the runtime compatibility of pipeline parameters before you execute your pipeline on the managed SageMaker service. By using local mode, you can test your SageMaker pipeline locally using a smaller dataset. This allows quick and easy debugging of errors in user scripts and the pipeline definition itself without incurring the costs of using the managed service.

Pipelines local mode leverages SageMaker jobs local mode under the hood. This is a feature in the SageMaker Python SDK that allows you to run SageMaker built-in or custom images locally using Docker containers. Pipelines local mode is built on top of SageMaker jobs local mode. Therefore, you can expect to see the same results as if you were running those jobs separately. For example, local mode still uses Amazon S3 to upload model artifacts and processing outputs. If you want data generated by local jobs to reside on local disk, you can use the setup mentioned in Local Mode.

Pipeline local mode currently supports the following step types:

- Training Step (p. 3213)
- Processing Step (p. 3211)
- Transform Step (p. 3217)
- Model Step (with Create Model arguments only)
- Condition Step (p. 3218)
- Fail Step (p. 3226)

As opposed to the managed Pipelines service which allows multiple steps to execute in parallel using Parallelism Configuration, the local pipeline executor runs the steps sequentially. Therefore, overall execution performance of a local pipeline may be poorer than one that runs on the cloud - this mostly depends on the size of the dataset, algorithm, as well as the power of your local computer. Also note that Pipelines runs in local mode are not recorded in SageMaker Experiments.

Note

Pipelines local mode is not compatible with SageMaker algorithms such as XGBoost. If you want to use these algorithms, you must use them in script mode.

In order to execute a pipeline locally, the sagemaker_session fields associated with the pipeline steps and the pipeline itself need to be of type LocalPipelineSession. The following example shows how you can define a SageMaker pipeline to execute locally.

```python
from sagemaker.workflow.pipeline_context import LocalPipelineSession

local_pipeline_session = LocalPipelineSession()

pytorch_estimator = PyTorch(
    sagemaker_session=local_pipeline_session,
    role=sagemaker.get_execution_role(),
    instance_type="ml.c5.xlarge",
)```
instance_count=1,
framework_version="1.8.0",
py_version="py36",
entry_point="/entry_point.py",

step = TrainingStep(
    name="MyTrainingStep",
    step_args=pytorch_estimator.fit(
        inputs=TrainingInput(s3_data="s3://my-bucket/my-data/train"),
    )
)

pipeline = Pipeline(
    name="MyPipeline",
    steps=[step],
sagemaker_session=local_pipeline_session
)

pipeline.create(
    role_arn=sagemaker.get_execution_role(),
    description="local pipeline example"
)

// pipeline will execute locally
execution = pipeline.start()
steps = execution.list_steps()

training_job_name = steps['PipelineExecutionSteps'][0]['Metadata']['TrainingJob']['Arn']
step_outputs = pipeline_session.sagemaker_client.describe_training_job(TrainingJobName = training_job_name)

Once you are ready to execute the pipeline on the managed SageMaker Pipelines service, you can do so by replacing LocalPipelineSession in the previous code snippet with PipelineSession (as shown in the following code sample) and rerunning the code.

```python
from sagemaker.workflow.pipeline_context import PipelineSession
pipeline_session = PipelineSession()
```

**Troubleshooting Amazon SageMaker Model Building Pipelines**

When using Amazon SageMaker Model Building Pipelines, you might run into issues for various reasons. This topic provides information about common errors and how to resolve them.

**Pipeline Definition Issues**

Your pipeline definition might not be formatted correctly. This can result in your execution failing or your job being inaccurate. These errors can be caught when the pipeline is created or when an execution occurs. If your definition doesn't validate, SageMaker Pipelines returns an error message identifying the character where the JSON file is malformed. To fix this problem, review the steps created using the SageMaker Python SDK for accuracy.

You can only include steps in a pipeline definition once. Because of this, steps cannot exist as part of a condition step and a pipeline in the same pipeline.

**Examining Pipeline Logs**

You can view the status of your steps using the following command:
Each step includes the following information:

- The ARN of the entity launched by the pipeline, such as SageMaker job ARN, model ARN, or model package ARN.
- The failure reason includes a brief explanation of the step failure.
- If the step is a condition step, it includes whether the condition is evaluated to true or false.
- If the execution reuses a previous job execution, the CacheHit lists the source execution.

You can also view the error messages and logs in the Amazon SageMaker Studio interface. For information about how to see the logs in Studio, see View a Pipeline Execution (p. 3270).

**Missing Permissions**

Correct permissions are required for the role that creates the pipeline execution, and the steps that create each of the jobs in your pipeline execution. Without these permissions, you may not be able to submit your pipeline execution or run your SageMaker jobs as expected. To ensure that your permissions are properly set up, see IAM Access Management (p. 3206).

**Job Execution Errors**

You may run into issues when executing your steps because of issues in the scripts that define the functionality of your SageMaker jobs. Each job has a set of CloudWatch logs. To view these logs from Studio, see View a Pipeline Execution (p. 3270). For information about using CloudWatch logs with SageMaker, see Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675).

**Property File Errors**

You may have issues when incorrectly implementing property files with your pipeline. To ensure that your implementation of property files works as expected, see Property Files and JsonGet (p. 3229).

### Create and Manage SageMaker Pipelines

You can use Amazon SageMaker Model Building Pipelines to create end-to-end workflows that manage and deploy SageMaker jobs. SageMaker Pipelines comes with SageMaker Python SDK integration, so you can build each step of your pipeline using a Python-based interface.

After your pipeline is deployed, you can view the directed acyclic graph (DAG) for your pipeline and manage your executions using Amazon SageMaker Studio. Using SageMaker Studio, you can get information about your current and historical pipelines, compare executions, see the DAG for your executions, get metadata information, and more. To learn how to view pipelines from SageMaker Studio, see View, Track, and Execute SageMaker Pipelines in SageMaker Studio (p. 3266).

#### Topics
- Define a Pipeline (p. 3250)
- Run a pipeline (p. 3263)
- View, Track, and Execute SageMaker Pipelines in SageMaker Studio (p. 3266)

### Define a Pipeline

To orchestrate your workflows with Amazon SageMaker Model Building Pipelines, you need to generate a directed acyclic graph (DAG) in the form of a JSON pipeline definition. The following image is a representation of the pipeline DAG that you create in this tutorial:
You can generate your JSON pipeline definition using the SageMaker Python SDK. The following tutorial shows how to generate a pipeline definition for a pipeline that solves a regression problem to determine the age of an abalone based on its physical measurements. For a Jupyter notebook that includes the content in this tutorial that you can run, see Orchestrating Jobs with Amazon SageMaker Model Building Pipelines.

**Topics**
- Prerequisites (p. 3251)
- Create a Pipeline (p. 3252)

**Prerequisites**

To run the following tutorial you must do the following:

- Set up your notebook instance as outlined in [Create a notebook instance](#). This gives your role permissions to read and write to Amazon S3, and create training, batch transform, and processing jobs in SageMaker.
- Grant your notebook permissions to get and pass its own role as shown in [Modifying a role permissions policy](#). Add the following JSON snippet to attach this policy to your role. Replace `<your-role-arn>` with the ARN used to create your notebook instance.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": "sts:AssumeRole",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            }
        }
    ]
}
```
Create and Manage Pipelines

Trust the SageMaker service principal by following the steps in Modifying a role trust policy. Add the following statement fragment to the trust relationship of your role:

```json
{
    "Sid": "",
    "Effect": "Allow",
    "Principal": {
        "Service": "sagemaker.amazonaws.com"
    },
    "Action": "sts:AssumeRole"
}
```

Set Up Your Environment

Create a new SageMaker session using the following code block. This returns the role ARN for the session. This role ARN should be the execution role ARN that you set up as a prerequisite.

```python
import boto3
import sagemaker
import sagemaker.session

region = boto3.Session().region_name
sagemaker_session = sagemaker.session.Session()
role = sagemaker_session.get_execution_role()
default_bucket = sagemaker_session.default_bucket()
model_package_group_name = f"AbaloneModelPackageGroupName"
```

Create a Pipeline

Run the following steps from your SageMaker notebook instance to create a pipeline including steps for preprocessing, training, evaluation, conditional evaluation, and model registration.

Step 1: Download the Dataset

This notebook uses the UCI Machine Learning Abalone Dataset. The dataset contains the following features:

- `length` – The longest shell measurement of the abalone.
- `diameter` – The diameter of the abalone perpendicular to its length.
- `height` – The height of the abalone with meat in the shell.
- `whole_weight` – The weight of the whole abalone.
- `shucked_weight` – The weight of the meat removed from the abalone.
- `viscera_weight` – The weight of the abalone viscera after bleeding.
- `shell_weight` – The weight of the abalone shell after meat removal and drying.
- `sex` – The sex of the abalone. One of 'M', 'F', or 'I', where 'I' is an infant abalone.
• rings – The number of rings in the abalone shell.

The number of rings in the abalone shell is a good approximation for its age using the formula
age = rings + 1.5. However, obtaining this number is a time-consuming task. You must cut the shell
through the cone, stain the section, and count the number of rings through a microscope. However,
the other physical measurements are easier to determine. This notebook uses the dataset to build a
predictive model of the variable rings using the other physical measurements.

To download the dataset

1. Download the dataset into your account's default Amazon S3 bucket.

   ```
   !mkdir -p data
   local_path = "data/abalone-dataset.csv"
   s3 = boto3.resource("s3")
   s3.Bucket(f"sagemaker-servicecatalog-seedcode-{region}").download_file("
   "dataset/abalone-dataset.csv",
   local_path
   )
   base_uri = f"s3://[default_bucket]/abalone"
   input_data_uri = sagemaker.s3.S3Uploader.upload(
   local_path=local_path,
   desired_s3_uri=base_uri,
   )
   print(input_data_uri)
   ```

2. Download a second dataset for batch transformation after your model is created.

   ```
   local_path = "data/abalone-dataset-batch"
   s3 = boto3.resource("s3")
   s3.Bucket(f"sagemaker-servicecatalog-seedcode-{region}").download_file("
   "dataset/abalone-dataset-batch",
   local_path
   )
   base_uri = f"s3://[default_bucket]/abalone"
   batch_data_uri = sagemaker.s3.S3Uploader.upload(
   local_path=local_path,
   desired_s3_uri=base_uri,
   )
   print(batch_data_uri)
   ```

Step 2: Define Pipeline Parameters

This code block defines the following parameters for your pipeline:

• processing_instance_count – The instance count of the processing job.
• input_data – The Amazon S3 location of the input data.
• batch_data – The Amazon S3 location of the input data for batch transformation.
• model_approval_status – The approval status to register the trained model with for CI/CD. For
  more information, see Automate MLOps with SageMaker Projects (p. 3281).

   ```
   from sagemaker.workflow.parameters import (ParameterInteger,
   ```
Step 3: Define a Processing Step for Feature Engineering

This section shows how to create a processing step to prepare the data from the dataset for training.

To create a processing step

1. Create a directory for the processing script.

```
!mkdir -p abalone
```

2. Create a file in the /abalone directory named preprocessing.py with the following content. This preprocessing script is passed in to the processing step for execution on the input data. The training step then uses the preprocessed training features and labels to train a model, and the evaluation step uses the trained model and preprocessed test features and labels to evaluate the model. The script uses scikit-learn to do the following:

- Fill in missing sex categorical data and encode it so it’s suitable for training.
- Scale and normalize all numerical fields except for rings and sex.
- Split the data into training, test, and validation datasets.

```
# Because this is a headerless CSV file, specify the column names here.
feature_columns_names = [
    "sex",
    "length",
    "diameter",
    "height",
]
"whole_weight",
"shucked_weight",
"viscera_weight",
"shell_weight",
]
label_column = "rings"

feature_columns_dtype = {
    "sex": str,
    "length": np.float64,
    "diameter": np.float64,
    "height": np.float64,
    "whole_weight": np.float64,
    "shucked_weight": np.float64,
    "viscera_weight": np.float64,
    "shell_weight": np.float64
}

label_column_dtype = {"rings": np.float64}

def merge_two_dicts(x, y):
    z = x.copy()
    z.update(y)
    return z

if __name__ == '__main__':
    base_dir = '/opt/ml/processing'
    
    df = pd.read_csv(f'{base_dir}/input/abalone-dataset.csv',
                    header=None,
                    names=feature_columns_names + [label_column],
                    dtype=merge_two_dicts(feature_columns_dtype, label_column_dtype)
    )
    numeric_features = list(feature_columns_names)
    numeric_features.remove("sex")
    numeric_transformer = Pipeline(
        steps=[
            ("imputer", SimpleImputer(strategy="median")),
            ("scaler", StandardScaler())
        ]
    )
    
    categorical_features = ["sex"]
    categorical_transformer = Pipeline(
        steps=[
            ("imputer", SimpleImputer(strategy="constant", fill_value="missing")),
            ("onehot", OneHotEncoder(handle_unknown="ignore"))
        ]
    )
    
    preprocess = ColumnTransformer(
        transformers=[
            ("num", numeric_transformer, numeric_features),
            ("cat", categorical_transformer, categorical_features)
        ]
    )
    
    y = df.pop("rings")
    X_pre = preprocess.fit_transform(df)
    y_pre = y.to_numpy().reshape(len(y), 1)
    X = np.concatenate((y_pre, X_pre), axis=1)
    np.random.shuffle(X)
3. Create an instance of an `SKLearnProcessor` to pass in to the processing step.

```python
from sagemaker.sklearn.processing import SKLearnProcessor

framework_version = "0.23-1"

sklearn_processor = SKLearnProcessor(
    framework_version=framework_version,
    instance_type="ml.m5.xlarge",
    instance_count=processing_instance_count,
    base_job_name="sklearn-abalone-process",
    role=role,
)
```

4. Create a processing step. This step takes in the `SKLearnProcessor`, the input and output channels, and the `preprocessing.py` script that you created. This is very similar to a processor instance's `run` method in the SageMaker Python SDK. The `input_data` parameter passed into `ProcessingStep` is the input data of the step itself. This input data is used by the processor instance when it runs.

   Note the "train", "validation", and "test" named channels specified in the output configuration for the processing job. Step Properties such as these can be used in subsequent steps and resolve to their runtime values at execution.

```python
from sagemaker.processing import ProcessingInput, ProcessingOutput
from sagemaker.workflow.steps import ProcessingStep

step_process = ProcessingStep(
    name="AbaloneProcess",
    processor=sklearn_processor,
    inputs=[
        ProcessingInput(source=input_data, destination="/opt/ml/processing/input"),
    ],
    outputs=[
        ProcessingOutput(output_name="train", source="/opt/ml/processing/train"),
        ProcessingOutput(output_name="validation", source="/opt/ml/processing/validation"),
        ProcessingOutput(output_name="test", source="/opt/ml/processing/test")
    ],
    code="abalone/preprocessing.py",
)
```

**Step 4: Define a Training step**

This section shows how to use the SageMaker XGBoost Algorithm to train a model on the training data output from the processing steps.

**To define a training step**

1. Specify the model path where you want to save the models from training.
2. Configure an estimator for the XGBoost algorithm and the input dataset. The training instance type is passed into the estimator. A typical training script loads data from the input channels, configures training with hyperparameters, trains a model, and saves a model to `model_dir` so that it can be hosted later. SageMaker uploads the model to Amazon S3 in the form of a `model.tar.gz` at the end of the training job.

```python
from sagemaker.estimator import Estimator

image_uri = sagemaker.image_uris.retrieve(
    framework="xgboost",
    region=region,
    version="1.0-1",
    py_version="py3",
    instance_type="ml.m5.xlarge"
)
xgb_train = Estimator(
    image_uri=image_uri,
    instance_type="ml.m5.xlarge",
    instance_count=1,
    output_path=model_path,
    role=role,
)
xgb_train.set_hyperparameters(
    objective="reg:linear",
    num_round=50,
    max_depth=5,
    eta=0.2,
    gamma=4,
    min_child_weight=6,
    subsample=0.7,
    silent=0
)
```

3. Create a `TrainingStep` using the estimator instance and properties of the `ProcessingStep`. In particular, pass in the S3Uri of the "train" and "validation" output channel to the `TrainingStep`.

```python
from sagemaker.inputs import TrainingInput
from sagemaker.workflow.steps import TrainingStep

step_train = TrainingStep(
    name="AbaloneTrain",
    estimator=xgb_train,
    inputs={
        "train": TrainingInput(
            s3_data=step_process.properties.ProcessingOutputConfig.Outputs["train"].S3Output.S3Uri,
            content_type="text/csv"
        ),
        "validation": TrainingInput(
            s3_data=step_process.properties.ProcessingOutputConfig.Outputs["validation"].S3Output.S3Uri,
            content_type="text/csv"
        )
    }
)
```
Step 5: Define a Processing Step for Model Evaluation

This section shows how to create a processing step to evaluate the accuracy of the model. The result of this model evaluation is used in the condition step to determine which execute path to take.

To define a processing step for model evaluation

1. Create a file in the /abalone directory named evaluation.py. This script is used in a processing step to perform model evaluation. It takes a trained model and the test dataset as input, then produces a JSON file containing classification evaluation metrics.

```python
##writefile abalone/evaluation.py
import json
import pathlib
import pickle
import tarfile
import joblib
import numpy as np
import pandas as pd
import xgboost
from sklearn.metrics import mean_squared_error

if __name__ == '__main__':
    model_path = f'/opt/ml/processing/model/model.tar.gz'
    with tarfile.open(model_path) as tar:
        tar.extractall(path='.')
    model = pickle.load(open('xgboost-model', 'rb'))
    test_path = '/opt/ml/processing/test/test.csv'
    df = pd.read_csv(test_path, header=None)
    y_test = df.iloc[:, 0].to_numpy()
    df.drop(df.columns[0], axis=1, inplace=True)
    X_test = xgboost.DMatrix(df.values)
    predictions = model.predict(X_test)
    mse = mean_squared_error(y_test, predictions)
    std = np.std(y_test - predictions)
    report_dict = {
        "regression_metrics": {
            "mse": {
                "value": mse,
                "standard_deviation": std
            }
        }
    }

output_dir = '/opt/ml/processing/evaluation'
pathlib.Path(output_dir).mkdir(parents=True, exist_ok=True)

evaluation_path = f'{output_dir}/evaluation.json'
with open(evaluation_path, 'w') as f:
    f.write(json.dumps(report_dict))
```
2. Create an instance of a `ScriptProcessor` that is used to create a `ProcessingStep`.

```python
from sagemaker.processing import ScriptProcessor

script_eval = ScriptProcessor(
    image_uri=image_uri,
    command=['python3'],
    instance_type='ml.m5.xlarge',
    instance_count=1,
    base_job_name='script-abalone-eval',
    role=role,
)
```

3. Create a `ProcessingStep` using the processor instance, the input and output channels, and the `evaluation.py` script. In particular, pass in the `S3ModelArtifacts` property from the `step_train` training step, as well as the `S3Uri` of the "test" output channel of the `step_process` processing step. This is very similar to a processor instance's `run` method in the SageMaker Python SDK.

```python
from sagemaker.workflow.properties import PropertyFile

evaluation_report = PropertyFile(
    name='EvaluationReport',
    output_name='evaluation',
    path='evaluation.json'
)

step_eval = ProcessingStep(
    name='AbaloneEval',
    processor=script_eval,
    inputs=[
        ProcessingInput(
            source=step_train.properties.ModelArtifacts.S3ModelArtifacts,
            destination='/opt/ml/processing/model'
        ),
        ProcessingInput(
            source=step_process.properties.ProcessingOutputConfig.Outputs['test'].S3Output.S3Uri,
            destination='/opt/ml/processing/test'
        )
    ],
    outputs=[
        ProcessingOutput(output_name='evaluation', source='/opt/ml/processing/evaluation'),
    ],
    code='abalone/evaluation.py',
    property_files=[evaluation_report],
)
```

**Step 6: Define a CreateModelStep for Batch Transformation**

**Important**
We recommend using Model Step (p. 3214) to create models as of v2.90.0 of the SageMaker Python SDK. CreateModelStep will continue to work in previous versions of the SageMaker Python SDK, but is no longer actively supported.

This section shows how to create a SageMaker model from the output of the training step. This model is used for batch transformation on a new dataset. This step is passed into the condition step and only executes if the condition step evaluates to true.
To define a CreateModelStep for batch transformation


   ```python
   from sagemaker.model import Model

   model = Model(
       image_uri=image_uri,
       model_data=step_train.properties.ModelArtifacts.S3ModelArtifacts,
       sagemaker_session=sagemaker_session,
       role=role,
   )
   ```

2. Define the model input for your SageMaker model.

   ```python
   from sagemaker.inputs import CreateModelInput

   inputs = CreateModelInput(
       instance_type="ml.m5.large",
       accelerator_type="ml.eia1.medium",
   )
   ```

3. Create your CreateModelStep using the CreateModelInput and SageMaker model instance you defined.

   ```python
   from sagemaker.workflow.steps import CreateModelStep

   step_create_model = CreateModelStep(
       name="AbaloneCreateModel",
       model=model,
       inputs=inputs,
   )
   ```

Step 7: Define a TransformStep to Perform Batch Transformation

This section shows how to create a TransformStep to perform batch transformation on a dataset after the model is trained. This step is passed into the condition step and only executes if the condition step evaluates to true.

To define a TransformStep to perform batch transformation

1. Create a transformer instance with the appropriate compute instance type, instance count, and desired output Amazon S3 bucket URI. Pass in the ModelName property from the step_create_model CreateModel step.

   ```python
   from sagemaker.transformer import Transformer

   transformer = Transformer(
       model_name=step_create_model.properties.ModelName,
       instance_type="ml.m5.xlarge",
       instance_count=1,
       output_path=f"s3://{default_bucket}/AbaloneTransform"
   )
   ```
2. Create a TransformStep using the transformer instance you defined and the batch_data pipeline parameter.

```python
from sagemaker.inputs import TransformInput
from sagemaker.workflow.steps import TransformStep

step_transform = TransformStep(
    name="AbaloneTransform",
    transformer=transformer,
    inputs=TransformInput(data=batch_data)
)
```

**Step 8: Define a RegisterModel Step to Create a Model Package**

**Important**
We recommend using Model Step (p. 3214) to register models as of v2.90.0 of the SageMaker Python SDK. RegisterModel will continue to work in previous versions of the SageMaker Python SDK, but is no longer actively supported.

This section shows how to construct an instance of RegisterModel. The result of executing RegisterModel in a pipeline is a model package. A model package is a reusable model artifacts abstraction that packages all ingredients necessary for inference. It consists of an inference specification that defines the inference image to use along with an optional model weights location. A model package group is a collection of model packages. You can use a ModelPackageGroup for SageMaker Pipelines to add a new version and model package to the group for every pipeline execution. For more information about model registry, see Register and Deploy Models with Model Registry (p. 2982).

This step is passed into the condition step and only executes if the condition step evaluates to True.

**To define a RegisterModel step to create a model package**

- Construct a RegisterModel step using the estimator instance you used for the training step. Pass in the S3ModelArtifacts property from the step_train training step and specify a ModelPackageGroup. SageMaker Pipelines creates this ModelPackageGroup for you.

```python
from sagemaker.model_metrics import MetricsSource, ModelMetrics
from sagemaker.workflow.step_collections import RegisterModel

model_metrics = ModelMetrics(
    model_statistics=MetricsSource(
        s3_uri="{}//evaluation.json".format(
            step_eval.arguments["ProcessingOutputConfig"]['Outputs'][0]['S3Output'])
        ["S3Uri"]
    ),
    content_type="application/json"
)

step_register = RegisterModel(
    name="AbaloneRegisterModel",
    estimator=xgb_train,
    model_data=step_train.properties.ModelArtifacts.S3ModelArtifacts,
    content_types=["text/csv"],
    response_types=["text/csv"],
    inference_instances=["ml.t2.medium", "ml.m5.xlarge"],
    transform_instances=["ml.m5.xlarge"],
    model_package_group_name=model_package_group_name,
    approval_status=model_approval_status,
    model_metrics=model_metrics
```
Step 9: Define a Condition Step to Verify Model Accuracy

A ConditionStep allows SageMaker Pipelines to support conditional execution in your pipeline DAG based on the condition of step properties. In this case, you only want to register a model package if the accuracy of that model, as determined by the model evaluation step, exceeds the required value. If the accuracy exceeds the required value, the pipeline also creates a SageMaker Model and runs batch transformation on a dataset. This section shows how to define the Condition step.

To define a condition step to verify model accuracy

1. Define a ConditionLessThanOrEqualTo condition using the accuracy value found in the output of the model evaluation processing step, step_eval. Get this output using the property file you indexed in the processing step and the respective JSONPath of the mean squared error value, "mse".

   ```python
   from sagemaker.workflow.conditions import ConditionLessThanOrEqualTo
   from sagemaker.workflow.condition_step import ConditionStep
   from sagemaker.workflow.functions import JsonGet

   cond_lte = ConditionLessThanOrEqualTo(
       left=JsonGet(
           step_name=step_eval.name, 
           property_file=evaluation_report, 
           json_path="regression_metrics.mse.value" 
       ),
       right=6.0
   )
   ```

2. Construct a ConditionStep. Pass the ConditionEquals condition in, then set the model package registration and batch transformation steps as the next steps if the condition passes.

   ```python
   step_cond = ConditionStep(
       name="AbaloneMSECond",
       conditions=[cond_lte],
       if_steps=[step_register, step_create_model, step_transform],
       else_steps=[],
   )
   ```

Step 10: Create a pipeline

Now that you've created all of the steps, combine them into a pipeline.

To create a pipeline

1. Define the following for your pipeline: name, parameters, and steps. Names must be unique within an (account, region) pair.

   **Note**
   A step can only appear once in either the pipeline's step list or the if/else step lists of the condition step. It cannot appear in both.

   ```python
   from sagemaker.workflow.pipeline import Pipeline

   pipeline_name = f"AbalonePipeline"
   ```
pipeline = Pipeline(
    name=pipeline_name,
    parameters=[
        processing_instance_count,
        model_approval_status,
        input_data,
        batch_data,
    ],
    steps=[step_process, step_train, step_eval, step_cond],
)

2. (Optional) Examine the JSON pipeline definition to ensure that it's well-formed.

```python
import json
json.loads(pipeline.definition())
```

This pipeline definition is ready to submit to SageMaker. In the next tutorial, you submit this pipeline to SageMaker and start an execution.

**Next step:** Run a pipeline (p. 3263)

### Run a pipeline

After you've created a pipeline definition using the SageMaker Python SDK, you can submit it to SageMaker to start your execution. The following tutorial shows how to submit a pipeline, start an execution, examine the results of that execution, and delete your pipeline.

**Topics**

- Prerequisites (p. 3263)
- Step 1: Start the Pipeline (p. 3263)
- Step 2: Examine a Pipeline Execution (p. 3264)
- Step 3: Override Default Parameters for a Pipeline Execution (p. 3265)
- Step 4: Stop and Delete a Pipeline Execution (p. 3266)

### Prerequisites

This tutorial requires the following:

- A SageMaker notebook instance.
- A SageMaker Pipelines pipeline definition. This tutorial assumes you're using the pipeline definition created by completing the Define a Pipeline (p. 3250) tutorial.

### Step 1: Start the Pipeline

First, you need to start the pipeline.

**To start the pipeline**

1. Examine the JSON pipeline definition to ensure that it's well-formed.

```python
import json
json.loads(pipeline.definition())
```
2. Submit the pipeline definition to the SageMaker Pipelines service to create a pipeline if it doesn’t exist, or update the pipeline if it does. The role passed in is used by SageMaker Pipelines to create all of the jobs defined in the steps.

```python
pipeline.upsert(role_arn=role)
```

3. Start a pipeline execution.

```python
execution = pipeline.start()
```

### Step 2: Examine a Pipeline Execution

Next, you need to examine the pipeline execution.

**To examine a pipeline execution**

1. Describe the pipeline execution status to ensure that it has been created and started successfully.

```python
execution.describe()
```

2. Wait for the execution to finish.

```python
execution.wait()
```

3. List the execution steps and their status.

```python
execution.list_steps()
```

Your output should look like the following:

```json
[{'StepName': 'AbaloneTransform',
'StartTime': datetime.datetime(2020, 11, 21, 2, 41, 27, 870000, tzinfo=tzlocal()),
'EndTime': datetime.datetime(2020, 11, 21, 2, 45, 50, 492000, tzinfo=tzlocal()),
'StepStatus': 'Succeeded',
'CacheHitResult': {'SourcePipelineExecutionArn': ''},
{'StepName': 'AbaloneRegisterModel',
'StartTime': datetime.datetime(2020, 11, 21, 2, 41, 26, 929000, tzinfo=tzlocal()),
'EndTime': datetime.datetime(2020, 11, 21, 2, 41, 28, 15000, tzinfo=tzlocal()),
'StepStatus': 'Succeeded',
'CacheHitResult': {'SourcePipelineExecutionArn': ''},
'Metadata': {'RegisterModel': {'Arn': 'arn:aws:sagemaker:us-east-2:111122223333:model-package/abalonemodelpackagegroupname/1'}}},
{'StepName': 'AbaloneCreateModel',
'StartTime': datetime.datetime(2020, 11, 21, 2, 41, 26, 895000, tzinfo=tzlocal()),
'EndTime': datetime.datetime(2020, 11, 21, 2, 41, 27, 708000, tzinfo=tzlocal()),
'StepStatus': 'Succeeded',
'CacheHitResult': {'SourcePipelineExecutionArn': ''},
'Metadata': {'Model': {'Arn': 'arn:aws:sagemaker:us-east-2:111122223333:model/pipelines-cfvy1tjuxdq8-abalonemodelpackagegroupname/1'}}},
{'StepName': 'AbaloneMSECond',
'StartTime': datetime.datetime(2020, 11, 21, 2, 41, 25, 558000, tzinfo=tzlocal()),
'EndTime': datetime.datetime(2020, 11, 21, 2, 41, 26, 329000, tzinfo=tzlocal()),
'StepStatus': 'Succeeded',
'CacheHitResult': {'SourcePipelineExecutionArn': ''},
'Metadata': {'Condition': {'Outcome': 'True'}}},
{'StepName': 'AbaloneEval',
'StartTime': datetime.datetime(2020, 11, 21, 2, 41, 25, 15000, tzinfo=tzlocal()),
'EndTime': datetime.datetime(2020, 11, 21, 2, 41, 26, 15000, tzinfo=tzlocal()),
'StepStatus': 'Succeeded',
'CacheHitResult': {'SourcePipelineExecutionArn': ''},
'Metadata': {'EvaluateModel': {'Arn': 'arn:aws:sagemaker:us-east-2:111122223333:evaluate-model/pipelines-cfvy1tjuxdq8-abaloneevalatemodel-jl94rai0ra'}}},
{'StepName': 'AbaloneEVAL',
'StartTime': datetime.datetime(2020, 11, 21, 2, 41, 25, 15000, tzinfo=tzlocal()),
'EndTime': datetime.datetime(2020, 11, 21, 2, 41, 26, 15000, tzinfo=tzlocal()),
'StepStatus': 'Succeeded',
'CacheHitResult': {'SourcePipelineExecutionArn': ''},
'Metadata': {'EvaluateModel': {'Arn': 'arn:aws:sagemaker:us-east-2:111122223333:evaluate-model/pipelines-cfvy1tjuxdq8-abaloneevalatemodel-jl94rai0ra'}}}
```
4. After your pipeline execution is complete, download the resulting `evaluation.json` file from Amazon S3 to examine the report.

```python
evaluation_json = sagemaker.s3.S3Downloader.read_file("/{}/evaluation.json".format(step_eval.arguments["ProcessingOutputConfig"]['Outputs'][0]['S3Output']['S3Uri']))
json.loads(evaluation_json)
```

## Step 3: Override Default Parameters for a Pipeline Execution

You can run additional executions of the pipeline by specifying different pipeline parameters to override the defaults.

**To override default parameters**

1. Create the pipeline execution. This starts another pipeline execution with the model approval status override set to "Approved". This means that the model package version generated by the `RegisterModel` step is automatically ready for deployment through CI/CD pipelines, such as with SageMaker Projects. For more information, see [Automate MLOps with SageMaker Projects](p. 3281).

```python
evaluation = pipeline.start(
    parameters=dict(
        ModelApprovalStatus="Approved",
    )
)
```

2. Wait for the execution to finish.

```python
evaluation.wait()
```

3. List the execution steps and their status.

```python
evaluation.list_steps()
```

4. After your pipeline execution is complete, download the resulting `evaluation.json` file from Amazon S3 to examine the report.
evaluation_json = sagemaker.s3.S3Downloader.read_file("/evaluation.json".format( 
    step_eval.arguments["ProcessingOutputConfig"]["Outputs"][0]["S3Output"]["S3Uri"] 
))
json.loads(evaluation_json)

### Step 4: Stop and Delete a Pipeline Execution

When you're finished with your pipeline, you can stop any ongoing executions and delete the pipeline.

**To stop and delete a pipeline execution**

1. Stop the pipeline execution.

   ```python
   execution.stop()
   ```

2. Delete the pipeline.

   ```python
   pipeline.delete()
   ```

### View, Track, and Execute SageMaker Pipelines in SageMaker Studio

To view, track, and execute Amazon SageMaker Pipelines in Amazon SageMaker Studio, you must sign in to Studio. For more information, see [Onboard to Amazon SageMaker Domain](#).

**Topics**

- [View a Pipeline](#)
- [View a Pipeline Execution](#)
- [View Experiment Entities Created by SageMaker Pipelines](#)
- [Execute a Pipeline](#)
- [Track the Lineage of a SageMaker ML Pipeline](#)

#### View a Pipeline

This procedure shows you how to directly find a pipeline and view its details page. You can also find pipelines that are part of a project listed in the project's details page. For information on finding a pipeline that is part of a project, see [Automate MLOps with SageMaker Projects](#).

**To view a list of pipelines**

1. In the left sidebar of Studio, choose the **SageMaker resources** icon (Arial).
2. Select **Pipelines** from the dropdown list.

3. Drag the right border of the **SageMaker resources** pane to the right to view all the columns. Use search to narrow the list of pipelines.

Search is a two-step process. First, you enter characters that match the column name you want to search. Second, you enter characters to match the item in that column.

You can have multiple search filters. An example, the following screenshot limits the displayed pipelines to those with a name that starts with `aba` and created by `Me`. For more information on searching in Studio, see [Search Experiments Using Amazon SageMaker Studio](p. 2246).
4. Open a pipeline to view details about the pipeline. The pipeline details tab opens and displays a list of pipeline executions. You can start an execution or choose one of the other tabs for more information about the pipeline. Use the Settings icon (⚙️) to choose which columns to display.

5. From the pipeline details page, choose one of the following tabs to view details about the pipeline:
   - **Executions** – Details about the executions. You can start an execution from this tab or the **Graph** tab.
   - **Graph** – The DAG for the pipeline.
- **Parameters** – Includes the model approval status.

- **Settings** – The metadata associated with the pipeline. You can download the pipeline definition file and edit the pipeline name and description from this tab.
View a Pipeline Execution

This procedure shows you how to view a pipeline execution. For information on how to view a list of pipeline executions, and how to use SageMaker search to narrow the executions in the list, see View a Pipeline (p. 3266).

To view details of a pipeline execution

1. In the execution list, open an execution to view details about the execution. The execution details tab opens and displays a graph of the steps in the pipeline. You can choose one of the other tabs to view information about the pipeline execution, which is similar to that shown when viewing the pipeline details.

2. Use search to find a step in the graph. Type characters that match a step name. You can drag the graph around or use the resizing icons on the lower-left side of the graph. The inset on the lower-right side of the graph displays where you are in the graph.

3. Choose one of the steps in the graph to see details about the step. In the preceding screenshot, a training step is chosen and displays the following tabs:
• **Input** – The training inputs. If an input source is from Amazon Simple Storage Service (Amazon S3), choose the link to view the file in the Amazon S3 console.

• **Output** – The training outputs, such as metrics, charts, files, and evaluation outcome. The graphs were produced using the Tracker APIs.
### Confusion metrics

Confusion matrix for our classifier

<table>
<thead>
<tr>
<th>True label</th>
<th>Predicted label 0</th>
<th>Predicted label 1</th>
<th>Predicted label 2</th>
<th>Predicted label 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.92</td>
<td>0</td>
<td>0.01</td>
<td>0.073</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>0.92</td>
<td>0.0095</td>
<td>0.071</td>
</tr>
<tr>
<td>2</td>
<td>0.007</td>
<td>0.019</td>
<td>0.84</td>
<td>0.13</td>
</tr>
<tr>
<td>3</td>
<td>0.071</td>
<td>0.086</td>
<td>0.16</td>
<td>0.68</td>
</tr>
</tbody>
</table>

### Precision-Recall curve

- No Skill
- Logistic

### ROC Curve

- No Skill
- Logistic
• **Logs** – The Amazon CloudWatch logs produced by the step.

![View logs in CloudWatch console](image)

• **Info** – The parameters and metadata associated with the step.

![Info](image)

**View Experiment Entities Created by SageMaker Pipelines**

When you create a pipeline and specify `pipeline_experiment_config`, SageMaker Pipelines creates the following SageMaker Experiments entities by default if they don't exist:

- An experiment for the pipeline
- A trial for every execution of the pipeline
- A trial component for each SageMaker job created in a pipeline step
For information on how experiments are integrated with pipelines, see Amazon SageMaker Experiments Integration (p. 3245). For more information on SageMaker Experiments, see Manage Machine Learning with Amazon SageMaker Experiments (p. 2231).

You can get to the list of trial components associated with a pipeline from either the pipeline executions list or the experiments list.

**To view the trial components list from the pipeline executions list**

1. To view the pipeline executions list, follow the first four steps in View a Pipeline (p. 3266).
2. On the top right of the screen, choose the **Settings** icon (⚙️) to open **TABLE PROPERTIES**.
3. Select **Experiment**. If experiment integration wasn't disabled when the pipeline was created, the experiment name and trial name are displayed in the executions list.

   **Note**
   Experiments integration was introduced in v2.41.0 of the Amazon SageMaker Python SDK. Pipelines created with an earlier version of the SDK aren't integrated with experiments by default.

4. Select one or more executions, open (right-click) the selection, then choose **View trial components generated by execution**.

**To view the trial components list from the experiments list**

1. In the left sidebar of Studio, choose the **SageMaker resources** icon (🔍).
2. Select **Experiments and trials** from the dropdown list.
3. Use search to filter the list to experiments created by a pipeline.
   a. Drag the right border of the **SageMaker resources** pane to the right until you can see the **Experiment type** column.
   b. In the search box, enter ex and choose **Experiment type**.
   c. In **Filter by values**, choose **Pipeline**, then choose **Apply**.

   To further narrow the search, you can add additional filters. For more information, see Search Experiments Using Amazon SageMaker Studio (p. 2246).
4. Open (right-click) an experiment name and choose **Open in trial component list**.
List of trial components

The following shows the list of trial components created by the pipeline.

<table>
<thead>
<tr>
<th>Status</th>
<th>Experiment name</th>
<th>Trial name</th>
<th>Trial component name</th>
<th>Trial component type</th>
<th>Created</th>
<th>Last modified</th>
</tr>
</thead>
<tbody>
<tr>
<td>Completed</td>
<td>pipeline-experiment</td>
<td>pipeline-trial</td>
<td>pipeline-trial-5pEjgEaYD6z...</td>
<td>Processing job</td>
<td>24 minutes ago</td>
<td>19 minutes ago</td>
</tr>
<tr>
<td>Completed</td>
<td>pipeline-experiment</td>
<td>pipeline-trial</td>
<td>pipeline-trial-5pEjgEaYD6z...</td>
<td>Training job</td>
<td>28 minutes ago</td>
<td>23 minutes ago</td>
</tr>
<tr>
<td>Completed</td>
<td>pipeline-experiment</td>
<td>pipeline-trial</td>
<td>pipeline-trial-5pEjgEaYD6z...</td>
<td>Processing job</td>
<td>35 minutes ago</td>
<td>28 minutes ago</td>
</tr>
</tbody>
</table>

Execute a Pipeline

This procedure shows you how to execute a pipeline. For information on how to view a list of pipeline executions, see View a Pipeline (p. 3266).

To start a pipeline execution

1. From the Executions or Graph tab in the execution list, choose Start an execution.
2. Enter or update the following required information:
   • **Name** – Must be unique to your account in the AWS Region.
   • **ProcessingInstanceType** – The instance type for processing.
   • **ProcessingInstanceCount** – The number of instances to use for processing.
   • **TrainingInstanceType** – The instance type for training.
   • **ModelApprovalStatus** – For your convenience.
   • **InputData** – The S3 URI of the input data.

3. Choose **Submit**.
   • To see details of the execution or to stop the execution, choose **View details** on the status banner.
   • To stop the execution, choose **Stop** on the status banner.
   • To resume the execution from where it was stopped, choose **Resume** on the status banner.
Note
If your pipeline fails, the status banner will show **Failed** status. After troubleshooting the failed step, choose *Retry* on the status banner to resume running the pipeline from that step.

For a list of registered models, see **Automate MLOps with SageMaker Projects** (p. 3281).

**Track the Lineage of a SageMaker ML Pipeline**

In this tutorial, you use Amazon SageMaker Studio to track the lineage of an Amazon SageMaker ML Pipeline.

The pipeline was created by the **Orchestrating Jobs with Amazon SageMaker Model Building Pipelines** notebook in the **Amazon SageMaker example GitHub repository**. For detailed information on how the pipeline was created, see **Define a Pipeline** (p. 3250).

Lineage tracking in Studio is centered around a directed acyclic graph (DAG). The DAG represents the steps in a pipeline. From the DAG you can track the lineage from any step to any other step. The following diagram displays the steps in the pipeline. These steps appear as a DAG in Studio.

![Diagram of pipeline with steps labeled](image)

**Prerequisites**

- Access to Amazon SageMaker Studio. For more information, see **Onboard to Amazon SageMaker Domain** (p. 35).

- Familiarity with the SageMaker Studio user interface. For more information, see **Amazon SageMaker Studio UI Overview** (p. 118).

- (Recommended) A completed run of the example notebook.

**To track the lineage of a pipeline**

1. Sign in to SageMaker Studio.
2. In the left sidebar of Studio, choose the **SageMaker resources** icon ( ![SageMaker icon](image) ).
3. In the drop-down menu, select **Pipelines**.
4. Use the **Search** box to filter the pipelines list. To view all available columns, drag the right border of the pane to the right. For more information, see *Search Experiments Using Amazon SageMaker Studio* (p. 2246).

The following screenshot shows the list filtered by a name that starts with "aba" and that was created on 12/5/20.
5. Double-click the AbalonePipeline pipeline to view the execution list and other details about the pipeline. The following screenshot shows the **TABLE PROPERTIES** pane open where you can choose which properties to view.

6. Choose the **Settings** tab and then choose **Download pipeline definition file**. You can view the file to see how the pipeline graph was defined.

7. On the **Execution** tab, double-click the first row in the execution list to view its execution graph and other details about the execution. Note that the graph matches the diagram displayed at the beginning of the tutorial.

You can drag the graph around (select an area not on the graph itself) or use the resizing icons on the lower-left side of the graph. The inset on the lower-right side of the graph displays your location in the graph.
8. On the **Graph** tab, choose the AbaloneProcess step to view details about the step.

9. Find the Amazon S3 paths to the training, validation, and test datasets in the **Output** tab, under **Files**.

   **Note**
   To get the full paths, right-click the path and then choose **Copy cell contents**.

   ```
   s3://sagemaker-eu-west-1-acct-id/sklearn-abalone-process-2020-12-05-17-28-28-509/output/train
   ```
10. Choose the AbaloneTrain step.

11. Find the Amazon S3 path to the model artifact in the **Output** tab, under **Files**:

   s3://sagemaker-eu-west-1-acct-id/AbaloneTrain/pipelines-6locnsqz4bfu-AbaloneTrain-NtfEpI0Ahu/output/model.tar.gz

12. Choose the AbaloneRegisterModel step.

13. Find the ARN of the model package in the **Output** tab, under **Files**:

   arn:aws:sagemaker:eu-west-1:acct-id:model-package/abalonemodelpackagegroupname/2

### Automate MLOps with SageMaker Projects

Create end-to-end ML solutions with CI/CD by using SageMaker projects.

Use SageMaker projects to create an MLOps solution to orchestrate and manage:

- Building custom images for processing, training, and inference
- Data preparation and feature engineering
- Training models
- Evaluating models
- Deploying models
- Monitoring and updating models
Why MLOps?

As you move from running individual artificial intelligence and machine learning (AI/ML) projects to using AI/ML to transform your business at scale, the discipline of ML Operations (MLOps) can help. MLOps accounts for the unique aspects of AI/ML projects in project management, CI/CD, and quality assurance, helping you improve delivery time, reduce defects, and make data science more productive. MLOps refers to a methodology that is built on applying DevOps practices to machine learning workloads. For a discussion of DevOps principles, see the white paper Introduction to DevOps on AWS. To learn more about implementation using AWS services, see Practicing CI/CD on AWS and Infrastructure as Code.

Like DevOps, MLOps relies on a collaborative and streamlined approach to the machine learning development lifecycle where the intersection of people, process, and technology optimizes the end-to-end activities required to develop, build, and operate machine learning workloads. MLOps focuses on the intersection of data science and data engineering in combination with existing DevOps practices to streamline model delivery across the machine learning development lifecycle. MLOps is the discipline of integrating ML workloads into release management, CI/CD, and operations. MLOps requires the integration of software development, operations, data engineering, and data science.

Challenges with MLOps

Although MLOps can provide valuable tools to help you scale your business, you might face certain issues as you integrate MLOps into your machine learning workloads.

Project management

- ML projects involve data scientists, a relatively new role, and one not often integrated into cross-functional teams. These new team members often speak a very different technical language than product owners and software engineers, compounding the usual problem of translating business requirements into technical requirements.

Communication and collaboration

- Building visibility on ML projects and enabling collaboration across different stakeholders such as data engineers, data scientists, ML engineers, and DevOps is becoming increasingly important to ensure successful outcomes.

Everything is code
• Use of production data in development activities, longer experimentation lifecycles, dependencies on data pipelines, retraining deployment pipelines, and unique metrics in evaluating the performance of a model.

• Models often have a lifecycle independent of the applications and systems integrating with those models.

• The entire end-to-end system is reproducible through versioned code and artifacts. DevOps projects use Infrastructure-as-Code (IaC) and Configuration-as-Code (CaC) to build environments, and Pipelines-as-Code (PaC) to ensure consistent CI/CD patterns. The pipelines have to integrate with Big Data and ML training workflows. That often means that the pipeline is a combination of a traditional CI/CD tool and another workflow engine. There are important policy concerns for many ML projects, so the pipeline may also need to enforce those policies. Biased input data produces biased results, an increasing concern for business stakeholders.

CI/CD

• In MLOps, the source data is a first-class input, along with source code. That’s why MLOps calls for versioning the source data and initiating pipeline runs when the source or inference data changes.

• Pipelines must also version the ML models, along with inputs and other outputs, in order to provide for traceability.

• Automated testing must include proper validation of the ML model during build phases and when the model is in production.

• Build phases may include model training and retraining, a time-consuming and resource-intensive process. Pipelines must be granular enough to only perform a full training cycle when the source data or ML code changes, not when related components change.

• Because machine learning code is typically a small part of an overall solution, a deployment pipeline may also incorporate the additional steps required to package a model for consumption as an API by other applications and systems.

Monitoring and logging

• The feature engineering and model training phases needed to capture model training metrics as well as model experiments. Tuning an ML model requires manipulating the form of the input data as well as algorithm hyperparameters, and systematically capture those experiments. Experiment tracking helps data scientists work more effectively and gives a reproducible snapshot of their work.

• Deployed ML models require monitoring of the data passed to the model for inference, along with the standard endpoint stability and performance metrics. The monitoring system must also capture the quality of model output, as evaluated by an appropriate ML metric.

Benefits of MLOps

Adopting MLOps practices gives you faster time-to-market for ML projects by delivering the following benefits.

• **Productivity**: Providing self-service environments with access to curated data sets lets data engineers and data scientists move faster and waste less time with missing or invalid data.

• **Repeatability**: Automating all the steps in the MLDC helps you ensure a repeatable process, including how the model is trained, evaluated, versioned, and deployed.

• **Reliability**: Incorporating CI/CD practices allows for the ability to not only deploy quickly but with increased quality and consistency.

• **Auditability**: Versioning all inputs and outputs, from data science experiments to source data to trained model, means that we can demonstrate exactly how the model was built and where it was deployed.
Data and model quality: MLOps lets us enforce policies that guard against model bias and track changes to data statistical properties and model quality over time.

What is a SageMaker Project?

SageMaker Projects help organizations set up and standardize developer environments for data scientists and CI/CD systems for MLOps engineers. Projects also help organizations set up dependency management, code repository management, build reproducibility, and artifact sharing.

You can provision SageMaker Projects from the AWS Service Catalog using custom or SageMaker-provided templates. For information about the AWS Service Catalog, see What Is AWS Service Catalog. With SageMaker Projects, MLOps engineers and organization admins can define their own templates or use SageMaker-provided templates. The SageMaker-provided templates bootstrap the ML workflow with source version control, automated ML pipelines, and a set of code to quickly start iterating over ML use cases.

When Should You Use a SageMaker Project?

While notebooks are helpful for model building and experimentation, a team of data scientists and ML engineers sharing code needs a more scalable way to maintain code consistency and strict version control.

Every organization has its own set of standards and practices that provide security and governance for its AWS environment. SageMaker provides a set of first-party templates for organizations that want to quickly get started with ML workflows and CI/CD. The templates include projects that use AWS-native services for CI/CD, such as AWS CodeBuild, AWS CodePipeline, and AWS CodeCommit. The templates also offer the option to create projects that use third-party tools, such as Jenkins and GitHub. For a list of the project templates that SageMaker provides, see Use SageMaker-Provided Project Templates (p. 3289).

Organizations often need tight control over the MLOps resources that they provision and manage. Such responsibility assumes certain tasks, including configuring IAM roles and policies, enforcing resource tags, enforcing encryption, and decoupling resources across multiple accounts. SageMaker Projects can support all these tasks through custom template offerings where organizations use AWS CloudFormation templates to define the resources needed for an ML workflow. Data Scientists can choose a template to bootstrap and pre-configure their ML workflow. These custom templates are created as AWS Service Catalog products and you can provision them in the Studio UI under Organization Templates. The AWS Service Catalog is a service that helps organizations create and manage catalogs of products that are approved for use on AWS. For more information about creating custom templates, see Build Custom SageMaker Project Templates – Best Practices.

SageMaker Projects can help you manage your Git repositories so that you can collaborate more efficiently across teams, ensure code consistency, and support CI/CD. SageMaker Projects can help you with the following tasks:

- Organize all entities of the ML lifecycle under one project.
- Establish a single-click approach to set up standard ML infrastructure for model training and deployment that incorporates best practices.
- Create and share templates for ML infrastructure to serve multiple use cases.
- Leverage SageMaker-provided pre-built templates to quickly start focusing on model building, or create custom templates with organization-specific resources and guidelines.
- Integrate with tools of your choice by extending the project templates. For an example, see Create a SageMaker Project to integrate with GitLab and GitLab Pipelines.
- Organize all entities of the ML lifecycle under one project.
What is in a SageMaker Project?

Customers have the flexibility to set up their projects with the resources that best serve their use case. The example below showcases the MLOps setup for an ML workflow, including model training and deployment.

A typical project with a SageMaker-provided template might include the following:

- One or more repositories with sample code to build and deploy ML solutions. These are working examples that you can clone locally and modify for your needs. You own this code and can take advantage of the version-controlled repositories for your tasks.
- A SageMaker pipeline that defines steps for data preparation, training, model evaluation, and model deployment, as shown in the following diagram.
- A CodePipeline or Jenkins pipeline that runs your SageMaker pipeline every time you check in a new version of the code. For information about CodePipeline, see What is AWS CodePipeline. For information about Jenkins, see Jenkins User Documentation.

- A model group that contains model versions. Every time you approve the resulting model version from a SageMaker pipeline run, you can deploy it to a SageMaker endpoint.

Each SageMaker project has a unique name and ID that are applied as tags to all of the SageMaker and AWS resources created in the project. With the name and ID, you can view all of the entities associated with your project. These include:

- Pipelines
- Registered models
- Deployed models (endpoints)
- Datasets
- AWS Service Catalog products
- CodePipeline and Jenkins pipelines
- CodeCommit and third-party Git repositories

Do I Need to Create a Project to Use SageMaker Pipelines?

No. SageMaker pipelines are standalone entities just like training jobs, processing jobs, and other SageMaker jobs. You can create, update, and run pipelines directly within a notebook by using the SageMaker Python SDK without using a SageMaker project.

Projects provide an additional layer to help you organize your code and adopt operational best practices that you need for a production-quality system.

SageMaker Studio Permissions Required to Use Projects

Users can view SageMaker provided project templates and create projects with those templates when you grant Projects permissions for users. You can grant these permissions when you onboard or update Amazon SageMaker Studio. There are two permissions to grant.

1. Grant Projects permissions for the Studio administrator to permit the Studio administrator to view the SageMaker-provided templates in the AWS Service Catalog console. The administrator can see what other Studio users create if you grant them permission to use SageMaker projects. The administrator can also view the AWS CloudFormation template that the SageMaker-provided project templates define in the AWS Service Catalog console. For information about using the AWS Service Catalog console, see What Is AWS Service Catalog in the AWS Service Catalog User Guide.

2. Allow Studio users who are configured to use the same execution role as the domain to create projects. This grants Studio users permission to use the SageMaker-provided project templates to create a project from within Studio.

**Important**

Do not manually create your roles. Always create roles through Studio Settings using the steps described in the following procedure.

For users who use any role other than the domain's execution role to view and use SageMaker-provided project templates, you need to grant Projects permissions to the individual user profiles.
The following procedures show how to grant Projects permissions after you onboard to Studio. For more information about onboarding to Studio, see Onboard to Amazon SageMaker Domain (p. 35).

**To grant Projects permissions for the administrator and domain execution role users**

1. Open the SageMaker console.
2. Choose Control Panel.
3. If you choose Quick setup to set up your SageMaker Domain, you have permissions to use project templates by default.
4. If you choose Standard setup to set up your SageMaker Domain, make sure you turn on the following options when you configure Studio settings:
   - Enable Amazon SageMaker project templates and Amazon SageMaker JumpStart for this account
   - Enable Amazon SageMaker project templates and Amazon SageMaker JumpStart for Studio users
   - Create the roles which are needed to use the latest updated AWS Service catalog of products for Projects and JumpStart
5. To confirm that your SageMaker Domain has active project template permissions:
   a. Open the SageMaker console.
   b. Choose Control Panel.
   c. Choose the Settings icon in the upper-right corner of the Domain card.
   d. Choose Studio Settings in the left side panel.
   e. Under Projects and JumpStart, make sure the following options are turned on:
      - Enable Amazon SageMaker project templates and Amazon SageMaker JumpStart for this account
      - Enable Amazon SageMaker project templates and Amazon SageMaker JumpStart for Studio users
      - Create the roles which are needed to use the latest updated AWS Service catalog of products for Projects and JumpStart
6. To view a list of your roles:
   a. Open the SageMaker console.
   b. Choose Control Panel.

A list of your roles appears in the Apps card under Projects.

**Important**
As of July 25, we require additional roles to use project templates. Here is the complete list of roles you should see under Projects:
AmazonSageMakerServiceCatalogProductsLaunchRole
AmazonSageMakerServiceCatalogProductsUseRole
AmazonSageMakerServiceCatalogProductsApiGatewayRole
AmazonSageMakerServiceCatalogProductsCloudformationRole
AmazonSageMakerServiceCatalogProductsCodeBuildRole
AmazonSageMakerServiceCatalogProductsCodePipelineRole
AmazonSageMakerServiceCatalogProductsEventsRole
AmazonSageMakerServiceCatalogProductsFirehoseRole
AmazonSageMakerServiceCatalogProductsGlueRole

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Create an MLOps Project using Amazon SageMaker Studio

This procedure demonstrates how to create an MLOps project using Amazon SageMaker Studio.

Prerequisites

- An IAM account or IAM Identity Center to sign in to Studio. For information, see Onboard to Amazon SageMaker Domain (p. 35).
- Permission to use SageMaker-provided project templates. For information, see SageMaker Studio Permissions Required to Use Projects (p. 3286).
- Basic familiarity with the Studio user interface. For information, see Amazon SageMaker Studio UI Overview (p. 118).

To create a project in Studio

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the Studio sidebar, choose the SageMaker resources icon (остоячая стрелка).
3. Select Projects from the dropdown list.
4. Choose Create project.

   The Create project tab opens displaying a list of available templates.
5. For SageMaker project templates, choose SageMaker templates. For more information about project templates, see MLOps Project Templates (p. 3288).
6. Choose MLOps template for model building, training, and deployment.
7. Choose Select project template.

   The Create project tab changes to display Project details.
8. Enter the following information:

   - For Project details, enter a name and description for your project.
   - Optionally, add tags, which are key-value pairs that you can use to track your projects.
9. Choose Create project and wait for the project to appear in the Projects list.

MLOps Project Templates

An Amazon SageMaker project template automates the setup and implementation of MLOps for your projects. A SageMaker project template is an AWS Service Catalog product that SageMaker makes available to Amazon SageMaker Studio users. These AWS Service Catalog products are visible in your AWS Service Catalog console after you enable permissions when you onboard or update Amazon SageMaker Studio. For information about enabling permissions to use SageMaker project templates, see SageMaker Studio Permissions Required to Use Projects (p. 3286). Use SageMaker project templates to create a project that is an end-to-end MLOps solution.

If you are an administrator, you can create custom project templates from scratch or modify one of the project templates provided by SageMaker. Studio users in your organization can use these custom project templates to create their projects.
Use SageMaker-Provided Project Templates

Amazon SageMaker provides project templates that create the infrastructure you need to create an MLOps solution for continuous integration and continuous deployment (CI/CD) of ML models. Use these templates to process data, extract features, train and test models, register the models in the SageMaker model registry, and deploy the models for inference. You can customize the seed code and the configuration files to suit your requirements.

**Important**

As of July 25, 2022, we require additional roles to use project templates. For a complete list of required roles and instructions on how to create them, see SageMaker Studio Permissions Required to Use Projects (p. 3286). If you do not have the new roles, you will get the error message `CodePipeline is not authorized to perform AssumeRole on role arn:aws:iam::xxx:role/service-role/AmazonSageMakerServiceCatalogProductsCodePipelineRole` when you try to create a new project and cannot proceed.

SageMaker project templates offer you the following choice of code repositories, workflow automation tools, and pipeline stages:

- **Code repository**: AWS CodeCommit or third-party Git repositories such as GitHub and Bitbucket
- **CI/CD workflow automation**: AWS CodePipeline or Jenkins
- **Pipeline stages**: Model building and training, model deployment, or both

The following discussion provides an overview of each template you can choose when you create your SageMaker project. You can also view the available templates in Studio by following Step 1: Create the Project of the Project walkthrough.

For step-by-step instructions on how to create a real project, you can follow one of the project walkthroughs:

- If you want to use the template MLOps template for model building, training, and deployment (p. 3290), see SageMaker MLOps Project Walkthrough (p. 3300).
- If you want to use the template MLOps template for model building, training, and deployment with third-party Git repositories using CodePipeline (p. 3293), see SageMaker MLOps Project Walkthrough Using Third-party Git Repos (p. 3305).
- If you want to use the template MLOps template for model building, training, and deployment with third-party Git repositories using Jenkins (p. 3294), see Create Amazon SageMaker projects using third-party source control and Jenkins.

**Topics**

- MLOps template for model building, training, and deployment (p. 3290)
- MLOps template for model building, training, deployment, and Amazon SageMaker Model Monitor (p. 3292)
- MLOps template for image building, model building, and model deployment (p. 3293)
- MLOps template for model building, training, and deployment with third-party Git repositories using CodePipeline (p. 3293)
- MLOps template for model building, training, and deployment with third-party Git repositories using Jenkins (p. 3294)
MLOps template for model building, training, and deployment

This template is a combination of the following two templates, each of which can be used independently, and contains all of the resources provided in those templates.

- **Code repository**: AWS CodeCommit
- **CI/CD workflow automation**: AWS CodePipeline

**MLOps template for model building and training**

Use this template when you want an MLOps solution to process data, extract features, train and test models, and register the models in the SageMaker model registry.

This template provides the following resources:

- An AWS CodeCommit repository that contains sample code that creates an Amazon SageMaker Model Building Pipelines pipeline in Python code and shows how to create and update the SageMaker pipeline. This repository also has a Python Jupyter Notebook that you can open and run in Studio.

- An AWS CodePipeline pipeline that has source and build steps. The source step points to the CodeCommit repository. The build step gets the code from that repository, creates and updates the SageMaker pipeline, starts a pipeline execution, and waits for the pipeline execution to complete.

- An Amazon S3 bucket to store artifacts, including CodePipeline and CodeBuild artifacts, and any artifacts generated from the SageMaker pipeline runs.

The following diagram illustrates the workflow and AWS resources used by this template to help you build and train your models.
MLOps template for model deployment

Use this template to automate the deployment of models in the SageMaker model registry to SageMaker endpoints for real-time inference. This template recognizes changes in the model registry. When a new model version is registered and approved, it automatically initiates a deployment.

The template provisions a CodeCommit repository with configuration files to specify the model deployment steps, AWS CloudFormation templates to define endpoints as infrastructure, and seed code for testing the endpoint.

This template provides the following resources:

- An AWS CodeCommit repository that contains sample code that deploys models to endpoints in staging and production environments.
- An AWS CodePipeline pipeline that has source, build, deploy-to-staging, and deploy-to-production steps. The source step points to the CodeCommit repository, and the build step gets the code from that repository and generates CloudFormation stacks to deploy. The deploy-to-staging and deploy-to-production steps deploy the CloudFormation stacks to their respective environments. There is a manual approval step between the staging and production build steps, so that a MLOps engineer must approve the model before it is deployed to production.

There is also a programmatic approval step with placeholder tests in the example code in the CodeCommit repository. You can add additional tests to replace the placeholders tests.

- An Amazon S3 bucket to store artifacts, including CodePipeline and CodeBuild artifacts, and any artifacts generated from the SageMaker pipeline runs.
- A CloudWatch event to initiate the pipeline when a model package version is approved or rejected.

The following diagram illustrates the workflow and AWS resources used by this template to help you deploy your models.
As previously mentioned, see Project Walkthrough for a demonstration that uses this template to create a real project.

MLOps template for model building, training, deployment, and Amazon SageMaker Model Monitor

This template is an extension of the MLOps template for model building, training, and deployment. It includes both the model building, training, and deployment components of the template, and an additional Amazon SageMaker Model Monitor template that provides the following types of monitoring:

- **Data Quality** – Monitor drift in data quality.
- **Model Quality** – Monitor drift in model quality metrics, such as accuracy.
- **Bias Drift for Models in Production** – Monitor bias in a model's predictions.

- **Code repository**: AWS CodeCommit
- **CI/CD workflow automation**: AWS CodePipeline

MLOps template for Amazon SageMaker Model Monitor

You can use this template for an MLOps solution to deploy one or more of the Amazon SageMaker data quality, model quality, model bias, and model explainability monitors to monitor a deployed model on a SageMaker inference endpoint.

This template provides the following resources:
• An AWS CodeCommit repository that contains sample Python code that gets the baselines used by the monitors from the SageMaker Model Registry, and updates the template’s parameters for the staging and production environments. It also contains a AWS CloudFormation template to create the Amazon SageMaker Model Monitors.

• An AWS CodePipeline pipeline that has source, build, and deploy steps. The source step points to the CodePipeline repository. The build step gets the code from that repository, gets the baseline from the Model Registry, and updates template parameters for the staging and production environments. The deploy steps deploy the configured monitors into the staging and production environments. The manual approval step, within the DeployStaging stage, requires you to verify that the production SageMaker endpoint is InService before approving and moving to the DeployProd stage.

• The template uses the same S3 bucket created by the MLOps template for model building, training, and deployment to store the monitors’ outputs.

• Two Amazon EventBridge events rules initiate the Amazon SageMaker Model Monitor AWS CodePipeline every time the staging SageMaker endpoint is updated, or a code change is committed to the CodePipeline repository.

MLOps template for image building, model building, and model deployment

This template is an extension of the MLOps template for model building, training, and deployment (p. 3290). It includes both the model building, training, and deployment components of that template and the following options:

• Include processing image–building pipeline
• Include training image–building pipeline
• Include inference image–building pipeline

For each of the components selected during project creation, the following are created by using the template:

• An Amazon ECR repository
• A SageMaker Image
• A CodeCommit repository containing a Dockerfile that you can customize
• A CodePipeline that is initiated by changes to the CodePipeline repository
• A CodeBuild project that builds a Docker image and registers it in the Amazon ECR repository
• An EventBridge rule that initiates the CodePipeline on a schedule

When the CodePipeline is initiated, it builds a new Docker container and registers it with an Amazon ECR repository. When a new container is registered with the Amazon ECR repository, a new ImageVersion is added to the SageMaker image. This initiates the model building pipeline, which in turn initiates the deployment pipeline.

The newly created image is used in the model building, training, and deployment portions of the workflow where applicable.

MLOps template for model building, training, and deployment with third-party Git repositories using CodePipeline

• Code repository: Third-party Git. Establish the AWS CodeStar connection from your AWS account to your GitHub user or organization. Add a tag with the key sagemaker and value true to this AWS CodeStar connection.
• CI/CD workflow automation: AWS CodePipeline
This template provides the following resources:

- Associations with one or more customer-specified Git repositories.
- An AWS CodePipeline pipeline that has source, build, deploy-to-staging, and deploy-to-production steps. The source step points to the third-party Git repository and the build step gets the code from that repository and generates CloudFormation stacks to deploy. The deploy-to-staging and deploy-to-production steps deploy the CloudFormation stacks to their respective environments. There is a manual approval step between the staging and production build steps, so that a MLOps engineer must approve the model before it is deployed to production.
- An AWS CodeBuild project to populate the Git repositories with the seed code information. This requires an AWS CodeStar connection from your AWS account to your account on the Git repository host.
- An Amazon S3 bucket to store artifacts, including CodePipeline and CodeBuild artifacts, and any artifacts generated from the SageMaker pipeline runs.

As previously mentioned, see Project Walkthrough Using Third-party Git Repos for a demonstration that uses this template to create a real project.

**MLOps template for model building, training, and deployment with third-party Git repositories using Jenkins**

- **Code repository**: Third-party Git. Establish the AWS CodeStar connection from your AWS account to your GitHub user or organization. Add a tag with the key `sagemaker` and value `true` to this AWS CodeStar connection.
- **CI/CD workflow automation**: Jenkins

This template provides the following resources:

- Associations with one or more customer-specified Git repositories.
- Seed code to generate Jenkins pipelines that have source, build, deploy-to-staging, and deploy-to-production steps. The source step points to the customer-specified Git repository. The build step gets the code from that repository and generates two CloudFormation stacks. The deploy steps deploy the CloudFormation stacks to their respective environments. There is an approval step between the staging step and the production step.
- An AWS CodeBuild project to populate the Git repositories with the seed code information. This requires an AWS CodeStar connection from your AWS account to your account on the Git repository host.
- An Amazon S3 bucket to store artifacts of the SageMaker project and SageMaker pipeline.

The template creates the association between your project and the source control repositories, but you need to perform additional manual steps to establish communication between your AWS account and Jenkins. For the detailed steps, see Create Amazon SageMaker projects using third-party source control and Jenkins.

The instructions help you build the architecture shown in the following diagram, with GitHub as the source control repository in this example. As shown, you are attaching your Git repository to the project to check in and manage code versions. Jenkins initiates the model build pipeline when it detects changes to the model build code in the Git repository. You are also connecting the project to Jenkins to orchestrate your model deployment steps, which start when you approve the model registered in the model registry, or when Jenkins detects changes to the model deployment code.
In summary, the steps guide you through the following tasks:

1. Establish the connection between your AWS and GitHub accounts.
2. Create the Jenkins account and import needed plugins.
3. Create the Jenkins IAM user and permissions policy.
4. Set the AWS credentials for the Jenkins IAM user on your Jenkins server.
5. Create an API token for communication with your Jenkins server.
6. Use a CloudFormation template to set up an EventBridge rule to monitor the model registry for newly-approved models.
7. Create the SageMaker project, which seeds your GitHub repositories with model build and deploy code.
8. Create your Jenkins model build pipeline with the model build seed code.
9. Create your Jenkins model deploy pipeline with the model deploy seed code.

Update SageMaker Projects to Use Third-Party Git Repositories

The managed policy attached to the AmazonSageMakerServiceCatalogProductsUseRole role was updated on July 27, 2021 for use with the third-party Git templates. Users who onboard to Amazon SageMaker Studio after this date and enable project templates use the new policy. Users who onboarded prior to this date must update the policy to use these templates. Use one of the following options to update the policy:

- Delete role and toggle Studio settings
  1. In the IAM console, delete AmazonSageMakerServiceCatalogProductsUseRole.
  2. In the Studio control panel, choose Edit Settings.
  3. Toggle both settings and then choose Submit.
- In the IAM console, add the following permissions to AmazonSageMakerServiceCatalogProductsUseRole:

```json
{
    "Effect": "Allow",
    "Action": [
        "codestar-connections:UseConnection"
    ],
    "Resource": "arn:aws:codestar-connections:*:*:connection/**",
    "Condition": {
        "StringEqualsIgnoreCase": {
```
Create Custom Project Templates

If the SageMaker-provided templates do not meet your needs (for example, you want to have more complex orchestration in the CodePipeline with multiple stages or custom approval steps), create your own templates.

We recommend starting by using SageMaker-provided templates to understand how to organize your code and resources and build on top of it. To do this, after you enable administrator access to the SageMaker templates, log in to the https://console.aws.amazon.com/servicecatalog/, choose Portfolios, then choose Imported. For information about AWS Service Catalog, see Overview of AWS Service Catalog in the AWS Service Catalog User Guide.

Create your own project templates to customize your MLOps project. SageMaker project templates are AWS Service Catalog–provisioned products to provision the resources for your MLOps project.

To create a custom project template, complete the following steps.

1. Create a portfolio. For information, see Step 3: Create an AWS Service Catalog Portfolio.
2. Create a product. A product is a CloudFormation template. You can create multiple versions of the product. For information, see Step 4: Create an AWS Service Catalog Product.

For the product to work with SageMaker projects, add the following parameters to your product template.

```
SageMakerProjectName:
  Type: String
  Description: Name of the project

SageMakerProjectId:
  Type: String
  Description: Service generated Id of the project.
```

**Important**

We recommend that you wrap the CodeCommit repository into the SageMaker code repository for the project's repositories to be visible in VPC mode. The sample template and required addition are shown in the following code samples.

Original (sample) template:

```
ModelBuildCodeCommitRepository:
  Type: AWS::CodeCommit::Repository
  Properties:
    # Max allowed length: 100 chars
    RepositoryName: !Sub sagemaker-${SageMakerProjectName}-${SageMakerProjectId}-modelbuild # max: 10+33+15+10=68
```

3296
RepositoryDescription: !Sub SageMaker Model building workflow infrastructure as code for the Project ${SageMakerProjectName}

Code:

S3:
  Bucket: !Sub ${SEEDCODE_BUCKETNAME}
  Key: toolchain/model-building-workflow-v1.0.zip
  BranchName: main

Additional content to add in VPC mode:

SageMakerRepository:
  Type: AWS::SageMaker::CodeRepository
  Properties:
    GitConfig:
      RepositoryUrl: !GetAtt ModelBuildCodeCommitRepository.CloneUrlHttp
      Branch: main

3. Add a launch constraint. A launch constraint designates an IAM role that AWS Service Catalog assumes when a user launches a product. For information, see [Step 6: Add a Launch Constraint to Assign an IAM Role](#).

4. Provision the product on [https://console.aws.amazon.com/servicecatalog/](https://console.aws.amazon.com/servicecatalog/) to test the template. If you are satisfied with your template, continue to the next step to make the template available in Studio.

5. Grant access to the AWS Service Catalog portfolio that you created in step 1 to your Studio execution role. Use either the Studio domain execution role or a user role that has Studio access. For information about adding a role to the portfolio, see [Step 7: Grant End Users Access to the Portfolio](#).

6. To make your project template available in your Organization templates list in Studio, create a tag with the following key and value to the AWS Service Catalog product you created in step 2.

   • **key**: sagemaker:studio-visibility
   • **value**: true

After you complete these steps, Studio users in your organization can create a project with the template you created by following the steps in [Create an MLOps Project using Amazon SageMaker Studio](#) and choosing Organization templates when you choose a template.

### View Project Resources

After you create a project, view the resources associated with the project in Amazon SageMaker Studio.

#### To create a project in Studio

1. Sign in to Studio. For more information, see [Onboard to Amazon SageMaker Domain](#).
2. Choose SageMaker Resources, and then choose Projects.
3. Double-click the name of the project for which you want to view details.

   A tab with the project details appears.

On the project details tab, you can view the following entities associated with the project.

- **Repositories**: Code repositories (repos) associated with this project. If you use a SageMaker-provided template when you create your project, it creates a AWS CodeCommit repo or a third-party Git repo. For more information about CodeCommit, see [What is AWS CodeCommit](#).
- **Pipelines**: SageMaker ML pipelines that define steps to prepare data, train, and deploy models. For information about SageMaker ML pipelines, see [Create and Manage SageMaker Pipelines](#).
• Experiments: One or more Amazon SageMaker Autopilot experiments associated with the project. For information about Autopilot, see Automate model development with Amazon SageMaker Autopilot (p. 318).

• Model groups: Groups of model versions that were created by pipeline executions in the project. For information about model groups, see Create a Model Group (p. 2983).

• Endpoints: SageMaker endpoints that host deployed models for real-time inference. When a model version is approved, it is deployed to an endpoint.

• Settings: Settings for the project. This includes the name and description of the project, information about the project template and SourceModelPackageGroupName, and metadata about the project.

Update an MLOps Project in Amazon SageMaker Studio

This procedure demonstrates how to update an MLOps project in Amazon SageMaker Studio. You can update the Description, template version, and template parameters.

Prerequisites

• An IAM account or IAM Identity Center to sign in to Studio. For information, see Onboard to Amazon SageMaker Domain (p. 35).

• Basic familiarity with the Studio user interface. For information, see Amazon SageMaker Studio UI Overview (p. 118).

• Add the following custom inline policies to the specified roles:

User-created role having AmazonSageMakerFullAccess

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action":[
            "servicecatalog:CreateProvisionedProductPlan",
            "servicecatalog:DescribeProvisionedProductPlan",
            "servicecatalog:DeleteProvisionedProductPlan"
         ],
         "Resource": "*"
      }
   ]
}
```

AmazonSageMakerServiceCatalogProductsLaunchRole

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": [
            "cloudformation:CreateChangeSet",
            "cloudformation:DeleteChangeSet",
            "cloudformation:DescribeChangeSet"
         ],
         "Resource": "arn:aws:cloudformation:*:*:stack/SC-*"
      },
      {
```
"Effect": "Allow",
"Action": [
   "codecommit:PutRepositoryTriggers"
],
"Resource": "arn:aws:codecommit:*:*:sagemaker-*"
"

To update a project in Studio

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the Studio sidebar, choose the SageMaker resources icon (🔍).
3. Select Projects from the dropdown list.
   A list of your projects appears.
4. You can open the Project update dialog box in one of the following ways:
   a. You can open it from the projects list.
      Right-click the target project and choose Update from the dropdown list.
   b. You can open it from the project tab.
      i. Double-click the project in the projects list.
      ii. Choose Update from the Actions menu in the upper-right corner of the project tab.
5. In the Update project dialog box, you can edit the Description, template version, and template parameters.
6. Choose Show Diff.
   A dialog box displays your original and updated project settings. Any change in your project settings can modify or delete resources in the current project. The dialog box displays these changes as well.
7. You may need to wait a few minutes for the Update button to become active. Choose Update.
8. The project update may take a few minutes to complete. Select Settings in the project tab and ensure the parameters have been updated correctly.

Delete an MLOps Project using Amazon SageMaker Studio

This procedure demonstrates how to delete an MLOps project using Amazon SageMaker Studio.

Prerequisites

Note
You can only delete projects in Studio that you have created. This condition is part of the service catalog permission servicecatalog:TerminateProvisionedProduct in the AmazonSageMakerFullAccess policy. If needed, you can update this policy to remove this condition.

• An IAM account or IAM Identity Center to sign in to Studio. For information, see Onboard to Amazon SageMaker Domain (p. 35).
• Basic familiarity with the Studio user interface. For information, see Amazon SageMaker Studio UI Overview (p. 118).
To delete a project in Amazon SageMaker Studio

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. In the Studio sidebar, choose the SageMaker resources icon ( ).
3. Select Projects from the dropdown list.
4. Select the target project from the dropdown list. If you don't see your project, type the project name and apply the filter to find your project.
5. **You can delete a Studio project in one of the following ways:**
   a. You can delete the project from the projects list.
      Right-click the target project and choose **Delete** from the dropdown list.
      **Note**
      This functionality is supported in Studio version v3.17.1 or higher. For more information, see Shut down and Update SageMaker Studio (p. 179).
   b. You can delete a project from the Project details section.
      i. Once you've found your project, double-click it to view its details.
      ii. Choose **Delete** from the Actions menu.
6. Confirm your choice by choosing Delete from the Delete Project window.

**SageMaker MLOps Project Walkthrough**

This walkthrough uses the template MLOps template for model building, training, and deployment (p. 3290) to demonstrate using MLOps projects to create a CI/CD system to build, train, and deploy models.

**Prerequisites**

To complete this walkthrough, you need:

- An IAM account or IAM Identity Center to sign in to Studio. For information, see Onboard to Amazon SageMaker Domain (p. 35).
- Permission to use SageMaker-provided project templates. For information, see SageMaker Studio Permissions Required to Use Projects (p. 3286).
- Basic familiarity with the Studio user interface. For information, see Amazon SageMaker Studio UI Overview (p. 118).

**Topics**

- Step 1: Create the Project (p. 3300)
- Step 2: Clone the Code Repository (p. 3301)
- Step 3: Make a Change in the Code (p. 3302)
- Step 4: Approve the Model (p. 3304)
- (Optional) Step 5: Deploy the Model Version to Production (p. 3304)
- Step 6: Clean Up Resources (p. 3304)

**Step 1: Create the Project**

In this step, you create a SageMaker MLOps project by using a SageMaker-provided project template to build, train, and deploy models.
To create the SageMaker MLOps project

1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. Choose SageMaker resources, and then select Projects from the dropdown list.
3. Choose Create project.

   The Create project tab appears.
4. For SageMaker project templates, choose Organization templates, then choose MLOps template for model building, training, and deployment.
5. For Project details, enter a name and description for your project.

When the project appears in the Projects list with a Status of Created, move on to the next step.

Important
As of July 25, 2022, we require additional roles to use project templates. If you see the error message CodePipeline is not authorized to perform AssumeRole on role arn:aws:iam::xxx:role/service-role/AmazonSageMakerServiceCatalogProductsCodePipelineRole, see Steps 5-6 of SageMaker Studio Permissions Required to Use Projects (p. 3286) for a complete list of required roles and instructions on how to create them.

Step 2: Clone the Code Repository

After you create the project, two CodeCommit repositories are created in the project. One of the repositories contains code to build and train a model, and one contains code to deploy the model. In this step, you clone the repository to your local SageMaker project that contains the code to build and train the model to the local Studio environment so that you can work with the code.

To clone the code repository

1. Choose SageMaker resources, and then select Projects from the dropdown list.
2. Find the name of the project you created in the previous step and double-click on it to open the project tab for your project.
3. In the project tab, choose Repositories, and in the Local path column for the repository that ends with modelbuild, choose clone repo....
4. In the dialog box that appears, accept the defaults and choose Clone repository.
When clone of the repository is complete, the local path appears in the **Local path** column. Choose the path to open the local folder that contains the repository code in Studio.

**Step 3: Make a Change in the Code**

Now make a change to the pipeline code that builds the model and check in the change to initiate a new pipeline run. The pipeline run registers a new model version.

**To make a code change**

1. In Studio, choose the file browser icon (folder), and navigate to the pipelines/abalone folder. Double-click pipeline.py to open the code file.
2. In the pipeline.py file, find the line that sets the training instance type.

   ```python
   training_instance_type = ParameterString(
       name="TrainingInstanceType", default_value="ml.m5.xlarge"
   )
   ``

   Change `ml.m5.xlarge` to `ml.m5.large`, then type Ctrl+S to save the change.
3. Choose the **Git** icon (git). Stage, commit, and push the change in pipeline.py. For information about using Git in Studio, see [Clone a Git Repository in SageMaker Studio](#).
After pushing your code change, the MLOps system initiates a run of the pipeline that creates a new model version. In the next step, you approve the new model version to deploy it to production.

**Step 4: Approve the Model**

Now you approve the new model version that was created in the previous step to initiate a deployment of the model version to a SageMaker endpoint.

**To approve the model version**

1. Choose SageMaker resources, and then select Projects from the dropdown list.
2. Find the name of the project you created in the first step and double-click on it to open the project tab for your project.
3. In the project tab, choose Model groups, then double-click the name of the model group that appears.
5. In the model Update model version status dialog box, in the Status dropdown list, select Approve, then choose Update status.

Approving the model version causes the MLOps system to deploy the model to staging. To view the endpoint, choose the Endpoints tab on the project tab.

**(Optional) Step 5: Deploy the Model Version to Production**

Now you can deploy the model version to the production environment.

**Note**

To complete this step, you need to be an administrator in your Studio domain. If you are not an administrator, skip this step.

**To deploy the model version to the production environment**

1. Log in to the CodePipeline console at https://console.aws.amazon.com/codepipeline/
2. Choose Pipelines, then choose the pipeline with the name sagemaker-projectname-projectid-modeldeploy, where projectname is the name of your project, and projectid is the ID of your project.
3. In the DeployStaging stage, choose Review.
4. In the Review dialog box, choose Approve.

Approving the DeployStaging stage causes the MLOps system to deploy the model to production. To view the endpoint, choose the Endpoints tab on the project tab in Studio.

**Step 6: Clean Up Resources**

To stop incurring charges, clean up the resources that were created in this walkthrough. To do this, complete the following steps.

**Note**

To delete the AWS CloudFormation stack and the Amazon S3 bucket, you need to be an administrator in Studio. If you are not an administrator, ask your administrator to complete those steps.

1. In the Studio sidebar, choose the SageMaker resources icon (✔).
2. Choose Projects from the dropdown list.
3. Select the target project from the dropdown list. If you don't see your project, type the project name and apply the filter to find your project.
4. You can delete a Studio project in one of the following ways:
   a. You can delete the project from the projects list.
      
      Right-click the target project and choose Delete from the dropdown list.
      
      Note
      This functionality is supported in Studio version v3.17.1 or higher. For more information, see Shut down and Update SageMaker Studio (p. 179).
   b. You can delete a project from the Project details section.
      
      i. When you've found your project, double-click it to view its details in the main panel.
      ii. Choose Delete from the Actions menu.
5. Confirm your choice by choosing Delete from the Delete Project window.
   
   This deletes the AWS Service Catalog provisioned product that the project created. This includes the CodeCommit, CodePipeline, and CodeBuild resources created for the project.
6. Delete the AWS CloudFormation stacks that the project created. There are two stacks, one for staging and one for production. The names of the stacks are sagemaker-projectname-project-id-deploy-staging and sagemaker-projectname-project-id-deploy-prod, where projectname is the name of your project, and project-id is the ID of your project.
   
   For information about how to delete a AWS CloudFormation stack, see Deleting a stack on the AWS CloudFormation console in the AWS CloudFormation User Guide.
7. Delete the Amazon S3 bucket that the project created. The name of the bucket is sagemaker-project-project-id, where project-id is the ID of your project.

SageMaker MLOps Project Walkthrough Using Third-party Git Repos

This walkthrough uses the template MLOps template for model building, training, and deployment with third-party Git repositories using CodePipeline (p. 3293) to demonstrate how to use MLOps projects to create a CI/CD system to build, train, and deploy models.

Prerequisites

To complete this walkthrough, you need:

- An IAM or IAM Identity Center account to sign in to Studio. For information, see Onboard to Amazon SageMaker Domain (p. 35).
- Permission to use SageMaker-provided project templates. For information, see SageMaker Studio Permissions Required to Use Projects (p. 3286).
- Basic familiarity with the Studio user interface. For information, see Amazon SageMaker Studio UI Overview (p. 118).
- Two GitHub repositories initialized with a README. You input these repositories into the project template, which will seed these repos with model build and deploy code.

Topics

- Step 1: Set up the GitHub connection (p. 3306)
- Step 2: Create the Project (p. 3306)
• Step 3: Make a Change in the Code (p. 3307)
• Step 4: Approve the Model (p. 3307)
• (Optional) Step 5: Deploy the Model Version to Production (p. 3308)
• Step 6: Clean Up Resources (p. 3308)

Step 1: Set up the GitHub connection

In this step, you connect to your GitHub repositories using an AWS CodeStar connection. The SageMaker project uses this connection to access your source code repositories.

To set up the GitHub connection:
1. Log in to the CodePipeline console at https://console.aws.amazon.com/codepipeline/
2. Under Settings in the navigation pane, choose Connections.
3. Choose Create connection.
4. For Select a provider, select GitHub.
5. For Connection name, enter a name.
6. Choose Connect to GitHub.
7. If the AWS Connector GitHub app isn't previously installed, choose Install new app.
   This displays a list of all the GitHub personal accounts and organizations to which you have access.
8. Choose the account where you want to establish connectivity for use with SageMaker projects and GitHub repositories.
9. Choose Configure.
10. You can optionally select your specific repositories or choose All repositories.
11. Choose Save. When the app is installed, you're redirected to the Connect to GitHub page and the installation ID is automatically populated.
12. Choose Connect.
13. Add a tag with the key sagemaker and value true to this AWS CodeStar connection.
14. Copy the connection ARN to save for later. You use the ARN as a parameter in the project creation step.

Step 2: Create the Project

In this step, you create a SageMaker MLOps project by using a SageMaker-provided project template to build, train, and deploy models.

To create the SageMaker MLOps project
1. Sign in to Studio. For more information, see Onboard to Amazon SageMaker Domain (p. 35).
2. Choose SageMaker resources, and then select Projects from the dropdown list.
3. Choose Create project.
   The Create project tab appears.
4. For SageMaker project templates, choose MLOps template for model building, training, and deployment with third-party Git repositories.
5. Choose Select project template.
6. Under ModelBuild CodeRepository Info, provide the following parameters:
• For **URL**, enter the URL of your Git repository for the model build code in https://*git-url*.git format.

• For **Branch**, enter the branch to use from your Git repository for pipeline activities.

• For **Full Repository Name**, enter the Git repository name in the format of *username/repository name* or *organization/repository name*.

• For **Codestar Connection ARN**, enter the ARN of the AWS CodeStar connection you created in Step 1.

• The **Sample Code** toggle switch lets you choose whether to populate the repository with model build seed code. We can leave it on for this demo.

7. Under **ModelDeploy CodeRepository Info**, provide the following parameters:

• For **URL**, enter the URL of your Git repository for the model deploy code in https://*git-url*.git format.

• For **Branch**, enter the branch to use from your Git repository for pipeline activities.

• For **Full Repository Name**, enter the Git repository name in the format of *username/repository name* or *organization/repository name*.

• For **Codestar Connection ARN**, enter the ARN of the AWS CodeStar connection you created in Step 1.

• The **Sample Code** toggle switch lets you choose whether to populate the repository with model deployment seed code. We can leave it on for this demo.

8. Choose **Create Project**.

The project appears in the **Projects** list with a **Status** of **Created**.

**Step 3: Make a Change in the Code**

Now make a change to the pipeline code that builds the model and commit the change to initiate a new pipeline run. The pipeline run registers a new model version.

**To make a code change**

1. In your model build GitHub repo, navigate to the pipelines/abalone folder. Double-click **pipeline.py** to open the code file.

2. In the **pipeline.py** file, find the line that sets the training instance type.

   ```python
   training_instance_type = ParameterString(
       name="TrainingInstanceType", default_value="ml.m5.xlarge"
   )
   ```

   Open the file for editing, change `ml.m5.xlarge` to `ml.m5.large`, then commit.

After you commit your code change, the MLOps system initiates a run of the pipeline that creates a new model version. In the next step, you approve the new model version to deploy it to production.

**Step 4: Approve the Model**

Now you approve the new model version that was created in the previous step to initiate a deployment of the model version to a SageMaker endpoint.

**To approve the model version**

1. Choose **SageMaker resources**, and then select **Projects** from the dropdown list.
2. Find the name of the project you created in the first step and double-click on it to open the project tab for your project.

3. In the project tab, choose **Model groups**, then double-click the name of the model group that appears.

   The model group tab appears.

4. In the model group tab, double-click **Version 2**. The **Version 2** tab opens. Choose **Update status**.

5. In the model **Update model version status** dialog box, in the **Status** dropdown list, select **Approve** and then choose **Update status**.

   Approving the model version causes the MLOps system to deploy the model to staging. To view the endpoint, choose the **Endpoints** tab on the project tab.

### (Optional) Step 5: Deploy the Model Version to Production

Now you can deploy the model version to the production environment.

**Note**
To complete this step, you need to be an administrator in your Studio domain. If you are not an administrator, skip this step.

**To deploy the model version to the production environment**

1. Log in to the CodePipeline console at [https://console.aws.amazon.com/codepipeline/](https://console.aws.amazon.com/codepipeline/)

2. Choose **Pipelines**, then choose the pipeline with the name `sagemaker-projectname-projectid-modeldeploy`, where `projectname` is the name of your project, and `projectid` is the ID of your project.

3. In the **DeployStaging** stage, choose **Review**.

4. In the **Review** dialog box, choose **Approve**.

   Approving the **DeployStaging** stage causes the MLOps system to deploy the model to production. To view the endpoint, choose the **Endpoints** tab on the project tab in Studio.

### Step 6: Clean Up Resources

To stop incurring charges, clean up the resources that were created in this walkthrough.

**Note**
To delete the AWS CloudFormation stack and the Amazon S3 bucket, you need to be an administrator in Studio. If you are not an administrator, ask your administrator to complete those steps.

1. In the Studio sidebar, choose the **SageMaker resources** icon (🔍).

2. Choose **Projects** from the dropdown list.

3. Select the target project from the dropdown list. If you don’t see your project, type the project name and apply the filter to find your project.

4. **You can delete a Studio project in one of the following ways:**

   a. **You can delete the project from the projects list.**

      Right-click the target project and choose **Delete** from the dropdown list.

      **Note**
      This functionality is supported in Studio version v3.17.1 or higher. For more information, see [Shut down and Update SageMaker Studio](p. 179).
b. **You can delete a project from the Project details section.**
   i. When you've found your project, double-click it to view its details in the main panel.
   ii. Choose **Delete** from the **Actions** menu.

5. Confirm your choice by choosing **Delete** from the **Delete Project** window.

This deletes the AWS Service Catalog provisioned product that the project created. This includes the CodeCommit, CodePipeline, and CodeBuild resources created for the project.

6. Delete the AWS CloudFormation stacks that the project created. There are two stacks, one for staging and one for production. The names of the stacks are `sagemaker-projectname-project-id-deploy-staging` and `sagemaker-projectname-project-id-deploy-prod`, where `projectname` is the name of your project, and `project-id` is the ID of your project.

   For information about how to delete a AWS CloudFormation stack, see Deleting a stack on the AWS CloudFormation console in the **AWS CloudFormation User Guide**.

7. Delete the Amazon S3 bucket that the project created. The name of the bucket is `sagemaker-project-project-id`, where `project-id` is the ID of your project.

---

**Amazon SageMaker ML Lineage Tracking**

Amazon SageMaker ML Lineage Tracking creates and stores information about the steps of a machine learning (ML) workflow from data preparation to model deployment. With the tracking information, you can reproduce the workflow steps, track model and dataset lineage, and establish model governance and audit standards.

With SageMaker Lineage Tracking data scientists and model builders can do the following:

- Keep a running history of model discovery experiments.
- Establish model governance by tracking model lineage artifacts for auditing and compliance verification.

**Topics**

- Lineage Tracking Entities (p. 3310)
- Amazon SageMaker–Created Tracking Entities (p. 3312)
- Manually Create Tracking Entities (p. 3314)
- Querying Lineage Entities (p. 3317)
- Cross-Account Lineage Tracking (p. 3323)

The following diagram shows an example lineage graph that Amazon SageMaker automatically creates in an end-to-end model training and deployment ML workflow.
Tracking entities maintain a representation of all the elements of your end-to-end machine learning workflow. You can use this representation to establish model governance, reproduce your workflow, and maintain a record of your work history.

Amazon SageMaker automatically creates tracking entities for trial components and their associated trials and experiments when you create SageMaker jobs such as processing jobs, training jobs, and batch transform jobs. In additional to auto tracking, you can also manually create tracking entities to model custom steps in your workflow. For more information, see Manage Machine Learning with Amazon SageMaker Experiments (p. 2231).

SageMaker also automatically creates tracking entities for the other steps in a workflow so you can track the workflow from end to end. For more information, see Amazon SageMaker–Created Tracking Entities (p. 3312).

You can create additional entities to supplement those created by SageMaker. For more information, see Manually Create Tracking Entities (p. 3314).

SageMaker reuses any existing entities rather than creating new ones. For example, there can be only one artifact with a unique SourceUri.
Key concepts for querying lineage

- **Lineage** – Metadata that tracks the relationships between various entities in your ML workflows.
- **QueryLineage** – The action to inspect your lineage and discover relationships between entities.
- **Lineage entities** – The metadata elements of which your lineage is composed.
- **Cross-account lineage** – Your ML workflow may span more than one account. With cross-account lineage, you can configure multiple accounts to automatically create lineage associations between shared entity resources. QueryLineage then can return entities even from these shared accounts.

The following tracking entities are defined:

**Experiment entities**

- **Trial component** – A stage of a machine learning trial. Includes processing jobs, training jobs, and batch transform jobs.
- **Trial** – A combination of trial components that generally produces a model.
- **Experiment** – A grouping of trials generally focused on solving a specific use case.

**Lineage entities**

- **Trial Component** – Represents processing, training, and transform jobs in the lineage. Also part of experiment management.
- **Context** – Provides a logical grouping of other tracking or experiment entities. Conceptually, experiments and trials are contexts. Some examples are an endpoint and a model package.
- **Action** – Represents an action or activity. Generally, an action involves at least one input artifact or output artifact. Some examples are a workflow step and a model deployment.
- **Artifact** – Represents a URI addressable object or data. An artifact is generally either an input or an output to a trial component or action. Some examples include a dataset (S3 bucket URI), or an image (Amazon ECR registry path).
- **Association** – Links other tracking or experiment entities, such as an association between the location of training data and a training job.

An association has an optional **AssociationType** property. The following values are available along with the suggested use for each type. SageMaker places no restrictions on their use:

- **ContributedTo** – The source contributed to the destination or had a part in enabling the destination. For example, the training data contributed to the training job.
- **AssociatedWith** – The source is connected to the destination. For example, an approval workflow is associated with a model deployment.
- **DerivedFrom** – The destination is a modification of the source. For example, a digest output of a channel input for a processing job is derived from the original inputs.
- **Produced** – The source generated the destination. For example, a training job produced a model artifact.
- **SameAs** – When the same lineage entity used in different accounts.

**Common properties**

- **Type property**

  The action, artifact, and context entities have a **type** property, **ActionType**, **ArtifactType**, and **ContextType**, respectively. This property is a custom string which can associate meaningful information with the entity and be used as a filter in the List APIs.
• **Source property**

The action, artifact, and context entities have a Source property. This property provides the underlying URI that the entity represents. Some examples are:
- An UpdateEndpoint action where the source is the EndpointArn.
- An image artifact for a processing job where the source is the ImageUri.
- An Endpoint context where the source is the EndpointArn.

• **Metadata property**

The action and artifact entities have an optional Metadata property which can provide the following information:
- ProjectId – For example, the ID of the SageMaker MLOps project to which a model belongs.
- GeneratedBy – For example, the SageMaker pipeline execution that registered a model package version.
- Repository – For example, the repository that contains an algorithm.
- CommitId – For example, the commit ID of an algorithm version.

### Amazon SageMaker–Created Tracking Entities

Amazon SageMaker automatically creates tracking entities for SageMaker jobs, models, model packages, and endpoints if the data is available. There is no limit to the number of lineage entities created by SageMaker.

For information on how you can manually create tracking entities, see [Manually Create Tracking Entities](p. 3314).

**Topics**
- Tracking Entities for SageMaker Jobs (p. 3312)
- Tracking Entities for Model Packages (p. 3313)
- Tracking Entities for Endpoints (p. 3313)

### Tracking Entities for SageMaker Jobs

SageMaker creates a trial component for and associated with each SageMaker job. SageMaker creates artifacts to track the job metadata and associations between each artifact and the job.

Artifacts are created for the following job properties and associated with the Amazon Resource Name (ARN) of the SageMaker job. The artifact SourceUri is listed in parentheses.

**Training Job**
- The image that contains the training algorithm (TrainingImage).
- The data source of each input channel (S3Uri).
- The location for the model (S3OutputPath).
- The location for the managed spot checkpoint data (S3Uri).

**Processing Job**
- The container to be run by the processing job (ImageUri).
- The data location for each processing input and processing output (S3Uri).
Transform Job

- The input data source to be transformed (S3Uri).
- The results of the transform (S3OutputPath).

**Note**
Amazon Simple Storage Service (Amazon S3) artifacts are tracked based on the Amazon S3 URI values provided to the Create API, for example `CreateTrainingJob`, and not on the Amazon S3 key and hash or etag values from each file.

Tracking Entities for Model Packages

The following entities are created:

Model Packages

- A context for each model package group.
- An artifact for each model package.
- An association between each model package artifact and the context for each model package group to which the package belongs to.
- An action for the creation of a model package version.
- An association between the model package artifact and the creation action.
- An association between the model package artifact and each model package group context to which the package belongs to.
- Inference containers
  - An artifact for the image used in each container defined in the model package.
  - An artifact for the model used in each container.
  - An association between each artifact and the model package artifact.
- Algorithms
  - An artifact for each algorithm defined in the model package.
  - An artifact for the model created by each algorithm.
  - An association between each artifact and the model package artifact.

Tracking Entities for Endpoints

The following entities are created by Amazon SageMaker:

Endpoints

- A context for each endpoint
- An action for the model deployment that created each endpoint
- An artifact for each model deployed to the endpoint
- An artifact for the image used in the model
- An artifact for the model package for the model
- An artifact for each image deployed to the endpoint
- An association between each artifact and the model deployment action
Manually Create Tracking Entities

You can manually create tracking entities for any property. For information on the tracking entities that Amazon SageMaker automatically creates, see Amazon SageMaker–Created Tracking Entities (p. 3312).

You can add tags to all entities except associations. Tags are arbitrary key-value pairs that provide custom information. You can filter or sort a list or search query by tags. For more information, see Tagging AWS resources in the AWS General Reference.

For a sample notebook that demonstrates how to create lineage entities, see the Amazon SageMaker Lineage notebook in the Amazon SageMaker example GitHub repository.

Topics
• Manually Create Entities (p. 3314)
• Manually Track a Workflow (p. 3315)
• Limits (p. 3316)

Manually Create Entities

The following procedure shows you how to create and associate artifacts between a SageMaker training job and endpoint. You perform the following steps:

Import tracking entities and associations

1. Import the lineage tracking entities.

import sys
!{sys.executable} -m pip install -q sagemaker
from sagemaker import get_execution_role
from sagemaker.session import Session
from sagemaker.lineage import context, artifact, association, action
import boto3
boto_session = boto3.Session(region_name=region)
sagemaker_client = boto_session.client("sagemaker")

2. Create the input and output artifacts.

code_location_arn = artifact.Artifact.create(
    artifact_name='source-code-location',
    source_uri='s3://...',
    artifact_type='code-location'
).artifact_arn

# Similar constructs for train_data_location_arn and test_data_location_arn
model_location_arn = artifact.Artifact.create(
    artifact_name='model-location',
    source_uri='s3://...',
    artifact_type='model-location'
).artifact_arn

3. Train the model and get the trial_component_arn that represents the training job.

4. Associate the input artifacts and output artifacts with the training job (trial component).

input_artifacts = [code_location_arn, train_data_location_arn, test_data_location_arn, model_location_arn]
for artifact_arn in input_artifacts:
try:
    association.Association.create(
        source_arn=artifact_arn,
        destination_arn=trial_component_arn,
        association_type='ContributedTo'
    )
except:
    logging.info('association between {} and {} already exists', artifact_arn, trial_component_arn)

output_artifacts = [model_location_arn]
for artifact_arn in output_artifacts:
    try:
        association.Association.create(
            source_arn=trial_component_arn,
            destination_arn=artifact_arn,
            association_type='Produced'
        )
    except:
        logging.info('association between {} and {} already exists', artifact_arn, trial_component_arn)

5. Create the inference endpoint.

predictor = mnist_estimator.deploy(initial_instance_count=1,
    instance_type='ml.m4.xlarge')

6. Create the endpoint context.

from sagemaker.lineage import context

describe_endpoint = sagemaker_client.describe_endpoint(EndpointName=predictor.endpoint_name)
endpoint_arn = describe_endpoint['EndpointArn']

endpoint_context_arn = context.Context.create(
    context_name=predictor.endpoint_name,
    context_type='Endpoint',
    source_uri=endpoint_arn
).context_arn

7. Associate the training job (trial component) and endpoint context.

association.Association.create(
    source_arn=trial_component_arn,
    destination_arn=endpoint_context_arn
)

**Manually Track a Workflow**

You can manually track the workflow created in the previous section.

Given the endpoint Amazon Resource Name (ARN) from the previous example, the following procedure shows you how to track the workflow back to the datasets used to train the model that was deployed to the endpoint. You perform the following steps:

**To track a workflow from endpoint to training data source**

1. Import the tracking entities.

   ```python
   import sys
   ```
Manually Create Entities

```python
!{sys.executable} -m pip install -q sagemaker
from sagemaker import get_execution_role
from sagemaker.session import Session
from sagemaker.lineage import context, artifact, association, action
import boto3
boto_session = boto3.Session(region_name=region)
sagemaker_client = boto_session.client("sagemaker")

2. Get the endpoint context from the endpoint ARN.

```python
endpoint_context_arn = sagemaker_client.list_contexts(
    SourceUri=endpoint_arn)['ContextSummaries'][0]['ContextArn']
```

3. Get the trial component from the association between the trial component and the endpoint context.

```python
trial_component_arn = sagemaker_client.list_associations(
    DestinationArn=endpoint_context_arn)['AssociationSummaries'][0]['SourceArn']
```

4. Get the training data location artifact from the association between the trial component and the endpoint context.

```python
train_data_location_artifact_arn = sagemaker_client.list_associations(
    DestinationArn=trial_component_arn, SourceType='Model')['AssociationSummaries'][0][
    'SourceArn']
```

5. Get the training data location from the training data location artifact.

```python
train_data_location = sagemaker_client.describe_artifact(
    Arn=train_data_location_artifact_arn)['Source']['SourceUri']
print(train_data_location)
```

Response:

s3://sagemaker-sample-data-us-east-2/mxnet/mnist/train

Limits

You can create an association between any entities, experiment, and lineage, except the following:

- You cannot create an association between two experiment entities. Experiment entities consist of experiments, trials, and trial components.
- You can create an association with another association.

An error occurs if you try to create an entity that already exists.

Maximum number of manually created lineage entities

- Actions: 3000
- Artifacts: 6000
- Associations: 6000
- Contexts: 500
There is no limit to the number of lineage entities automatically created by Amazon SageMaker.

**Querying Lineage Entities**

Amazon SageMaker automatically generates graphs of lineage entities as you use them. You can query this data to answer a variety of questions. You can query your lineage entities to:

- Retrieve all data sets that went into the creation of a model.
- Retrieve all jobs that went into the creation of an endpoint.
- Retrieve all models that use a data set.
- Retrieve all endpoints that use a model.
- Retrieve which endpoints are derived from a certain data set.
- Retrieve the pipeline execution that created a training job.
- Retrieve the relationships between entities for investigation, governance, and reproducibility.
- Retrieve all downstream trials that use the artifact.
- Retrieve all upstream trials that use the artifact.
- Retrieve a list of artifacts that use the provided S3 uri.
- Retrieve upstream artifacts that use the dataset artifact.
- Retrieve downstream artifacts that use the dataset artifact.
- Retrieve datasets that use the image artifact.
- Retrieve actions that use the context.
- Retrieve processing jobs that use the endpoint.
- Retrieve transform jobs that use the endpoint.
- Retrieve trial components that use the endpoint.
- Retrieve the ARN for the pipeline execution associated with the model package group.
- Retrieve all artifacts that use the action.
- Retrieve all upstream datasets that use the model package approval action.
- Retrieve model package from model package approval action.
- Retrieve downstream endpoint contexts that use the endpoint.
- Retrieve the ARN for the pipeline execution associated with the trial component.
- Retrieve datasets that use the trial component.
- Retrieve models that use the trial component.
- Explore your lineage for visualization.

**Topics**

- Getting Started with Querying Lineage Entities (p. 3318)

**Limitations**

- Lineage querying is not available in the following Regions:
  - Asia Pacific (Osaka) – ap-northeast-3
  - Europe (Milan) – eu-south-1
  - Africa (Cape Town) – af-south
  - Asia Pacific (Jakarta) – ap-southeast-3
• The maximum depth of relationships to discover is currently limited to 10.
• Filtering is limited to the following properties: last modified date, created date, type, and lineage entity type.

**Getting Started with Querying Lineage Entities**

The easiest way to get started is either via the:

• Amazon SageMaker SDK for Python which has defined many common use cases.
• For a notebook that demonstrates how to use SageMaker Lineage APIs to query relationships across the lineage graph, see sagemaker-lineage-multihop-queries.ipynb.

The following examples show how to use the LineageQuery and LineageFilter APIs to construct queries to answer questions about the Lineage Graph and extract entity relationships for a few use cases.

**Example Using the LineageQuery API to find entity associations**

```python
from sagemaker.lineage.context import Context, EndpointContext
from sagemaker.lineage.action import Action
from sagemaker.lineage.association import Association
from sagemaker.lineage.artifact import Artifact, ModelArtifact, DatasetArtifact
from sagemaker.lineage.query import (LineageQuery, LineageFilter, LineageSourceEnum, LineageEntityEnum, LineageQueryDirectionEnum,
)

# Find the endpoint context and model artifact that should be used for the lineage queries.
contexts = Context.list(source_uri=endpoint_arn)
context_name = list(contexts)[0].context_name
endpoint_context = EndpointContext.load(context_name=context_name)

query_filter = LineageFilter(entities=[LineageEntityEnum.ARTIFACT], sources=[LineageSourceEnum.DATASET])

# Providing this 'LineageFilter' to the 'LineageQuery' constructs a query that traverses through the given context 'endpoint_context'
# and find all datasets.
query_result = LineageQuery(sagemaker_session).query(start_arns=[endpoint_context.context_arn], query_filter=query_filter, direction=LineageQueryDirectionEnum.ASCENDANTS, include_edges=False,
)

# Parse through the query results to get the lineage objects corresponding to the datasets
dataset_artifacts = []
for vertex in query_result.vertices:
    ...
```

**Example Find all the datasets associated with an endpoint**

```python
# Define the LineageFilter to look for entities of type 'ARTIFACT' and the source of type 'DATASET'.
query_filter = LineageFilter(
    entities=[LineageEntityEnum.ARTIFACT], sources=[LineageSourceEnum.DATASET]
)

# Providing this 'LineageFilter' to the 'LineageQuery' constructs a query that traverses through the given context 'endpoint_context'
# and find all datasets.
query_result = LineageQuery(sagemaker_session).query(
    start_arns=[endpoint_context.context_arn],
    query_filter=query_filter,
    direction=LineageQueryDirectionEnum.ASCENDANTS,
    include_edges=False,
)

# Parse through the query results to get the lineage objects corresponding to the datasets
dataset_artifacts = []
for vertex in query_result.vertices:
    ...
```
dataset_artifacts.append(vertex.to_lineage_object().source.source_uri)

pp.pprint(dataset_artifacts)

Example Find the models associated with an endpoint

# Define the LineageFilter to look for entities of type `ARTIFACT` and the source of type `MODEL`.
query_filter = LineageFilter(
    entities=[LineageEntityEnum.ARTIFACT], sources=[LineageSourceEnum.MODEL]
)

# Providing this `LineageFilter` to the `LineageQuery` constructs a query that traverses through the given context `endpoint_context`
# and find all datasets.
query_result = LineageQuery(sagemaker_session).query(
    start_arns=[endpoint_context.context_arn],
    query_filter=query_filter,
    direction=LineageQueryDirectionEnum.ASCENDANTS,
    include_edges=False,
)

# Parse through the query results to get the lineage objects corresponding to the model
model_artifacts = []
for vertex in query_result.vertices:
    model_artifacts.append(vertex.to_lineage_object().source.source_uri)

# The results of the `LineageQuery` API call return the ARN of the model deployed to the endpoint along with
# the S3 URI to the model.tar.gz file associated with the model
pp.pprint(model_artifacts)

Example Find the trial components associated with the endpoint

# Define the LineageFilter to look for entities of type `TRIAL_COMPONENT` and the source of type `TRAINING_JOB`.
query_filter = LineageFilter(
    entities=[LineageEntityEnum.TRIAL_COMPONENT],
    sources=[LineageSourceEnum.TRAINING_JOB],
)

# Providing this `LineageFilter` to the `LineageQuery` constructs a query that traverses through the given context `endpoint_context`
# and find all datasets.
query_result = LineageQuery(sagemaker_session).query(
    start_arns=[endpoint_context.context_arn],
    query_filter=query_filter,
    direction=LineageQueryDirectionEnum.ASCENDANTS,
    include_edges=False,
)

# Parse through the query results to get the ARNs of the training jobs associated with this endpoint
trial_components = []
for vertex in query_result.vertices:
    trial_components.append(vertex.arn)

pp.pprint(trial_components)
Example Changing the focal point of lineage

The LineageQuery can be modified to have different start_arns which changes the focal point of lineage. In addition, the LineageFilter can take multiple sources and entities to expand the scope of the query.

In the following we use the model as the lineage focal point and find the endpoints and datasets associated with it.

```python
# Get the ModelArtifact
model_artifact_summary = list(Artifact.list(source_uri=model_package_arn))[0]
model_artifact = ModelArtifact.load(artifact_arn=model_artifact_summary.artifact_arn)
query_filter = LineageFilter(
    entities=[LineageEntityEnum.ARTIFACT],
    sources=[LineageSourceEnum.ENDPOINT, LineageSourceEnum.DATASET],
)
query_result = LineageQuery(sagemaker_session).query(
    start_arns=[model_artifact.artifact_arn],  # Model is the starting artifact
    query_filter=query_filter,
    # Find all the entities that descend from the model, i.e. the endpoint
    direction=LineageQueryDirectionEnum.DESCENDANTS,
    include_edges=False,
)
associations = []
for vertex in query_result.vertices:
    associations.append(vertex.to_lineage_object().source.source_uri)

query_result = LineageQuery(sagemaker_session).query(
    start_arns=[model_artifact.artifact_arn],  # Model is the starting artifact
    query_filter=query_filter,
    # Find all the entities that ascend from the model, i.e. the datasets
    direction=LineageQueryDirectionEnum.ASCENDANTS,
    include_edges=False,
)
for vertex in query_result.vertices:
    associations.append(vertex.to_lineage_object().source.source_uri)
p.p.pprint(associations)
```

Example Using LineageQueryDirectionEnum.BOTH to find ascendent and descendent relationships

When the direction is set to BOTH, the query traverses the graph to find ascendent and descendent relationships. This traversal takes place not only from the starting node, but from each node that is visited. For example; if a training job is run twice and both models generated by the training job are deployed to endpoints, the result of the query with direction set to BOTH shows both endpoints. This is because the same image is used for training and deploying the model. Since the image is common to the model, the start_arn and both the endpoints, appear in the query result.

```python
query_filter = LineageFilter(
    entities=[LineageEntityEnum.ARTIFACT],
    sources=[LineageSourceEnum.ENDPOINT, LineageSourceEnum.DATASET],
)
query_result = LineageQuery(sagemaker_session).query(
    start_arns=[model_artifact.artifact_arn],  # Model is the starting artifact
    query_filter=query_filter,
```
# This specifies that the query should look for associations both ascending and
descending for the start
  direction=LineageQueryDirectionEnum.BOTH,
  include_edges=False,
)
associations = []
for vertex in query_result.vertices:
  associations.append(vertex.to_lineage_object().source.source_uri)
pp.pprint(associations)

Example Directions in LineageQuery - ASCENDANTS vs. DESCENDANTS

To understand the direction in the Lineage Graph, take the following entity relationship graph - Dataset -> Training Job -> Model -> Endpoint

The endpoint is a descendant of the model, and the model is a descendant of the dataset. Similarly, the model is an ascendant of the endpoint. The direction parameter can be used to specify whether the query should return entities that are descendants or ascendants of the entity in start_arns. If the start_arns contains a model and the direction is DESCENDANTS, the query returns the endpoint. If the direction is ASCENDANTS, the query returns the dataset.

# In this example, we'll look at the impact of specifying the direction as ASCENDANT or DESCENDANT in a `LineageQuery`.
query_filter = LineageFilter(
  entities=[LineageEntityEnum.ARTIFACT],
  sources=[
    LineageSourceEnum.ENDPOINT,
    LineageSourceEnum.MODEL,
    LineageSourceEnum.DATASET,
    LineageSourceEnum.TRAINING_JOB,
  ],
)
query_result = LineageQuery(sagemaker_session).query(
  start_arns=[model_artifact.artifact_arn],
  query_filter=query_filter,
  direction=LineageQueryDirectionEnum.ASCENDANTS,
  include_edges=False,
)
ascendant_artifacts = []
# The lineage entity returned for the Training Job is a TrialComponent which can't be converted to a
# lineage object using the method `to_lineage_object()` so we extract the TrialComponent ARN.
for vertex in query_result.vertices:
  try:
    ascendant_artifacts.append(vertex.to_lineage_object().source.source_uri)
  except:
    ascendant_artifacts.append(vertex.arn)
print("Ascendant artifacts : ")
pp.pprint(ascendant_artifacts)
query_result = LineageQuery(sagemaker_session).query(
  start_arns=[model_artifact.artifact_arn],
  query_filter=query_filter,
  direction=LineageQueryDirectionEnum.DESCENDANTS,
  include_edges=False,
)
descendant_artifacts = []
for vertex in query_result.vertices:
    try:
        descendant_artifacts.append(vertex.to_lineage_object().source.source_uri)
    except:
        # Handling TrialComponents.
        descendant_artifacts.append(vertex.arn)

print("Descendant artifacts : ")
pp.pprint(descendant_artifacts)

Example SDK helper functions to make lineage queries easier

The classes EndpointContext, ModelArtifact, and DatasetArtifact have helper functions that are wrappers over the LineageQuery API to make certain lineage queries easier to leverage. The following example shows how to use these helper function.

# Find all the datasets associated with this endpoint
datasets = []
dataset_artifacts = endpoint_context.dataset_artifacts()
for dataset in dataset_artifacts:
    datasets.append(dataset.source.source_uri)
print("Datasets : ", datasets)

# Find the training jobs associated with the endpoint
training_job_artifacts = endpoint_context.training_job_arns()
training_jobs = []
for training_job in training_job_artifacts:
    training_jobs.append(training_job)
print("Training Jobs : ", training_jobs)

# Get the ARN for the pipeline execution associated with this endpoint (if any)
pipeline_executions = endpoint_context.pipeline_execution_arn()
if pipeline_executions:
    for pipeline in pipelines_executions:
        print(pipeline)

# Here we use the `ModelArtifact` class to find all the datasets and endpoints associated with the model

dataset_artifacts = model_artifact.dataset_artifacts()
endpoint_contexts = model_artifact.endpoint_contexts()
datasets = [dataset.source.source_uri for dataset in dataset_artifacts]
endpoints = [endpoint.source.source_uri for endpoint in endpoint_contexts]
print("Datasets associated with this model : ")
pp.pprint(datasets)
print("Endpoints associated with this model : ")
pp.pprint(endpoints)

# Here we use the `DatasetArtifact` class to find all the endpoints hosting models that were trained with a particular dataset
# Find the artifact associated with the dataset
dataset_artifact_arn = list(Artifact.list(source_uri=training_data))[0].artifact_arn
dataset_artifact = DatasetArtifact.load(artifact_arn=dataset_artifact_arn)

dataset_artifact_arn = list(Artifact.list(source_uri=training_data))[0].artifact_arn
dataset_artifact = DatasetArtifact.load(artifact_arn=dataset_artifact_arn)

# Find the endpoints that used this training dataset
endpoint_contexts = dataset_artifact.endpoint_contexts()
datasets = [endpoint.source.source_uri for endpoint in endpoint_contexts]
Example Getting a Lineage graph visualization

A helper class `Visualizer` is provided in the sample notebook `visualizer.py` to help plot the lineage graph. When the query response is rendered, a graph with the lineage relationships from the `StartArns` is displayed. From the `StartArns` the visualization shows the relationships with the other lineage entities returned in the `query_lineage` API action.

```python
# Graph APIs
# Here we use the boto3 `query_lineage` API to generate the query response to plot.
from visualizer import Visualizer
query_response = sm_client.query_lineage(
    StartArns=[endpoint_context.context_arn], Direction="Ascendants", IncludeEdges=True
)
 viz = Visualizer()
 viz.render(query_response, "Endpoint")
 query_response = sm_client.query_lineage(
    StartArns=[model_artifact.artifact_arn], Direction="Ascendants", IncludeEdges=True
)
 viz.render(query_response, "Model")
```

Cross-Account Lineage Tracking

Amazon SageMaker supports tracking lineage entities from a different AWS account. Other AWS accounts can share their lineage entities with you and you can access these lineage entities through direct API calls or SageMaker lineage queries.

SageMaker uses AWS Resource Access Manager to help you securely share your lineage resources. You can share your resources through the AWS RAM console.

Set Up Cross-Account Lineage Tracking

You can group and share your

- Tracking entities maintain a representation of all the elements of your end-to-end machine learning workflow. You can use this representation to establish model governance, reproduce your workflow, and maintain a record of your work history.

- Amazon SageMaker automatically creates tracking entities for trial components and their associated trials and experiments when you create SageMaker jobs such as processing jobs, training jobs, and batch transform jobs. In additional to auto tracking, you can also Manually Create Tracking Entities (p. 3314) to model custom steps in your workflow. For more information, see Manage Machine Learning with Amazon SageMaker Experiments (p. 2231).

- SageMaker also automatically creates tracking entities for the other steps in a workflow so you can track the workflow from end to end. For more information, see Amazon SageMaker–Created Tracking Entities (p. 3312).

- You can create additional entities to supplement those created by SageMaker. For more information, see Manually Create Tracking Entities (p. 3314).

- SageMaker reuses any existing entities rather than creating new ones. For example, there can be only one artifact with a unique `SourceUri`.
Key concepts for querying lineage

• **Lineage** – Metadata that tracks the relationships between various entities in your ML workflows.

• **QueryLineage** – The action to inspect your lineage and discover relationships between entities.

• **Lineage entities** – The metadata elements of which your lineage is composed.

• **Cross-account lineage** – Your ML workflow may span more than one account. With cross-account lineage, you can configure multiple accounts to automatically create lineage associations between shared entity resources. QueryLineage then can return entities even from these shared accounts.

The following tracking entities are defined:

**Experiment entities**

• Trial component – A stage of a machine learning trial. Includes processing jobs, training jobs, and batch transform jobs.

• Trial – A combination of trial components that generally produces a model.

• Experiment – A grouping of trials generally focused on solving a specific use case.

**Lineage entities**

• Trial Component – Represents processing, training, and transform jobs in the lineage. Also part of experiment management.

• Context – Provides a logical grouping of other tracking or experiment entities. Conceptually, experiments and trials are contexts. Some examples are an endpoint and a model package.

• Action – Represents an action or activity. Generally, an action involves at least one input artifact or output artifact. Some examples are a workflow step and a model deployment.

• Artifact – Represents a URI addressable object or data. An artifact is generally either an input or an output to a trial component or action. Some examples include a dataset (S3 bucket URI), or an image (Amazon ECR registry path).

• Association – Links other tracking or experiment entities, such as an association between the location of training data and a training job. An association has an optional AssociationType property. The following values are available along with the suggested use for each type. SageMaker places no restrictions on their use:
  • ContributedTo – The source contributed to the destination or had a part in enabling the destination. For example, the training data contributed to the training job.
  • AssociatedWith – The source is connected to the destination. For example, an approval workflow is associated with a model deployment.
  • DerivedFrom - The destination is a modification of the source. For example, a digest output of a channel input for a processing job is derived from the original inputs.
  • Produced – The source generated the destination. For example, a training job produced a model artifact.
  • SameAs – When the same lineage entity used in different accounts.

**Common properties**

• **Type property**
The action, artifact, and context entities have a `type` property, `ActionType`, `ArtifactType`, and `ContextType`, respectively. This property is a custom string which can associate meaningful information with the entity and be used as a filter in the List APIs.

- **Source property**
The action, artifact, and context entities have a `Source` property. This property provides the underlying URI that the entity represents. Some examples are:
  - An UpdateEndpoint action where the source is the `EndpointArn`.
  - An image artifact for a processing job where the source is the `ImageUri`.
  - An Endpoint context where the source is the `EndpointArn`.

- **Metadata property**
The action and artifact entities have an optional `Metadata` property which can provide the following information:
  - `ProjectId` – For example, the ID of the SageMaker MLOps project to which a model belongs.
  - `GeneratedBy` – For example, the SageMaker pipeline execution that registered a model package version.
  - `Repository` – For example, the repository that contains an algorithm.
  - `CommitId` – For example, the commit ID of an algorithm version.

(p. 3310) through a lineage group in Amazon SageMaker. SageMaker supports only one default lineage group per account. SageMaker creates the default lineage group whenever a lineage entity is created in your account. Every lineage entity owned by your account is assigned to this default lineage group. To share lineage entities with another account, you share this default lineage group with that account.

**Note**
You can share all lineage tracking entities in a lineage group or none.

Create a resource share for your lineage entities using AWS Resource Access Manager console. For more information, see [Sharing your AWS resources](https://docs.aws.amazon.com/ram/latest/userguide/awssource-sharing-resource.html) in the *AWS Resource Access Manager User Guide*.

**Note**
After the resource share is created, it can take a few minutes for the resource and principal associations to complete. Once the association is set, the shared account receives an invitation to join the resource share. The shared account must accept the invite to gain access to shared resources. For more information on accepting a resource share invite in AWS RAM, see [Using shared AWS resources](https://docs.aws.amazon.com/ram/latest/userguide/using-shared-resource-sharing.html) in the *AWS Resource Access Manager User Guide*.

### Your cross-account lineage tracking resource policy
Amazon SageMaker supports only one type of resource policy. The SageMaker resource policy must allow all of the following operations:

```
"sagemaker:DescribeAction"
"sagemaker:DescribeArtifact"
"sagemaker:DescribeContext"
"sagemaker:DescribeTrialComponent"
"sagemaker:AddAssociation"
"sagemaker:DeleteAssociation"
"sagemaker:QueryLineage"
```
Example The following is a SageMaker resource policy created using AWS Resource Access Manager for creating a resource share for an accounts lineage group.

```json
{

    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "FullLineageAccess",
            "Effect": "Allow",
            "Principal": {
                "AWS": "123456789012" #account-id
            },
            "Action": [
                "sagemaker:DescribeAction",
                "sagemaker:DescribeArtifact",
                "sagemaker:DescribeContext",
                "sagemaker:DescribeTrialComponent",
                "sagemaker:AddAssociation",
                "sagemaker:DeleteAssociation",
                "sagemaker:QueryLineage"
            ],
        }
    ]
}
```

**Tracking Cross-Account Lineage Entities**

With cross-account lineage tracking you can associate lineage entities in different accounts using the same AddAssociation API action. When you associate two lineage entities, SageMaker validates if you have permissions to perform the AddAssociation API action on both lineage entities. SageMaker then establishes the association. If you don't have the permissions, SageMaker does not create the association.

Once the cross-account association is established, you can access either lineage entity from the other through the QueryLineage API action. For more information, see [Querying Lineage Entities](p. 3317).

In addition to SageMaker automatically creating lineage entities, if you have cross-account access, SageMaker connects artifacts that reference the same object or data. If the data from one account is used in lineage tracking by different accounts, SageMaker creates an artifact in each account to track that data. With cross-account lineage, whenever SageMaker creates new artifacts, SageMaker checks if there are other artifacts created for the same data that are also shared with you. SageMaker then establishes associations between the newly created artifact and each of the artifacts shared with you with the AssociationType set to SameAs. You can then use the QueryLineage API action to traverse the lineage entities in your own account to lineage entities shared with you but owned by a different AWS account. For more information, see [Querying Lineage Entities](p. 3317).

**Topics**

- Accessing lineage resources from a different accounts (p. 3326)
- Authorization for querying cross-account lineage entities (p. 3327)

**Accessing lineage resources from a different accounts**

Once the cross-account access for sharing lineage has been set up, you can call the following SageMaker API actions directly with the ARN to describe the shared lineage entities from another account:

- **DescribeAction**
- **DescribeArtifact**
• DescribeContext
• DescribeTrialComponent

You can also manage Associations for lineage entities owned by different accounts that are shared with you, using the following SageMaker API actions:

• AddAssociation
• DeleteAssociation

For a notebook that demonstrates how to use SageMaker Lineage APIs to query lineage across accounts, see sagemaker-lineage-cross-account-with-ram.ipynb.

Authorization for querying cross-account lineage entities

Amazon SageMaker must validate that you have permissions to perform the QueryLineage API action on the StartArns. This is enforced through the resource policy attached to the LineageGroup. The result from this action includes all the lineage entities to which you have access, whether they are owned by your account or shared by another account. For more information, see Querying Lineage Entities (p. 3317).

Kubernetes Orchestration

You can orchestrate your SageMaker training and inference jobs with SageMaker Operators for Kubernetes and SageMaker Components for Kubeflow Pipelines. SageMaker Operators for Kubernetes make it easier for developers and data scientists using Kubernetes to train, tune, and deploy machine learning (ML) models in SageMaker. SageMaker Components for Kubeflow Pipelines allow you to move your data processing and training jobs from the Kubernetes cluster to SageMaker's machine learning-optimized managed service.

Contents

• SageMaker Operators for Kubernetes (p. 3327)
• SageMaker Components for Kubeflow Pipelines (p. 3370)

SageMaker Operators for Kubernetes

SageMaker Operators for Kubernetes make it easier for developers and data scientists using Kubernetes to train, tune, and deploy machine learning (ML) models in SageMaker. You can install these SageMaker Operators on your Kubernetes cluster in Amazon Elastic Kubernetes Service (Amazon EKS) to create SageMaker jobs natively using the Kubernetes API and command-line Kubernetes tools such as kubectl. This guide shows you how to set up the operators. The guide also explains how to use the operators to run model training, hyperparameter tuning, and inference (real-time and batch).

Important
The new version of SageMaker Operators for Kubernetes uses AWS Controllers for Kubernetes (ACK). For more information, see Migrate resources to the new SageMaker Operators for Kubernetes (p. 3367) or go directly to the ACK documentation.

There is no additional charge to use these operators. You do incur charges for any SageMaker resources that you use through these operators. The procedures and guidelines here assume you are familiar with Kubernetes and its basic commands.

Contents
What is an operator?

Kubernetes is built on top of what is called the controller pattern. This pattern allows applications and tools to listen to a central state manager (ETCD) and act when something happens. Examples of such applications include cloud-controller-manager and controller-manager. The controller pattern allows you to create decoupled experiences and not have to worry about how other components are integrated. To add new capabilities to Kubernetes, developers can extend the Kubernetes API by creating a custom resource that contains their application-specific or domain-specific logic and components. Operators in Kubernetes allow users to natively invoke these custom resources and automate associated workflows.

Permissions overview

The SageMaker Operators for Kubernetes allow you to manage jobs in SageMaker from your Kubernetes cluster. The operators access SageMaker resources on your behalf. The IAM role that the operator assumes to interact with AWS resources differs from the credentials you use to access the Kubernetes cluster. The role also differs from the role that SageMaker assumes when running your machine learning jobs. The following image explains this design and flow.
Authentication Layers in the SageMaker Operator for Kubernetes

Developer machine authenticates with cluster via RBAC and AWS credentials (if using AWS)

Kubernetes Cluster

SageMaker Operator for Kubernetes

Operator authenticates with SageMaker via IAM Role+Authentication Provider with SageMakerFullAccess permissions.

Amazon SageMaker

Training Job

SageMaker accesses AWS resources by assuming an IAM role (TrainingJob.RoleArn)

Amazon S3

Amazon EC2

(+ other AWS services)
Migrate resources to the new operator

The new Amazon SageMaker Operators for Kubernetes use AWS Controllers for Kubernetes (ACK) to train, tune, and deploy machine learning models with Amazon SageMaker. The new operators are not backwards compatible, so be sure to migrate any existing SageMaker Operators for Kubernetes resources from the old operator to the new operator. To get started with migrating resources, see Migrate resources to the new SageMaker Operators for Kubernetes (p. 3367).

IAM role-based setup and operator deployment

The following sections describe the steps to set up and deploy the operator.

Warning
The following steps do not install the latest version of SageMaker Operators for Kubernetes. To install the new SageMaker Operators for Kubernetes, see Migrate resources to the new SageMaker Operators for Kubernetes (p. 3367).

Prerequisites

This guide assumes that you've completed the following prerequisites:

- Installed the following tools on the client machine used to access your Kubernetes cluster:
  - kubectl Version 1.13 or later. Use a kubectl version that is within one minor version of your Amazon EKS cluster control plane. For example, a 1.13 kubectl client works with Kubernetes 1.13 and 1.14 clusters. OpenID Connect (OIDC) is not supported in versions earlier than 1.13.
  - eksctl Version 0.7.0 or later
  - AWS CLI Version 1.16.232 or later
  - (optional) Helm Version 3.0 or later
  - aws-iam-authenticator
  - Have IAM permissions to create roles and attach policies to roles.
  - Created a Kubernetes cluster on which to run the operators. It should either be Kubernetes version 1.13 or 1.14. For automated cluster creation using eksctl, see Getting Started with eksctl. It takes 20 to 30 minutes to provision a cluster.

Cluster-scoped deployment

Before you can deploy your operator using an IAM role, associate an OpenID Connect (OIDC) provider with your role to authenticate with the IAM service.

Create an OpenID Connect Provider for Your Cluster

The following instructions show how to create and associate an OIDC provider with your Amazon EKS cluster.

1. Set the local CLUSTER_NAME and AWS_REGION environment variables as follows:

```
# Set the Region and cluster
export CLUSTER_NAME="<your cluster name>"
export AWS_REGION="<your region>"
```

2. Use the following command to associate the OIDC provider with your cluster. For more information, see Enabling IAM Roles for Service Accounts on your Cluster.

```
eksctl utils associate-iam-oidc-provider --cluster ${CLUSTER_NAME} \
    --region ${AWS_REGION} --approve
```

Your output should look like the following:
Now that the cluster has an OIDC identity provider, you can create a role and give a Kubernetes ServiceAccount permission to assume the role.

Get the OIDC ID

To set up the ServiceAccount, obtain the OpenID Connect issuer URL using the following command:

```sh
aws eks describe-cluster --name ${CLUSTER_NAME} --region ${AWS_REGION} --query cluster.identity.oidc.issuer --output text
```

The command returns a URL like the following:

```sh
https://oidc.eks.${AWS_REGION}.amazonaws.com/id/D48675832CA65BD10A532F5970IDCID
```

In this URL, the value D48675832CA65BD10A532F5970IDCID is the OIDC ID. The OIDC ID for your cluster is different. You need this OIDC ID value to create a role.

If your output is None, it means that your client version is old. To work around this, run the following command:

```sh
aws eks describe-cluster --region ${AWS_REGION} --query cluster --name ${CLUSTER_NAME} --output text | grep OIDC
```

The OIDC URL is returned as follows:

```sh
OIDC https://oidc.eks.us-east-1.amazonaws.com/id/D48675832CA65BD10A532F5970IDCID
```

Create an IAM Role

1. Create a file named `trust.json` and insert the following trust relationship code block into it. Be sure to replace all `<OIDC ID>`, `<AWS account number>`, and `<EKS Cluster region>` placeholders with values corresponding to your cluster.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Principal": {
        "Federated": "arn:aws:iam::<AWS account number>:oidc-provider/oidc.eks.<EKS Cluster region>.amazonaws.com/id/<OIDC ID>"
      },
      "Action": "sts:AssumeRoleWithWebIdentity",
      "Condition": {
        "StringEquals": {
          "oidc.eks.<EKS Cluster region>.amazonaws.com/id/<OIDC ID>:aud": "sts.amazonaws.com",
        }
      }
    }
  ]
}
```
1. Run the following command to create a role with the trust relationship defined in `trust.json`. This role enables the Amazon EKS cluster to get and refresh credentials from IAM.

```bash
aws iam create-role --region ${AWS_REGION} --role-name <role name> --assume-role-policy-document file://trust.json --output=text
```

Your output should look like the following:

|--------------|-----------------------------------------------------------------
| ASSUMEROLEPOLICYDOCUMENT | 2012-10-17 |
| STATEMENT    | sts:AssumeRoleWithWebIdentity Allow |
| PRINCIPAL    | arn:aws:iam::123456789012:oidc-provider/oidc.eks.us-east-1.amazonaws.com/id/ |

Take note of ROLE ARN; you pass this value to your operator.

### Attach the AmazonSageMakerFullAccess Policy to the Role

To give the role access to SageMaker, attach the `AmazonSageMakerFullAccess` policy. If you want to limit permissions to the operator, you can create your own custom policy and attach it.

To attach AmazonSageMakerFullAccess, run the following command:

```bash
aws iam attach-role-policy --role-name <role name> --policy-arn arn:aws:iam::aws:policy/AmazonSageMakerFullAccess
```

The Kubernetes ServiceAccount `sagemaker-k8s-operator-default` should have AmazonSageMakerFullAccess permissions. Confirm this when you install the operator.

### Deploy the Operator

When deploying your operator, you can use either a YAML file or Helm charts.

#### Deploy the Operator Using YAML

This is the simplest way to deploy your operators. The process is as follows:

1. Download the installer script using the following command:

   ```bash
   ```

2. Edit the `installer.yaml` file to replace `eks.amazonaws.com/role-arn`. Replace the ARN here with the Amazon Resource Name (ARN) for the OIDC-based role you've created.

3. Use the following command to deploy the cluster:

   ```bash
   kubectl apply -f installer.yaml
   ```

#### Deploy the Operator Using Helm Charts

Use the provided Helm Chart to install the operator.
1. Clone the Helm installer directory using the following command:

   ```bash
git clone https://github.com/aws/amazon-sagemaker-operator-for-k8s.git
   ```

2. Navigate to the `amazon-sagemaker-operator-for-k8s/hack/charts/installer` folder. Edit the `rolebased/values.yaml` file, which includes high-level parameters for the chart. Replace the role ARN here with the Amazon Resource Name (ARN) for the OIDC-based role you've created.

3. Install the Helm Chart using the following command:

   ```bash
   kubectl create namespace sagemaker-k8s-operator-system
   helm install --namespace sagemaker-k8s-operator-system sagemaker-operator rolebased/
   ```

   If you decide to install the operator into a namespace other than the one specified, you need to adjust the namespace defined in the IAM role trust.json file to match.

4. After a moment, the chart is installed with a randomly generated name. Verify that the installation succeeded by running the following command:

   ```bash
   helm ls
   ```

   Your output should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>NAMESPACE</th>
<th>CHART</th>
<th>REVISION</th>
<th>UPDATED</th>
</tr>
</thead>
<tbody>
<tr>
<td>sagemaker-operator</td>
<td>sagemaker-k8s-operator-system</td>
<td>sagemaker-k8s-operator-system</td>
<td>1</td>
<td>2019-11-20</td>
</tr>
<tr>
<td>23:14:59.6777082 +0000 UTC deployed</td>
<td>sagemaker-k8s-operator-0.1.0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

   **Verify the operator deployment**

   1. You should be able to see the SageMaker Custom Resource Definitions (CRDs) for each operator deployed to your cluster by running the following command:

      ```bash
      kubectl get crd | grep sagemaker
      ```

      Your output should look like the following:

      | CRD Name                                                      | Creation Time       |
      |--------------------------------------------------------------|---------------------|
      | batchtransformjobs.sagemaker.aws.amazon.com                  | 2019-11-20T17:12:34Z|
      | endpointconfigs.sagemaker.aws.amazon.com                     | 2019-11-20T17:12:34Z|
      | hostingdeployments.sagemaker.aws.amazon.com                  | 2019-11-20T17:12:34Z|
      | hyperparametertuningjobs.sagemaker.aws.amazon.com            | 2019-11-20T17:12:34Z|
      | models.sagemaker.aws.amazon.com                              | 2019-11-20T17:12:34Z|
      | trainingjobs.sagemaker.aws.amazon.com                        | 2019-11-20T17:12:34Z|

   2. Ensure that the operator pod is running successfully. Use the following command to list all pods:

      ```bash
      kubectl -n sagemaker-k8s-operator-system get pods
      ```

      You should see a pod named `sagemaker-k8s-operator-controller-manager-*****` in the namespace `sagemaker-k8s-operator-system` as follows:

      | NAME                                                      | READY | STATUS     | RESTARTS |
      |----------------------------------------------------------|-------|------------|----------|
      | sagemaker-k8s-operator-controller-manager-12345678-r8abc  | 2/2   | Running    | 0        |
      | 23s                                                       |       |            |          |
Namespace-scoped deployment

You have the option to install your operator within the scope of an individual Kubernetes namespace. In this mode, the controller only monitors and reconciles resources with SageMaker if the resources are created within that namespace. This allows for finer-grained control over which controller is managing which resources. This is useful for deploying to multiple AWS accounts or controlling which users have access to particular jobs.

This guide outlines how to install an operator into a particular, predefined namespace. To deploy a controller into a second namespace, follow the guide from beginning to end and change out the namespace in each step.

Create an OpenID Connect Provider for Your Amazon EKS cluster

The following instructions show how to create and associate an OIDC provider with your Amazon EKS cluster.

1. Set the local CLUSTER_NAME and AWS_REGION environment variables as follows:

   ```shell
   # Set the region and cluster
   export CLUSTER_NAME="<your cluster name>"
   export AWS_REGION="<your region>"
   ```

2. Use the following command to associate the OIDC provider with your cluster. For more information, see Enabling IAM Roles for Service Accounts on your Cluster.

   ```shell
   eksctl utils associate-iam-oidc-provider --cluster ${CLUSTER_NAME} --region ${AWS_REGION} --approve
   ```

   Your output should look like the following:

   ```shell
   [ ] eksctl version 0.10.1
   [ ] using region us-east-1
   [ ] IAM OpenID Connect provider is associated with cluster "my-cluster" in "us-east-1"
   ```

   Now that the cluster has an OIDC identity provider, create a role and give a Kubernetes ServiceAccount permission to assume the role.

   **Get your OIDC ID**

   To set up the ServiceAccount, first obtain the OpenID Connect issuer URL using the following command:

   ```shell
   aws eks describe-cluster --name ${CLUSTER_NAME} --region ${AWS_REGION} --query cluster.identity.oidc.issuer --output text
   ```

   The command returns a URL like the following:

   ```shell
   https://oidc.eks.${AWS_REGION}.amazonaws.com/id/D48675832CA65BD10A532F597OIDCID
   ```

   In this URL, the value D48675832CA65BD10A532F597OIDCID is the OIDC ID. The OIDC ID for your cluster will be different. You need this OIDC ID value to create a role.

   If your output is None, it means that your client version is old. To work around this, run the following command:

   ```shell
   aws eks describe-cluster --region ${AWS_REGION} --query cluster --name ${CLUSTER_NAME} --output text | grep OIDC
   ```
The OIDC URL is returned as follows:

OIDC https://oidc.eks.us-east-1.amazonaws.com/id/D48675832CA65BD10A532F5970IDCID

Create your IAM Role

1. Create a file named `trust.json` and insert the following trust relationship code block into it. Be sure to replace all `<OIDC ID>`, `<AWS account number>`, `<EKS Cluster region>`, and `<Namespace>` placeholders with values corresponding to your cluster. For the purposes of this guide, `my-namespace` is used for the `<Namespace>` value.

   ```json
   {
   "Version": "2012-10-17",
   "Statement": [
   {
   "Effect": "Allow",
   "Principal": {
   "Federated": "arn:aws:iam::<AWS account number>:oidc-provider/oidc.eks.<EKS Cluster region>.amazonaws.com/id/<OIDC ID>"
   },
   "Action": "sts:AssumeRoleWithWebIdentity",
   "Condition": {
   "StringEquals": {
   "oidc.eks.<EKS Cluster region>.amazonaws.com/id/<OIDC ID>:aud": "sts.amazonaws.com",
   "oidc.eks.<EKS Cluster region>.amazonaws.com/id/<OIDC ID>:sub": "system:serviceaccount:<Namespace>:sagemaker-k8s-operator-default"
   }
   }
   }
   ]
   }
   ```

2. Run the following command to create a role with the trust relationship defined in `trust.json`. This role enables the Amazon EKS cluster to get and refresh credentials from IAM.

   ```bash
   aws iam create-role --region ${AWS_REGION} --role-name <role name> --assume-role-policy-document file://trust.json --output=text
   
   Your output should look like the following:
   
   ABCDEFSFDODNBSEXAMPLE     my-role
   ASSUMEROLEPOLICYDOCUMENT    2012-10-17
   STATEMENT    sts:AssumeRoleWithWebIdentity    Allow
   STRINGEQUALS    sts.amazonaws.com
   PRINCIPAL    arn:aws:iam::123456789012:oidc-provider/oidc.eks.us-east-1.amazonaws.com/id/
   
   Take note of ROLE ARN. You pass this value to your operator.

   **Attach the AmazonSageMakerFullAccess Policy to your Role**

   To give the role access to SageMaker, attach the AmazonSageMakerFullAccess policy. If you want to limit permissions to the operator, you can create your own custom policy and attach it.

   To attach AmazonSageMakerFullAccess, run the following command:

   ```bash
   aws iam attach-role-policy --role-name <role name> --policy-arn arn:aws:iam::123456789012:policy/AmazonSageMakerFullAccess
   ```
aws iam attach-role-policy --role-name <role name> --policy-arn arn:aws:iam::aws:policy/AmazonSageMakerFullAccess

The Kubernetes ServiceAccount sagemaker-k8s-operator-default should have AmazonSageMakerFullAccess permissions. Confirm this when you install the operator.

**Deploy the Operator to Your Namespace**

When deploying your operator, you can use either a YAML file or Helm charts.

**Deploy the Operator to Your Namespace Using YAML**

There are two parts to deploying an operator within the scope of a namespace. The first is the set of CRDs that are installed at a cluster level. These resource definitions only need to be installed once per Kubernetes cluster. The second part is the operator permissions and deployment itself.

If you have not already installed the CRDs into the cluster, apply the CRD installer YAML using the following command:

```
kubectl apply -f https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/release/rolebased/namespaced/crd.yaml
```

To install the operator onto the cluster:

1. Download the operator installer YAML using the following command:

   ```
   ```

2. Update the installer YAML to place the resources into your specified namespace using the following command:

   ```
   sed -i -e 's/PLACEHOLDER-NAMESPACE/<YOUR NAMESPACE>/g' operator.yaml
   ```

3. Edit the `operator.yaml` file to place resources into your eks.amazonaws.com/role-arn. Replace the ARN here with the Amazon Resource Name (ARN) for the OIDC-based role you've created.

4. Use the following command to deploy the cluster:

   ```
   kubectl apply -f operator.yaml
   ```

**Deploy the Operator to Your Namespace Using Helm Charts**

There are two parts needed to deploy an operator within the scope of a namespace. The first is the set of CRDs that are installed at a cluster level. These resource definitions only need to be installed once per Kubernetes cluster. The second part is the operator permissions and deployment itself. When using helm charts you have to first create the namespace using `kubectl`.

1. Clone the Helm installer directory using the following command:

   ```
   git clone https://github.com/aws/amazon-sagemaker-operator-for-k8s.git
   ```

2. Navigate to the `amazon-sagemaker-operator-for-k8s/hack/charts/installer/namespaced` folder. Edit the `rolebased/values.yaml` file, which includes high-level parameters for the chart. Replace the role ARN here with the Amazon Resource Name (ARN) for the OIDC-based role you've created.
3. Install the Helm Chart using the following command:

```
helm install crds crd_chart/
```

4. Create the required namespace and install the operator using the following command:

```
kubectl create namespace <namespace>
helm install --namespace <namespace> op operator_chart/
```

5. After a moment, the chart is installed with the name `sagemaker-operator`. Verify that the installation succeeded by running the following command:

```
helm ls
```

Your output should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>NAMESPACE</th>
<th>REVISION</th>
<th>UPDATED</th>
</tr>
</thead>
<tbody>
<tr>
<td>sagemaker-operator</td>
<td>my-namespace</td>
<td>1</td>
<td>2019-11-20 23:14:59.6777082 +0000 UTC</td>
</tr>
</tbody>
</table>

Verify the operator deployment to your namespace

1. You should be able to see the SageMaker Custom Resource Definitions (CRDs) for each operator deployed to your cluster by running the following command:

```
kubectl get crd | grep sagemaker
```

Your output should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>CREATION-TIME</th>
</tr>
</thead>
<tbody>
<tr>
<td>batchtransformjobs.sagemaker.aws.amazon.com</td>
<td>2019-11-20T17:12:34Z</td>
</tr>
<tr>
<td>endpointconfigs.sagemaker.aws.amazon.com</td>
<td>2019-11-20T17:12:34Z</td>
</tr>
<tr>
<td>hostingdeployments.sagemaker.aws.amazon.com</td>
<td>2019-11-20T17:12:34Z</td>
</tr>
<tr>
<td>hyperparametertuningjobs.sagemaker.aws.amazon.com</td>
<td>2019-11-20T17:12:34Z</td>
</tr>
<tr>
<td>models.sagemaker.aws.amazon.com</td>
<td>2019-11-20T17:12:34Z</td>
</tr>
<tr>
<td>trainingjobs.sagemaker.aws.amazon.com</td>
<td>2019-11-20T17:12:34Z</td>
</tr>
</tbody>
</table>

2. Ensure that the operator pod is running successfully. Use the following command to list all pods:

```
kubectl -n my-namespace get pods
```

You should see a pod named `sagemaker-k8s-operator-controller-manager-*****` in the namespace `my-namespace` as follows:

<table>
<thead>
<tr>
<th>NAME</th>
<th>READY</th>
<th>STATUS</th>
<th>RESTARTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>sagemaker-k8s-operator-controller-manager-12345678-r8abc</td>
<td>2/2</td>
<td>Running</td>
<td>0</td>
</tr>
</tbody>
</table>

Install the SageMaker logs kubectl plugin

As part of the SageMaker Operators for Kubernetes, you can use the smlogs plugin for kubectl. This enables SageMaker CloudWatch logs to be streamed with kubectl. kubectl must be installed onto
your `PATH`. The following commands place the binary in the `sagemaker-k8s-bin` directory in your home directory, and add that directory to your `PATH`.

```bash
export os="linux"
wget https://amazon-sagemaker-operator-for-k8s-us-east-1.s3.amazonaws.com/kubectl-smlogs-plugin/v1/${os}.amd64.tar.gz
tar xvzf ${os}.amd64.tar.gz

# Move binaries to a directory in your homedir.
mkdir ~/sagemaker-k8s-bin
cp ./kubectl-smlogs.${os}.amd64/kubectl-smlogs ~/sagemaker-k8s-bin/.

# This line adds the binaries to your PATH in your .bashrc.
echo 'export PATH=$PATH:~/sagemaker-k8s-bin' >> ~/.bashrc

# Source your .bashrc to update environment variables:
source ~/.bashrc
```

Use the following command to verify that the `kubectl` plugin is installed correctly:

```
kubectl smlogs
```

If the `kubectl` plugin is installed correctly, your output should look like the following:

```
View SageMaker logs via Kubernetes

Usage:
    smlogs [command]

Aliases:
    smlogs, SMLogs, Smlogs

Available Commands:
    BatchTransformJob       View BatchTransformJob logs via Kubernetes
    TrainingJob             View TrainingJob logs via Kubernetes
    help                    Help about any command

Flags:
    -h, --help   help for smlogs

Use "smlogs [command] --help" for more information about a command.
```

**Clean up resources**

To uninstall the operator from your cluster, you must first make sure to delete all SageMaker resources from the cluster. Failure to do so causes the operator delete operation to hang. Run the following commands to stop all jobs:

```
# Delete all SageMaker jobs from Kubernetes
kubectl delete --all --all-namespaces hyperparametertrainingjob.sagemaker.aws.amazon.com
kubectl delete --all --all-namespaces trainingjobs.sagemaker.aws.amazon.com
kubectl delete --all --all-namespaces batchtransformjob.sagemaker.aws.amazon.com
kubectl delete --all --all-namespaces hostingdeployment.sagemaker.aws.amazon.com
```

You should see output similar to the following:

```
$ kubectl delete --all --all-namespaces trainingjobs.sagemaker.aws.amazon.com
```

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After you delete all SageMaker jobs, see Delete operators (p. 3339) to delete the operator from your cluster.

## Delete operators

### Delete cluster-based operators

**Operators installed using YAML**

To uninstall the operator from your cluster, make sure that all SageMaker resources have been deleted from the cluster. Failure to do so causes the operator delete operation to hang.

**Note**

Before deleting your cluster, be sure to delete all SageMaker resources from the cluster. See Clean up resources (p. 3338) for more information.

After you delete all SageMaker jobs, use kubectl to delete the operator from the cluster:

```
# Delete the operator and its resources
kubectl delete -f /installer.yaml
```

You should see output similar to the following:

```
$ kubectl delete -f raw-yaml/installer.yaml
namespace "sagemaker-k8s-operator-system" deleted
customresourcedefinition.apiextensions.k8s.io "batchtransformjobs.sagemaker.aws.amazon.com" deleted
customresourcedefinition.apiextensions.k8s.io "endpointconfigs.sagemaker.aws.amazon.com" deleted
customresourcedefinition.apiextensions.k8s.io "hostingdeployments.sagemaker.aws.amazon.com" deleted
customresourcedefinition.apiextensions.k8s.io "hyperparametertuningjobs.sagemaker.aws.amazon.com" deleted
customresourcedefinition.apiextensions.k8s.io "models.sagemaker.aws.amazon.com" deleted
"hyperparametertuningjobs.sagemaker.aws.amazon.com" deleted
customresourcedefinition.apiextensions.k8s.io "trainingjobs.sagemaker.aws.amazon.com" deleted
role.rbac.authorization.k8s.io "sagemaker-k8s-operator-leader-election-role" deleted
clusterrole.rbac.authorization.k8s.io "sagemaker-k8s-operator-manager-role" deleted
clusterrole.rbac.authorization.k8s.io "sagemaker-k8s-operator-proxy-role" deleted
rolebinding.rbac.authorization.k8s.io "sagemaker-k8s-operator-leader-election-rolebinding" deleted
clusterrolebinding.rbac.authorization.k8s.io "sagemaker-k8s-operator-leader-election-rolebinding" deleted
clusterrolebinding.rbac.authorization.k8s.io "sagemaker-k8s-operator-manager-rolebinding" deleted
clusterrolebinding.rbac.authorization.k8s.io "sagemaker-k8s-operator-proxy-rolebinding" deleted
service "sagemaker-k8s-operator-controller-manager-metrics-service" deleted
deployment.apps "sagemaker-k8s-operator-controller-manager" deleted
secrets "sagemaker-k8s-operator-abcde" deleted
```
Operators installed using Helm Charts

To delete the operator CRDs, first delete all the running jobs. Then delete the Helm Chart that was used to deploy the operators using the following commands:

```
# get the helm charts
helm ls

# delete the charts
helm delete <chart_name>
```

Delete namespace-based operators

Operators installed with YAML

To uninstall the operator from your cluster, first make sure that all SageMaker resources have been deleted from the cluster. Failure to do so causes the operator delete operation to hang.

**Note**
Before deleting your cluster, be sure to delete all SageMaker resources from the cluster. See [Clean up resources](p. 3338) for more information.

After you delete all SageMaker jobs, use `kubectl` to first delete the operator from the namespace and then the CRDs from the cluster. Run the following commands to delete the operator from the cluster:

```
# Delete the operator using the same yaml file that was used to install the operator
kubectl delete -f operator.yaml

# Now delete the CRDs using the CRD installer yaml

# Now you can delete the namespace if you want
kubectl delete namespace <namespace>
```

Operators installed with Helm Charts

To delete the operator CRDs, first delete all the running jobs. Then delete the Helm Chart that was used to deploy the operators using the following commands:

```
# Delete the operator
helm delete <chart_name>

# delete the crds
helm delete crds

# optionally delete the namespace
kubectl delete namespace <namespace>
```

Troubleshooting

Debugging a Failed Job

- Check the job status by running the following:

```
kubectl get <CRD Type> <job name>
```
If the job was created in SageMaker, you can use the following command to see the STATUS and the SageMaker Job Name:

```
kubectl get <crd type> <job name>
```

You can use `smlogs` to find the cause of the issue using the following command:

```
kubectl smlogs <crd type> <job name>
```

You can also use the `describe` command to get more details about the job using the following command. The output has an additional field that has more information about the status of the job.

```
kubectl describe <crd type> <job name>
```

If the job was not created in SageMaker, then use the logs of the operator's pod to find the cause of the issue as follows:

```
$ kubectl get pods -A | grep sagemaker
# Output:
sagemaker-k8s-operator-system   sagemaker-k8s-operator-controller-manager-5cd7df4d74-wh22z   2/2     Running   0          3h33m
$ kubectl logs -p <pod name> -c manager -n sagemaker-k8s-operator-system
```

Deleting an Operator CRD

If deleting a job is not working, check if the operator is running. If the operator is not running, then you have to delete the finalizer using the following steps:

1. In a new terminal, open the job in an editor using `kubectl edit` as follows:

   ```
kubectl edit <crd type> <job name>
```

2. Edit the job to delete the finalizer by removing the following two lines from the file. Save the file and the job is be deleted.

   ```
finalizers:
- sagemaker-operator-finalizer
```

Images and SMlogs in each Region

The following table lists the available operator images and SMLogs in each region.

<table>
<thead>
<tr>
<th>Region</th>
<th>Controller Image</th>
<th>Linux SMLogs</th>
</tr>
</thead>
<tbody>
<tr>
<td>us-east-1</td>
<td>957583890962.dkr.ecr.us-east-1.amazonaws.com/amazon-sagemaker-operator-for-k8s:v1</td>
<td><a href="https://s3.us-east-1.amazonaws.com/amazon-sagemaker-operator-for-k8s-us-east-1/kubectl-smlogs-plugin/v1/linux.amd64.tar.gz">https://s3.us-east-1.amazonaws.com/amazon-sagemaker-operator-for-k8s-us-east-1/kubectl-smlogs-plugin/v1/linux.amd64.tar.gz</a></td>
</tr>
</tbody>
</table>
Using Amazon SageMaker Jobs

To run an Amazon SageMaker job using the Operators for Kubernetes, you can either apply a YAML file or use the supplied Helm Charts.

Important
The new version of SageMaker Operators for Kubernetes uses AWS Controllers for Kubernetes (ACK). For more information, see Migrate resources to the new SageMaker Operators for Kubernetes (p. 3367) or go directly to the ACK documentation.

All sample operator jobs in the following tutorials use sample data taken from a public MNIST dataset. In order to run these samples, download the dataset into your Amazon S3 bucket. You can find the dataset in Download the MNIST Dataset.

For more ML with the ACK SageMaker controller, see also those SageMaker tutorials.

Contents

- TrainingJob operator (p. 3342)
- HyperParameterTuningJob operator (p. 3347)
- BatchTransformJob operator (p. 3352)
- HostingDeployment operator (p. 3355)
- ProcessingJob operator (p. 3360)
- HostingAutoscalingPolicy (HAP) Operator (p. 3364)

TrainingJob operator

Training job operators reconcile your specified training job spec to SageMaker by launching it for you in SageMaker. You can learn more about SageMaker training jobs in the SageMaker CreateTrainingJob API documentation.

Topics

- Create a TrainingJob Using a YAML File (p. 3342)
- Create a TrainingJob Using a Helm Chart (p. 3343)
- List TrainingJobs (p. 3344)
- Describe a TrainingJob (p. 3344)
- View Logs from TrainingJobs (p. 3346)
- Delete TrainingJobs (p. 3346)

Create a TrainingJob Using a YAML File

1. Download the sample YAML file for training using the following command:
wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/xgboost-mnist-trainingjob.yaml

2. Edit the xgboost-mnist-trainingjob.yaml file to replace the roleArn parameter with your <sagemaker-execution-role>, and outputPath with your Amazon S3 bucket that the SageMaker execution role has write access to. The roleArn must have permissions so that SageMaker can access Amazon S3, Amazon CloudWatch, and other services on your behalf. For more information on creating an SageMaker ExecutionRole, see SageMaker Roles. Apply the YAML file using the following command:

kubectl apply -f xgboost-mnist-trainingjob.yaml

Create a TrainingJob Using a Helm Chart

You can use Helm Charts to run TrainingJobs.

1. Clone the GitHub repository to get the source using the following command:

   git clone https://github.com/aws/amazon-sagemaker-operator-for-k8s.git

2. Navigate to the amazon-sagemaker-operator-for-k8s/hack/charts/training-jobs/ folder and edit the values.yaml file to replace values like rolearn and outputPath with values that correspond to your account. The RoleARN must have permissions so that SageMaker can access Amazon S3, Amazon CloudWatch, and other services on your behalf. For more information on creating an SageMaker ExecutionRole, see SageMaker Roles.

Create the TrainingJob

With the roles and Amazon S3 buckets replaced with appropriate values in values.yaml, you can create a training job using the following command:

helm install . --generate-name

Your output should look like the following:

|---------------------|-------------------|-------------|----------------------------------|

Verify Your Training Helm Chart

To verify that the Helm Chart was created successfully, run:

helm ls

Your output should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>STATUS</th>
<th>NAMESPACE</th>
<th>REVISION</th>
<th>UPDATED</th>
</tr>
</thead>
</table>
helm install creates a TrainingJob Kubernetes resource. The operator launches the actual training job in SageMaker and updates the TrainingJob Kubernetes resource to reflect the status of the job in SageMaker. You incur charges for SageMaker resources used during the duration of your job. You do not incur any charges once your job completes or stops.

**Note:** SageMaker does not allow you to update a running training job. You cannot edit any parameter and re-apply the file/config. Either change the metadata name or delete the existing job and create a new one. Similar to existing training job operators like TFJob in Kubeflow, update is not supported.

**List TrainingJobs**

Use the following command to list all jobs created using the Kubernetes operator:

```bash
kubectl get TrainingJob
```

The output listing all jobs should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>STATUS</th>
<th>SECONDARY-STATUS</th>
<th>CREATION-TIME</th>
</tr>
</thead>
<tbody>
<tr>
<td>SAGEMAKER-JOB-NAME</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>xgboost-mnist-from-for-s3</td>
<td>InProgress</td>
<td>Starting</td>
<td>2019-11-20T23:42:35Z</td>
</tr>
<tr>
<td>xgboost-mnist-from-for-s3-examplef1eab94e0ed4671d5a8f</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A training job continues to be listed after the job has completed or failed. You can remove a TrainingJob job from the list by following the Delete a Training Job steps. Jobs that have completed or stopped do not incur any charges for SageMaker resources.

**TrainingJob Status Values**

The STATUS field can be one of the following values:

- Completed
- InProgress
- Failed
- Stopped
- Stopping

These statuses come directly from the SageMaker official API documentation.

In addition to the official SageMaker status, it is possible for STATUS to be SynchronizingK8sJobWithSageMaker. This means that the operator has not yet processed the job.

**Secondary Status Values**

The secondary statuses come directly from the SageMaker official API documentation. They contain more granular information about the status of the job.

**Describe a TrainingJob**

You can get more details about the training job by using the describe kubectl command. This is typically used for debugging a problem or checking the parameters of a training job. To get information about your training job, use the following command:
kubectl describe trainingjob xgboost-mnist-from-for-s3

The output for your training job should look like the following:

Name: xgboost-mnist-from-for-s3
Namespace: default
Labels: <none>
Annotations: <none>
API Version: sagemaker.aws.amazon.com/v1
Kind: TrainingJob
Metadata:
  Finalizers:
    sagemaker-operator-finalizer
  Generation: 2
  Resource Version: 23119
  Self Link: /apis/sagemaker.aws.amazon.com/v1/namespaces/default/trainingjobs/xgboost-mnist-from-for-s3
  UID: 6d7u1u1-0bef-11ea-b94e-0ed467example
Spec:
  Algorithm Specification:
    Training Image: 8256416981234.dkr.ecr.us-east-2.amazonaws.com/xgboost:1
    Training Input Mode: File
  Hyper Parameters:
    Name: eta
    Value: 0.2
    Name: gamma
    Value: 4
    Name: max_depth
    Value: 5
    Name: min_child_weight
    Value: 6
    Name: num_class
    Value: 10
    Name: num_round
    Value: 10
    Name: objective
    Value: multi:softmax
    Name: silent
    Value: 0
  Input Data Config:
    Channel Name: train
    Compression Type: None
    Content Type: text/csv
    Data Source:
      S3 Data Source:
        S3 Data Distribution Type: FullyReplicated
        S3 Data Type: S3Prefix
        S3 Uri: https://s3-us-east-2.amazonaws.com/my-bucket/sagemaker/xgboost-mnist/train/
    Channel Name: validation
    Compression Type: None
    Content Type: text/csv
    Data Source:
      S3 Data Source:
        S3 Data Distribution Type: FullyReplicated
        S3 Data Type: S3Prefix
        S3 Uri: https://s3-us-east-2.amazonaws.com/my-bucket/sagemaker/xgboost-mnist/validation/
  Output Data Config:
    S3 Output Path: s3://my-bucket/sagemaker/xgboost-mnist/xgboost/
    Region: us-east-2
    Resource Config:
      Instance Count: 1
Instance Type: ml.m4.xlarge
Volume Size In GB: 5
Role Arn: arn:aws:iam::12345678910:role/service-role/AmazonSageMaker-ExecutionRole
Stopping Condition:
Max Runtime In Seconds: 86400
Training Job Name: xgboost-mnist-from-for-s3-6d7fa0af0bef11eb94e0example
Status:
Last Check Time: 2019-11-20T23:44:29Z
Sage Maker Training Job Name: xgboost-mnist-from-for-s3-6d7fa0af0bef11eb94e0example
Secondary Status: Downloading
Training Job Status: InProgress
Events: <none>

View Logs from TrainingJobs

Use the following command to see the logs from the kmeans-mnist training job:

```bash
cubectl smlogs trainingjob xgboost-mnist-from-for-s3
```

Your output should look similar to the following. The logs from instances are ordered chronologically.

"xgboost-mnist-from-for-s3" has SageMaker TrainingJobName "xgboost-mnist-from-for-s3-123456789" in region "us-east-2", status "InProgress" and secondary status "Starting"

```
xgboost-mnist-from-for-s3-6d7fa0af0bef11eb94e0example/algo-1-1574293123 2019-11-20 23:45:24.7 +0000 UTC Arguments: train
xgboost-mnist-from-for-s3-6d7fa0af0bef11eb94e0example/algo-1-1574293123 2019-11-20 23:45:24.7 +0000 UTC [2019-11-20:23:45:22:INFO] File size need to be processed in the node: 1122.95mb. Available memory size in the node: 8586.0mb
```

Delete TrainingJobs

Use the following command to stop a training job on Amazon SageMaker:

```bash
cubectl delete trainingjob xgboost-mnist-from-for-s3
```

This command removes the SageMaker training job from Kubernetes. This command returns the following output:

```
trainingjob.sagemaker.aws.amazon.com "xgboost-mnist-from-for-s3" deleted
```

If the job is still in progress on SageMaker, the job stops. You do not incur any charges for SageMaker resources after your job stops or completes.

**Note:** SageMaker does not delete training jobs. Stopped jobs continue to show on the SageMaker console. The delete command takes about 2 minutes to clean up the resources from SageMaker.
HyperParameterTuningJob operator

Hyperparameter tuning job operators reconcile your specified hyperparameter tuning job spec to SageMaker by launching it in SageMaker. You can learn more about SageMaker hyperparameter tuning jobs in the SageMaker CreateHyperParameterTuningJob API documentation.

Topics
- Create a HyperparameterTuningJob Using a YAML File (p. 3347)
- Create a HyperparameterTuningJob using a Helm Chart (p. 3347)
- List HyperparameterTuningJobs (p. 3348)
- Describe a HyperparameterTuningJob (p. 3349)
- View Logs from HyperparameterTuningJobs (p. 3351)
- Delete a HyperparameterTuningJob (p. 3352)

Create a HyperparameterTuningJob Using a YAML File

1. Download the sample YAML file for the hyperparameter tuning job using the following command:

   ```bash
   wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/xgboost-mnist-hpo.yaml
   ```

2. Edit the `xgboost-mnist-hpo.yaml` file to replace the `roleArn` parameter with your `sagemaker-execution-role`. For the hyperparameter tuning job to succeed, you must also change the `s3InputPath` and `s3OutputPath` to values that correspond to your account. Apply the updates YAML file using the following command:

   ```bash
   kubectl apply -f xgboost-mnist-hpo.yaml
   ```

Create a HyperparameterTuningJob using a Helm Chart

You can use Helm Charts to run hyperparameter tuning jobs.

1. Clone the GitHub repository to get the source using the following command:

   ```bash
   git clone https://github.com/aws/amazon-sagemaker-operator-for-k8s.git
   ```

2. Navigate to the `amazon-sagemaker-operator-for-k8s/hack/charts/hyperparameter-tuning-jobs/` folder.

3. Edit the `values.yaml` file to replace the `roleArn` parameter with your `sagemaker-execution-role`. For the hyperparameter tuning job to succeed, you must also change the `s3InputPath` and `s3OutputPath` to values that correspond to your account.

Create the HyperparameterTuningJob

With the roles and Amazon S3 paths replaced with appropriate values in `values.yaml`, you can create a hyperparameter tuning job using the following command:

```bash
helm install . --generate-name
```

Your output should look similar to the following:

```
NAME: chart-1574292948
LAST DEPLOYED: Wed Nov 20 23:35:49 2019
```

3347
NAMESPACE: default
STATUS: deployed
REVISION: 1
TEST SUITE: None
NOTES:
Thanks for installing the sagemaker-k8s-hyperparametertuningjob.

Verify Chart Installation

To verify that the Helm Chart was created successfully, run the following command:

```
helm ls
```

Your output should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>NAMESPACE</th>
<th>REVISION</th>
<th>UPDATED</th>
</tr>
</thead>
<tbody>
<tr>
<td>chart-1474292948 UTC deployed</td>
<td>default</td>
<td>1</td>
<td>2019-11-20 23:35:49.9136092 +0000</td>
</tr>
<tr>
<td>STATUS</td>
<td>CHART APP VERSION</td>
<td></td>
<td></td>
</tr>
<tr>
<td>chart-1574292948 UTC deployed</td>
<td>default</td>
<td>1</td>
<td>2019-11-20 23:35:49.9136092 +0000</td>
</tr>
<tr>
<td>rolebased-1574291698 UTC deployed</td>
<td>default</td>
<td>1</td>
<td>2019-11-20 23:35:49.9136092 +0000</td>
</tr>
</tbody>
</table>

`helm install` creates a HyperParameterTuningJob Kubernetes resource. The operator launches the actual hyperparameter optimization job in SageMaker and updates the HyperParameterTuningJob Kubernetes resource to reflect the status of the job in SageMaker. You incur charges for SageMaker resources used during the duration of your job. You do not incur any charges once your job completes or stops.

**Note:** SageMaker does not allow you to update a running hyperparameter tuning job. You cannot edit any parameter and re-apply the file/config. You must either change the metadata name or delete the existing job and create a new one. Similar to existing training job operators like TFJob in Kubeflow, update is not supported.

List HyperparameterTuningJobs

Use the following command to list all jobs created using the Kubernetes operator:

```
kubectl get hyperparametertuningjob
```

Your output should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>STATUS</th>
<th>CREATION-TIME</th>
<th>COMPLETED</th>
<th>INPROGRESS</th>
<th>ERRORS</th>
<th>STOPPED</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEST-TRAINING-JOB</td>
<td>Completed</td>
<td>2019-10-17T01:15:52Z</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>xgboost-mnist-hpo</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>xgboost92f5e3cf07b11e9bf6c06d6-009-4c7a123</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>xgboost92f5e3cf07b11e9bf6c123</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A hyperparameter tuning job continues to be listed after the job has completed or failed. You can remove a hyperparametertuningjob from the list by following the steps in Delete a Hyperparameter Tuning Job. Jobs that have completed or stopped do not incur any charges for SageMaker resources.

Hyperparameter Tuning Job Status Values

The STATUS field can be one of the following values:

- Completed
- InProgress
• Failed
• Stopped
• Stopping

These statuses come directly from the SageMaker official API documentation.

In addition to the official SageMaker status, it is possible for STATUS to be SynchronizingK8sJobWithSageMaker. This means that the operator has not yet processed the job.

Status Counters

The output has several counters, like COMPLETED and INPROGRESS. These represent how many training jobs have completed and are in progress, respectively. For more information about how these are determined, see TrainingJobStatusCounters in the SageMaker API documentation.

Best TrainingJob

This column contains the name of the TrainingJob that best optimized the selected metric.

To see a summary of the tuned hyperparameters, run:

```bash
kubectl describe hyperparametertuningjob xgboost-mnist-hpo
```

To see detailed information about the TrainingJob, run:

```bash
kubectl describe trainingjobs <job name>
```

Spawned TrainingJobs

You can also track all 10 training jobs in Kubernetes launched by HyperparameterTuningJob by running the following command:

```bash
kubectl get trainingjobs
```

Describe a HyperparameterTuningJob

You can obtain debugging details using the describe kubectl command.

```bash
kubectl describe hyperparametertuningjob xgboost-mnist-hpo
```

In addition to information about the tuning job, the SageMaker Operator for Kubernetes also exposes the best training job found by the hyperparameter tuning job in the describe output as follows:

```
Name: xgboost-mnist-hpo
Namespace: default
Labels: <none>
Annotations: kubectl.kubernetes.io/last-applied-configuration:
  {"apiVersion":"sagemaker.aws.amazon.com/v1","kind":"HyperparameterTuningJob","metadata":{"annotations":{},"name":"xgboost-mnist-hpo","namespace":...},
API Version: sagemaker.aws.amazon.com/v1
Kind: HyperparameterTuningJob
Metadata:
  Creation Timestamp: 2019-10-17T01:15:52Z
  Finalizers:
    sagemaker-operator-finalizer
  Generation: 2
  Resource Version: 8167
```
Self Link: /apis/sagemaker.aws.amazon.com/v1/namespaces/default/
hyperparametertuningjobs/xgboost-mnist-hpo
UID: a92f5e3c-f07b-11e9-bf6c-06d6f303uidu
Spec:
  Hyper Parameter Tuning Job Config:
  Hyper Parameter Tuning Job Objective:
    Metric Name: validation: error
    Type: Minimize
  Parameter Ranges:
    Integer Parameter Ranges:
      Max Value: 20
      Min Value: 10
      Name: num_round
      Scaling Type: Linear
  Resource Limits:
    Max Number Of Training Jobs: 10
    Max Parallel Training Jobs: 10
  Strategy: Bayesian
  Training Job Early Stopping Type: Off
  Hyper Parameter Tuning Job Name: xgboosta92f5e3cf07b11e9bf6c06d6
  Region: us-east-2
  Training Job Definition:
    Algorithm Specification:
      Training Image: 12345678910.dkr.ecr.us-east-2.amazonaws.com/xgboost:1
    Training Input Mode: File
    Input Data Config:
      Channel Name: train
      Content Type: text/csv
      Data Source:
        s3DataSource:
          s3DataDistributionType: FullyReplicated
          s3DataType: S3Prefix
          s3Uri: https://s3-us-east-2.amazonaws.com/my-bucket/sagemaker/xgboost-mnist/train/
      Channel Name: validation
      Content Type: text/csv
      Data Source:
        s3DataSource:
          s3DataDistributionType: FullyReplicated
          s3DataType: S3Prefix
          s3Uri: https://s3-us-east-2.amazonaws.com/my-bucket/sagemaker/xgboost-mnist/validation/
    Output Data Config:
      s3OutputPath: https://s3-us-east-2.amazonaws.com/my-bucket/sagemaker/xgboost-mnist/
      xgboost
    Resource Config:
      Instance Count: 1
      Instance Type: ml.m4.xlarge
      Volume Size In GB: 5
      Role Arn: arn:aws:iam::123456789012:role/service-role/AmazonSageMaker-ExecutionRole
  Static Hyper Parameters:
    Name: base_score
    Value: 0.5
    Name: booster
    Value: gbtree
    Name: csv_weights
    Value: 0
    Name: dsplit
    Value: row
    Name: grow_policy
    Value: depthwise
    Name: lambda_bias
    Value: 0.0
    Name: max_bin
    Value: 256
<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>max_leaves</td>
<td>0</td>
</tr>
<tr>
<td>normalize_type</td>
<td>tree</td>
</tr>
<tr>
<td>objective</td>
<td>reg:linear</td>
</tr>
<tr>
<td>one_drop</td>
<td>0</td>
</tr>
<tr>
<td>prob_buffer_row</td>
<td>1.0</td>
</tr>
<tr>
<td>process_type</td>
<td>default</td>
</tr>
<tr>
<td>rate_drop</td>
<td>0.0</td>
</tr>
<tr>
<td>refresh_leaf</td>
<td>1</td>
</tr>
<tr>
<td>sample_type</td>
<td>uniform</td>
</tr>
<tr>
<td>scale_pos_weight</td>
<td>1.0</td>
</tr>
<tr>
<td>silent</td>
<td>0</td>
</tr>
<tr>
<td>sketch_eps</td>
<td>0.03</td>
</tr>
<tr>
<td>skip_drop</td>
<td>0.0</td>
</tr>
<tr>
<td>tree_method</td>
<td>auto</td>
</tr>
<tr>
<td>tweedie_variance_power</td>
<td>1.5</td>
</tr>
</tbody>
</table>

Stopping Condition:
Max Runtime In Seconds: 86400

Status:
Best Training Job:
Creation Time: 2019-10-17T01:16:14Z
Final Hyper Parameter Tuning Job Objective Metric:
Metric Name: validation: error
Value: 
Objective Status: Succeeded
Training End Time: 2019-10-17T01:20:24Z
Training Job Arn: arn:aws:sagemaker:us-east-2:123456789012:training-job/xgboostha92f5e3cf07b11e9bf6c06d6-009-4sample
Training Job Name: xgboostha92f5e3cf07b11e9bf6c06d6-009-4c7a3059
Training Job Status: Completed
Training Start Time: 2019-10-17T01:18:35Z
Tuned Hyper Parameters:
<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>num_round</td>
<td>18</td>
</tr>
</tbody>
</table>

Hyper Parameter Tuning Job Status: Completed
Last Check Time: 2019-10-17T01:21:01Z
SageMaker Hyper Parameter Tuning Job Name: xgboostha92f5e3cf07b11e9bf6c06d6
Training Job Status Counters:
Completed: 10
In Progress: 0
Non Retryable Error: 0
Retryable Error: 0
Stopped: 0
Total Error: 0
Events: <none>

View Logs from HyperparameterTuningJobs

Hyperparameter tuning jobs do not have logs, but all training jobs launched by them do have logs. These logs can be accessed as if they were a normal training job. For more information, see View Logs from Training Jobs.
Delete a HyperparameterTuningJob

Use the following command to stop a hyperparameter job in SageMaker.

```
kubectl delete hyperparametertuningjob xgboost-mnist-hpo
```

This command removes the hyperparameter tuning job and associated training jobs from your Kubernetes cluster and stops them in SageMaker. Jobs that have stopped or completed do not incur any charges for SageMaker resources. SageMaker does not delete hyperparameter tuning jobs. Stopped jobs continue to show on the SageMaker Console.

Your output should look like the following:

```
hyperparametertuningjob.sagemaker.aws.amazon.com "xgboost-mnist-hpo" deleted
```

**Note:** The delete command takes about 2 minutes to clean up the resources from SageMaker.

**BatchTransformJob operator**

Batch transform job operators reconcile your specified batch transform job spec to SageMaker by launching it in SageMaker. You can learn more about SageMaker batch transform job in the SageMaker CreateTransformJob API documentation.

**Topics**
- Create a BatchTransformJob Using a YAML File (p. 3352)
- Create a BatchTransformJob Using a Helm Chart (p. 3352)
- List BatchTransformJobs (p. 3353)
- Describe a BatchTransformJob (p. 3354)
- View Logs from BatchTransformJobs (p. 3355)
- Delete a BatchTransformJob (p. 3355)

**Create a BatchTransformJob Using a YAML File**

1. Download the sample YAML file for the batch transform job using the following command:

   ```
wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/xgboost-mnist-batchtransform.yaml
   ```

2. Edit the file `xgboost-mnist-batchtransform.yaml` to change necessary parameters to replace the inputdataconfig with your input data and s3OutputPath with your Amazon S3 buckets that the SageMaker execution role has write access to.

3. Apply the YAML file using the following command:

   ```
kubectl apply -f xgboost-mnist-batchtransform.yaml
   ```

**Create a BatchTransformJob Using a Helm Chart**

You can use Helm Charts to run batch transform jobs.

**Get the Helm installer directory**

Clone the GitHub repository to get the source using the following command:
git clone https://github.com/aws/amazon-sagemaker-operator-for-k8s.git

Configure the Helm Chart

Navigate to the `amazon-sagemaker-operator-for-k8s/hack/charts/batch-transform-jobs/` folder.

Edit the `values.yaml` file to replace the `inputdataconfig` with your input data and `outputPath` with your S3 buckets to which the SageMaker execution role has write access.

Create a BatchTransformJob

1. Use the following command to create a batch transform job:

   ```
   helm install . --generate-name
   ```

   Your output should look like the following:

   ```
   NAME: chart-1574292948
   LAST DEPLOYED: Wed Nov 20 23:35:49 2019
   NAMESPACE: default
   STATUS: deployed
   REVISION: 1
   TEST SUITE: None
   NOTES:
   Thanks for installing the sagemaker-k8s-batch-transform-job.
   ```

2. To verify that the Helm Chart was created successfully, run the following command:

   ```
   helm ls
   ```

   This command creates a `BatchTransformJob` Kubernetes resource. The operator launches the actual transform job in SageMaker and updates the `BatchTransformJob` Kubernetes resource to reflect the status of the job in SageMaker. You incur charges for SageMaker resources used during the duration of your job. You do not incur any charges once your job completes or stops.

   **Note:** SageMaker does not allow you to update a running batch transform job. You cannot edit any parameter and re-apply the file/config. You must either change the metadata name or delete the existing job and create a new one. Similar to existing training job operators like TFJob in Kubeflow, update is not supported.

   List BatchTransformJobs

   Use the following command to list all jobs created using the Kubernetes operator:

   ```
   kubectl get batchtransformjob
   ```
Your output should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>STATUS</th>
<th>CREATION-TIME</th>
<th>SAGEMAKER-JOB-NAME</th>
</tr>
</thead>
<tbody>
<tr>
<td>xgboost-mnist-batch-transform</td>
<td>Completed</td>
<td>2019-11-18T03:44:00Z</td>
<td>xgboost-mnist-</td>
</tr>
<tr>
<td>a88fb19809b511eaac440aa8axgboost</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A batch transform job will continue to be listed after the job has completed or failed. You can remove a hyperparameter tuning job from the list by following the Delete a Batch Transform Job steps. Jobs that have completed or stopped do not incur any charges for SageMaker resources.

**Batch Transform Status Values**

The STATUS field can be one of the following values:

- Completed
- InProgress
- Failed
- Stopped
- Stopping

These statuses come directly from the SageMaker official API documentation.

In addition to the official SageMaker status, it is possible for STATUS to be `SynchronizingK8sJobWithSageMaker`. This means that the operator has not yet processed the job.

**Describe a BatchTransformJob**

You can obtain debugging details using the describe kubectl command.

```
kubectl describe batchtransformjob xgboost-mnist-batch-transform
```

Your output should look like the following:

```
Name:         xgboost-mnist-batch-transform
Namespace:    default
Labels:       <none>
Annotations:  kubectl.kubernetes.io/last-applied-configuration:
               "apiVersion":"sagemaker.aws.amazon.com/v1","kind":"BatchTransformJob","metadata":{"annotations":{},"name":"xgboost-mnist","namespace":...}
API Version:  sagemaker.aws.amazon.com/v1
Kind:         BatchTransformJob
Metadata:
               Creation Timestamp:  2019-11-18T03:44:00Z
               Finalizers:
               - sagemaker-operator-finalizer
               Generation:        2
               Resource Version:  21990924
               Self Link:         /apis/sagemaker.aws.amazon.com/v1/namespaces/default/batchtransformjobs/xgboost-mnist
               UID:               a88fb198-09b5-11ea-ac44-0aa8a9UIDNUM
Spec:
    Model Name:  TrainingJob-20190814SMJOb-IKEB
    Region:      us-east-1
    Transform Input:
                Content Type:  text/csv
    Data Source:
```
SageMaker Operators for Kubernetes

S 3 Data Source:
S 3 Data Type: S3Prefix
S 3 Uri:        s3://my-bucket/mnist_kmeans_example/input
Transform Job Name:   xgboost-mnist-a88fb19809b511eaac440aa8a9SMJOB
Transform Output:
   S 3 Output Path:  s3://my-bucket/mnist_kmeans_example/output
Transform Resources:
   Instance Count:  1
   Instance Type:   ml.m4.xlarge
Status:
   Last Check Time:                2019-11-19T22:50:40Z
   Sage Maker Transform Job Name:  xgboost-mnist-a88fb19809b511eaac440aaSMJOB
   Transform Job Status:           Completed
   Events:                           <none>

**View Logs from BatchTransformJobs**

Use the following command to see the logs from the xgboost-mnist batch transform job:

```
kubectl smlogs batchtransformjob xgboost-mnist-batch-transform
```

**Delete a BatchTransformJob**

Use the following command to stop a batch transform job in SageMaker.

```
kubectl delete batchTransformJob xgboost-mnist-batch-transform
```

Your output should look like the following:

```
batchtransfo...xgboost-mnist" deleted
```

This command removes the batch transform job from your Kubernetes cluster, as well as stops them in SageMaker. Jobs that have stopped or completed do not incur any charges for SageMaker resources. Delete takes about 2 minutes to clean up the resources from SageMaker.

**Note**: SageMaker does not delete batch transform jobs. Stopped jobs continue to show on the SageMaker console.

**HostingDeployment operator**

HostingDeployment operators support creating and deleting an endpoint, as well as updating an existing endpoint, for real-time inference. The hosting deployment operator reconciles your specified hosting deployment job spec to SageMaker by creating models, endpoint-configs and endpoints in SageMaker. You can learn more about SageMaker inference in the SageMaker CreateEndpoint API documentation.

**Topics**

- Configure a HostingDeployment Resource (p. 3356)
- Create a HostingDeployment (p. 3356)
- List HostingDeployments (p. 3356)
- Describe a HostingDeployment (p. 3357)
- Invoking the Endpoint (p. 3358)
- Update HostingDeployment (p. 3359)
- Delete the HostingDeployment (p. 3359)
Configure a HostingDeployment Resource

Download the sample YAML file for the hosting deployment job using the following command:

```
wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/xgboost-mnist-hostingdeployment.yaml
```

The `xgboost-mnist-hostingdeployment.yaml` file has the following components that can be edited as required:

- **ProductionVariants.** A production variant is a set of instances serving a single model. SageMaker load-balances between all production variants according to set weights.
- **Models.** A model is the containers and execution role ARN necessary to serve a model. It requires at least a single container.
- **Containers.** A container specifies the dataset and serving image. If you are using your own custom algorithm instead of an algorithm provided by SageMaker, the inference code must meet SageMaker requirements. For more information, see Using Your Own Algorithms with SageMaker.

Create a HostingDeployment

To create a HostingDeployment, use `kubectl` to apply the file `hosting.yaml` with the following command:

```
kubectl apply -f hosting.yaml
```

SageMaker creates an endpoint with the specified configuration. You incur charges for SageMaker resources used during the lifetime of your endpoint. You do not incur any charges once your endpoint is deleted.

The creation process takes approximately 10 minutes.

List HostingDeployments

To verify that the HostingDeployment was created, use the following command:

```
kubectl get hostingdeployments
```

Your output should look like the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>STATUS</th>
<th>SAGEMAKER-ENDPOINT-NAME</th>
</tr>
</thead>
<tbody>
<tr>
<td>host-xgboost</td>
<td>Creating</td>
<td>host-xgboost-def0e83e0d5f11eaaa450aSMLOGS</td>
</tr>
</tbody>
</table>

HostingDeployment Status Values

The status field can be one of several values:

- **SynchronizingK8sJobWithSageMaker:** The operator is preparing to create the endpoint.
- **ReconcilingEndpoint:** The operator is creating, updating, or deleting endpoint resources. If the HostingDeployment remains in this state, use `kubectl describe` to see the reason in the Additional field.
- **OutOfService:** Endpoint is not available to take incoming requests.
- **Creating:** `CreateEndpoint` is executing.
- **Updating:** `UpdateEndpoint` or `UpdateEndpointWeightsAndCapacities` is executing.
• **SystemUpdating**: Endpoint is undergoing maintenance and cannot be updated or deleted or re-scaled until it has completed. This maintenance operation does not change any customer-specified values such as VPC config, KMS encryption, model, instance type, or instance count.

• **RollingBack**: Endpoint fails to scale up or down or change its variant weight and is in the process of rolling back to its previous configuration. Once the rollback completes, endpoint returns to an **InService** status. This transitional status only applies to an endpoint that has autoscaling enabled and is undergoing variant weight or capacity changes as part of an `UpdateEndpointWeightsAndCapacities` call or when the `UpdateEndpointWeightsAndCapacities` operation is called explicitly.

• **InService**: Endpoint is available to process incoming requests.

• **Deleting**: `DeleteEndpoint` is executing.

• **Failed**: Endpoint could not be created, updated, or re-scaled. Use `DescribeEndpoint:FailureReason` for information about the failure. `DeleteEndpoint` is the only operation that can be performed on a failed endpoint.

### Describe a HostingDeployment

You can obtain debugging details using the `describe kubectl` command.

```
kubectl describe hostingdeployment
```

Your output should look like the following:

```plaintext
Name:         host-xgboost
Namespace:    default
Labels:       <none>
Annotations:  kubectl.kubernetes.io/last-applied-configuration:
    {}" name": "host-xgboost", "metadata": {}"
API Version:  sagemaker.aws.amazon.com/v1
Kind:         HostingDeployment
Metadata:
    Creation Timestamp:  2019-11-22T19:40:00Z
    Finalizers:        1
    Generation:        1
    Resource Version:  4258134
    Self Link:         /apis/sagemaker.aws.amazon.com/v1/namespaces/default/hostingdeployments/host-xgboost
    UID:               def0e83e-0d5f-11ea-aa45-0a3507uiduid
Spec:
    Containers:
        Container Hostname:  xgboost
        Image:               123456789012.dkr.ecr.us-east-2.amazonaws.com/xgboost:latest
        Model Data URL:      s3://my-bucket/inference/xgboost-mnist/model.tar.gz
    Models:
        Containers:        xgboost
        Execution Role Arn: arn:aws:iam::123456789012:role/service-role/AmazonSageMaker-ExecutionRole
        Name:               xgboost-model
        Primary Container:  xgboost
        Production Variants:
            Initial Instance Count:  1
            Instance Type:          ml.c5.large
            Model Name:             xgboost-model
            Variant Name:           all-traffic
            Region:                 us-east-2
```

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The status field provides more information using the following fields:

- **Additional**: Additional information about the status of the hosting deployment. This field is optional and only gets populated in case of error.
- **Creation Time**: When the endpoint was created in SageMaker.
- **Endpoint ARN**: The SageMaker endpoint ARN.
- **Endpoint Config Name**: The SageMaker name of the endpoint configuration.
- **Endpoint Name**: The SageMaker name of the endpoint.
- **Endpoint Status**: The status of the endpoint.
- **Endpoint URL**: The HTTPS URL that can be used to access the endpoint. For more information, see Deploy a Model on SageMaker Hosting Services.
- **FailureReason**: If a create, update, or delete command fails, the cause is shown here.
- **Last Check Time**: The last time the operator checked the status of the endpoint.
- **Last Modified Time**: The last time the endpoint was modified.
- **Model Names**: A key-value pair of HostingDeployment model names to SageMaker model names.

### Invoking the Endpoint

Once the endpoint status is InService, you can invoke the endpoint in two ways: using the AWS CLI, which does authentication and URL request signing, or using an HTTP client like cURL. If you use your own client, you need to do AWS v4 URL signing and authentication on your own.

To invoke the endpoint using the AWS CLI, run the following command. Make sure to replace the Region and endpoint-name with your endpoint's Region and SageMaker endpoint name. This information can be obtained from the output of `kubectl describe`.

```
# Invoke the endpoint with mock input data.
aws sagemaker-runtime invoke-endpoint \   --region us-east-2 \   --endpoint-name <endpoint name> \   --body $(seq 784 | xargs echo | sed 's/ /,/g') \   >(cat) \   --content-type text/csv > /dev/null
```

For example, if your Region is `us-east-2` and your endpoint config name is `host-xgboost-f56b6b280d7511ea824b129926example`, then the following command would invoke the endpoint:

```
aws sagemaker-runtime invoke-endpoint \   --region us-east-2 \   --endpoint-name host-xgboost-f56b6b280d7511ea824b1299example \   --body $(seq 784 | xargs echo | sed 's/ /,/g') \   >(cat) \   --content-type text/csv > /dev/null
```

```
4.95847082138
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```
Here, 4.95847082138 is the prediction from the model for the mock data.

**Update HostingDeployment**

1. Once a HostingDeployment has a status of InService, it can be updated. It might take about 10 minutes for HostingDeployment to be in service. To verify that the status is InService, use the following command:

   ```
kubectl get hostingdeployments
   ```

2. The HostingDeployment can be updated before the status is InService. The operator waits until the SageMaker endpoint is InService before applying the update.

   To apply an update, modify the `hosting.yaml` file. For example, change the `initialInstanceCount` field from 1 to 2 as follows:

   ```yaml
   apiVersion: sagemaker.aws.amazon.com/v1
   kind: HostingDeployment
   metadata:
     name: host-xgboost
   spec:
     region: us-east-2
     productionVariants:
     - variantName: all-traffic
       modelName: xgboost-model
       initialInstanceCount: 2
       instanceType: ml.c5.large
     models:
     - name: xgboost-model
       executionRoleArn: arn:aws:iam::123456789012:role/service-role/AmazonSageMaker-ExecutionRole
       primaryContainer: xgboost
       containers:
       - xgboost
         containerHostname: xgboost
         modelDataUrl: s3://my-bucket/inference/xgboost-mnist/model.tar.gz
         image: 123456789012.dkr.ecr.us-east-2.amazonaws.com/xgboost:latest
   ```

3. Save the file, then use `kubectl` to apply your update as follows. You should see the status change from InService to ReconcilingEndpoint, then Updating.

   ```
   $ kubectl apply -f hosting.yaml
   hostingdeployment.sagemaker.aws.amazon.com/host-xgboost configured
   
   $ kubectl get hostingdeployments
   NAME           STATUS     SAGEMAKER-ENDPOINT-NAME
   host-xgboost   ReconcilingEndpoint host-xgboost-def0e83e0d5f11eaaa450a350abcdef
   
   $ kubectl get hostingdeployments
   NAME           STATUS     SAGEMAKER-ENDPOINT-NAME
   host-xgboost   Updating   host-xgboost-def0e83e0d5f11eaaa450a3507abcdef
   ```

SageMaker deploys a new set of instances with your models, switches traffic to use the new instances, and drains the old instances. As soon as this process begins, the status becomes Updating. After the update is complete, your endpoint becomes InService. This process takes approximately 10 minutes.

**Delete the HostingDeployment**

1. Use `kubectl` to delete a HostingDeployment with the following command:
Your output should look like the following:

```
hostingdeployment.sagemaker.aws.amazon.com "host-xgboost" deleted
```

2. To verify that the hosting deployment has been deleted, use the following command:

```
kubectl get hostingdeployments
No resources found.
```

Endpoints that have been deleted do not incur any charges for SageMaker resources.

**ProcessingJob operator**

ProcessingJob operators are used to launch Amazon SageMaker processing jobs. For more information on SageMaker processing jobs, see [CreateProcessingJob](#).

**Topics**

- Create a ProcessingJob Using a YAML File (p. 3360)
- List ProcessingJobs (p. 3361)
- Describe a ProcessingJob (p. 3362)
- Delete a ProcessingJob (p. 3363)

**Create a ProcessingJob Using a YAML File**

Follow these steps to create an Amazon SageMaker processing job by using a YAML file:

1. Download the `kmeans_preprocessing.py` pre-processing script.

```
wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/kmeans_preprocessing.py
```

2. In one of your Amazon Simple Storage Service (Amazon S3) buckets, create a `mnist_kmeans_example/processing_code` folder and upload the script to the folder.

3. Download the `kmeans-mnist-processingjob.yaml` file.

```
wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/kmeans-mnist-processingjob.yaml
```

4. Edit the YAML file to specify your `sagemaker-execution-role` and replace all instances of `my-bucket` with your S3 bucket.

```
... metadata:
  name: kmeans-mnist-processing
...
  roleArn: arn:aws:iam::<acct-id>:role/service-role/<sagemaker-execution-role>
...
  processingOutputConfig:
    outputs:
      ...
        s3Output:
```

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The `sagemaker-execution-role` must have permissions so that SageMaker can access your S3 bucket, Amazon CloudWatch, and other services on your behalf. For more information on creating an execution role, see SageMaker Roles.

5. Apply the YAML file using one of the following commands.

   For cluster-scoped installation:

   ```bash
   kubectl apply -f kmeans-mnist-processingjob.yaml
   ```

   For namespace-scoped installation:

   ```bash
   kubectl apply -f kmeans-mnist-processingjob.yaml -n <NAMESPACE>
   ```

**List ProcessingJobs**

Use one of the following commands to list all the jobs created using the ProcessingJob operator. `SAGEMAKER-JOB-NAME` comes from the metadata section of the YAML file.

For cluster-scoped installation:

```bash
kubectl get ProcessingJob kmeans-mnist-processing
```

For namespace-scoped installation:

```bash
kubectl get ProcessingJob -n <NAMESPACE> kmeans-mnist-processing
```

Your output should look similar to the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>STATUS</th>
<th>CREATION-TIME</th>
<th>SAGEMAKER-JOB-NAME</th>
</tr>
</thead>
</table>

The output lists all jobs regardless of their status. To remove a job from the list, see Delete a Processing Job.

**ProcessingJob Status**

- **SynchronizingK8sJobWithSageMaker** – The job is first submitted to the cluster. The operator has received the request and is preparing to create the processing job.
- **Reconciling** – The operator is initializing or recovering from transient errors, along with others. If the processing job remains in this state, use the `kubectl describe` command to see the reason in the Additional field.
- **InProgress | Completed | Failed | Stopping | Stopped** – Status of the SageMaker processing job. For more information, see DescribeProcessingJob.
- **Error** – The operator cannot recover by reconciling.
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Jobs that have completed, stopped, or failed do not incur further charges for SageMaker resources.

Describe a ProcessingJob
Use one of the following commands to get more details about a processing job. These commands are
typically used for debugging a problem or checking the parameters of a processing job.
For cluster-scoped installation:
kubectl describe processingjob kmeans-mnist-processing

For namespace-scoped installation:
kubectl describe processingjob kmeans-mnist-processing -n <NAMESPACE>

The output for your processing job should look similar to the following.
$ kubectl describe ProcessingJob kmeans-mnist-processing
Name:
kmeans-mnist-processing
Namespace:
default
Labels:
<none>
Annotations: kubectl.kubernetes.io/last-applied-configuration:
{"apiVersion":"sagemaker.aws.amazon.com/
v1","kind":"ProcessingJob","metadata":{"annotations":{},"name":"kmeans-mnistprocessing",...
API Version: sagemaker.aws.amazon.com/v1
Kind:
ProcessingJob
Metadata:
Finalizers:
sagemaker-operator-finalizer
Generation:
2
Resource Version: 21746658
Self Link:
/apis/sagemaker.aws.amazon.com/v1/namespaces/default/processingjobs/
kmeans-mnist-processing
UID:
7410ed52-fd18-11ea-b19a-165ae9f9e385
Spec:
App Specification:
Container Entrypoint:
python
/opt/ml/processing/code/kmeans_preprocessing.py
Image Uri: 763104351884.dkr.ecr.us-west-2.amazonaws.com/pytorch-training:1.5.0-cpupy36-ubuntu16.04
Environment:
Name:
MYVAR
Value: my_value
Name:
MYVAR2
Value: my_value2
Network Config:
Processing Inputs:
Input Name: mnist_tar
s3Input:
Local Path:
/opt/ml/processing/input
s3DataType:
S3Prefix
s3InputMode: File
s3Uri:
s3://<s3bucket>-us-west-2/algorithms/kmeans/mnist/mnist.pkl.gz
Input Name:
source_code
s3Input:
Local Path:
/opt/ml/processing/code
s3DataType:
S3Prefix
s3InputMode: File
s3Uri:
s3://<s3bucket>/mnist_kmeans_example/processing_code/
kmeans_preprocessing.py

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Delete a ProcessingJob

When you delete a processing job, the SageMaker processing job is removed from Kubernetes but the job isn't deleted from SageMaker. If the job status in SageMaker is InProgress the job is stopped. Processing jobs that are stopped do not incur any charges for SageMaker resources. Use one of the following commands to delete a processing job.

For cluster-scoped installation:

```bash
kubectl delete processingjob kmeans-mnist-processing
```

For namespace-scoped installation:

```bash
kubectl delete processingjob kmeans-mnist-processing -n <NAMESPACE>
```

The output for your processing job should look similar to the following.

```bash
processingjob.sagemaker.aws.amazon.com "kmeans-mnist-processing" deleted
```

**Note**

SageMaker does not delete the processing job. Stopped jobs continue to show in the SageMaker console. The delete command takes a few minutes to clean up the resources from SageMaker.
HostingAutoscalingPolicy (HAP) Operator

The HostingAutoscalingPolicy (HAP) operator takes a list of resource IDs as input and applies the same policy to each of them. Each resource ID is a combination of an endpoint name and a variant name. The HAP operator performs two steps: it registers the resource IDs and then applies the scaling policy to each resource ID. Delete undoes both actions. You can apply the HAP to an existing SageMaker endpoint or you can create a new SageMaker endpoint using the HostingDeployment operator. You can read more about SageMaker autoscaling in the Application Autoscaling Policy documentation.

**Note**
In your kubectl commands, you can use the short form, hap, in place of hostingautoscalingpolicy.

**Topics**
- Create a HostingAutoscalingPolicy Using a YAML File (p. 3364)
- List HostingAutoscalingPolicies (p. 3366)
- Describe a HostingAutoscalingPolicy (p. 3367)
- Update a HostingAutoscalingPolicy (p. 3367)
- Delete a HostingAutoscalingPolicy (p. 3367)
- Update or Delete an Endpoint with a HostingAutoscalingPolicy (p. 3367)

Create a HostingAutoscalingPolicy Using a YAML File

Use a YAML file to create a HostingAutoscalingPolicy (HAP) that applies a predefined or custom metric to one or multiple SageMaker endpoints.

Amazon SageMaker requires specific values in order to apply autoscaling to your variant. If these values are not specified in the YAML spec, the HAP operator applies the following default values.

```yaml
# Do not change
Namespace                    = "sagemaker"
# Do not change
ScalableDimension            = "sagemaker:variant:DesiredInstanceCount"
# Only one supported
PolicyType                   = "TargetTrackingScaling"
# This is the default policy name but can be changed to apply a custom policy
DefaultAutoscalingPolicyName = "SageMakerEndpointInvocationScalingPolicy"
```

Use the following samples to create a HAP that applies a predefined or custom metric to one or multiple endpoints.

**Sample 1: Apply a Predefined Metric to a Single Endpoint Variant**

1. Download the sample YAML file for a predefined metric using the following command:

   ```bash
   wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/hap-predefined-metric.yaml
   ```

2. Edit the YAML file to specify your endpointName, variantName, and region.

3. Use one of the following commands to apply a predefined metric to a single resource ID (endpoint name and variant name combination).

   For cluster-scoped installation:

   ```bash
   kubectl apply -f hap-predefined-metric.yaml
   ```

   For namespace-scoped installation:
Sample 2: Apply a Custom Metric to a Single Endpoint Variant

1. Download the sample YAML file for a custom metric using the following command:

   ```bash
   wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/hap-custom-metric.yaml
   ```

2. Edit the YAML file to specify your `endpointName`, `variantName`, and `region`.

3. Use one of the following commands to apply a custom metric to a single resource ID (endpoint name and variant name combination) in place of the recommended `SageMakerVariantInvocationsPerInstance`.

   **Note**
   Amazon SageMaker does not check the validity of your YAML spec.

   For cluster-scoped installation:

   ```bash
   kubectl apply -f hap-custom-metric.yaml
   ```

   For namespace-scoped installation:

   ```bash
   kubectl apply -f hap-custom-metric.yaml -n <NAMESPACE>
   ```

Sample 3: Apply a Scaling Policy to Multiple Endpoints and Variants

You can use the HAP operator to apply the same scaling policy to multiple resource IDs. A separate `scaling_policy` request is created for each resource ID (endpoint name and variant name combination).

1. Download the sample YAML file for a predefined metric using the following command:

   ```bash
   wget https://raw.githubusercontent.com/aws/amazon-sagemaker-operator-for-k8s/master/samples/hap-predefined-metric.yaml
   ```

2. Edit the YAML file to specify your `region` and multiple `endpointName` and `variantName` values.

3. Use one of the following commands to apply a predefined metric to multiple resource IDs (endpoint name and variant name combinations).

   For cluster-scoped installation:

   ```bash
   kubectl apply -f hap-predefined-metric.yaml
   ```

   For namespace-scoped installation:

   ```bash
   kubectl apply -f hap-predefined-metric.yaml -n <NAMESPACE>
   ```

Considerations for Hosting Autoscaling Policies for Multiple Endpoints and Variants

The following considerations apply when you use multiple resource IDs:
If you apply a single policy across multiple resource IDs, one PolicyARN is created per resource ID. Five endpoints have five PolicyARNs. When you run the describe command on the policy, the responses show up as one job and include a single job status.

If you apply a custom metric to multiple resource IDs, the same dimension or value is used for all the resource ID (variant) values. For example, if you apply a customer metric for instances 1-5, and the endpoint variant dimension is mapped to variant 1, when variant 1 exceeds the metrics, all endpoints are scaled up or down.

The HAP operator supports updating the list of resource IDs. If you modify, add, or delete resource IDs to the spec, the autoscaling policy is removed from the previous list of variants and applied to the newly specified resource ID combinations. Use the describe command to list the resource IDs to which the policy is currently applied.

List HostingAutoscalingPolicies

Use one of the following commands to list all HostingAutoscalingPolicies (HAPs) created using the HAP operator.

For cluster-scoped installation:

```
kubectl get hap
```

For namespace-scoped installation:

```
kubectl get hap -n <NAMESPACE>
```

Your output should look similar to the following:

<table>
<thead>
<tr>
<th>NAME</th>
<th>STATUS</th>
<th>CREATION-TIME</th>
</tr>
</thead>
<tbody>
<tr>
<td>hap-predefined</td>
<td>Created</td>
<td>2021-07-13T21:32:21Z</td>
</tr>
</tbody>
</table>

Use the following command to check the status of your HostingAutoscalingPolicy (HAP).

```
kubectl get hap <job-name>
```

One of the following values is returned:

- Reconciling – Certain types of errors show the status as Reconciling instead of Error. Some examples are server-side errors and endpoints in the Creating or Updating state. Check the Additional field in status or operator logs for more details.
- Created
- Error

To view the autoscaling endpoint to which you applied the policy

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the left side panel, expand Inference.
3. Choose Endpoints.
4. Select the name of the endpoint of interest.
5. Scroll to the Endpoint runtime settings section.
Describe a HostingAutoscalingPolicy

Use the following command to get more details about a HostingAutoscalingPolicy (HAP). These commands are typically used for debugging a problem or checking the resource IDs (endpoint name and variant name combinations) of a HAP.

```
kubectl describe hap <job-name>
```

Update a HostingAutoscalingPolicy

The HostingAutoscalingPolicy (HAP) operator supports updates. You can edit your YAML spec to change the values and then reapply the policy. The HAP operator deletes the existing policy and applies the new policy.

Delete a HostingAutoscalingPolicy

Use one of the following commands to delete a HostingAutoscalingPolicy (HAP) policy.

For cluster-scoped installation:

```
kubectl delete hap hap-predefined
```

For namespace-scoped installation:

```
kubectl delete hap hap-predefined -n <NAMESPACE>
```

This command deletes the scaling policy and deregisters the scaling target from Kubernetes. This command returns the following output:

```
hostingautoscalingpolicies.sagemaker.aws.amazon.com "hap-predefined" deleted
```

Update or Delete an Endpoint with a HostingAutoscalingPolicy

To update an endpoint that has a HostingAutoscalingPolicy (HAP), use the `kubectl delete` command to remove the HAP, update the endpoint, and then reapply the HAP.

To delete an endpoint that has a HAP, use the `kubectl delete` command to remove the HAP before you delete the endpoint.

Migrate resources to the new SageMaker Operators for Kubernetes

The new Amazon SageMaker Operators for Kubernetes uses AWS Controllers for Kubernetes (ACK) to train, tune, and deploy machine learning models with Amazon SageMaker. ACK is a framework for building Kubernetes custom controllers, where each controller communicates with an AWS service API. These controllers allow Kubernetes users to provision AWS resources like databases or message queues using the Kubernetes API. For a list of all ACK service controllers, see Services in the ACK documentation.

Note

The new SageMaker Operators for Kubernetes are not backwards compatible. Use the following steps to migrate your resources.

For more information, see the ACK documentation or the ACK SageMaker controller GitHub repository. For a list of supported SageMaker resources, refer to the ACK API Reference. To get started with hands-on examples, see Tutorials (p. 3370).
Prerequisites

To successfully migrate resources to the new SageMaker Operators for Kubernetes, you must:


2. If you are using *HostingAutoscalingPolicy* resources (p. 3369), install the new Application Auto Scaling Operator. See Setup in *Scale SageMaker Workloads with Application Auto Scaling* for step-by-step instructions. This step is optional if you are not using *HostingAutoscalingPolicy* resources.

If permissions are configured correctly, then the ACK SageMaker service controller can determine the specification and status of the AWS resource and reconcile the resource as if the ACK controller originally created it.

Adopt resources

The new SageMaker Operators for Kubernetes provide the ability to adopt resources that were not originally created by the ACK service controller. For more information, see *Adopt Existing AWS Resources* in the ACK documentation.

The following steps show how the new SageMaker Operators for Kubernetes can adopt an existing SageMaker endpoint. Save the following sample to a file named *adopt-endpoint-sample.yaml*.

```yaml
apiVersion: services.k8s.aws/v1alpha1
kind: AdoptedResource
metadata:
  name: adopt-endpoint-sample
spec:
  aws:
    # resource to adopt, not created by ACK
    nameOrID: xgboost-endpoint
  kubernetes:
    group: sagemaker.services.k8s.aws
    kind: Endpoint
    metadata:
      # target K8s CR name
      name: xgboost-endpoint

Submit the custom resource (CR) using `kubectl apply`:

```bash
kubectl apply -f adopt-endpoint-sample.yaml
```

Use `kubectl describe` to check the status conditions of your adopted resource.

```bash
kubectl describe adoptedresource adopt-endpoint-sample
```

Verify that the ACK.Adopted condition is `True`. The output should look similar to the following example:

```yaml
---
kind: AdoptedResource
metadata:
  annotations:
    kubectl.kubernetes.io/last-applied-configuration: |
      "apiVersion": "services.k8s.aws/v1alpha1",
      "kind": "AdoptedResource",
      "metadata": {
        "annotations": {},
        "name": "xgboost-endpoint",
        "namespace": "default"
      },
      "spec": {
        "aws": {"nameOrID": "xgboost-endpoint"},
        "kubernetes": {
          "group": "sagemaker.services.k8s.aws",
          "kind": "Endpoint",
          "metadata": {
            "name": "xgboost-endpoint"
          }
        }
      }
```
Check that your resource exists in your cluster:

```bash
cubectl describe endpoints.sagemaker xgboost-endpoint
```

**HostingAutoscalingPolicy resources**

The HostingAutoscalingPolicy (HAP) resource consists of multiple Application Auto Scaling resources: ScalableTarget and ScalingPolicy. When adopting a HAP resource with ACK, you need to first install the Application Auto Scaling controller. To adopt HAP resources, you need to adopt both ScalableTarget and ScalingPolicy resources. You can find the resource identifier for these resources in the status of the HostingAutoscalingPolicy resource (status.ResourceIDList).

**HostingDeployment resources**

The HostingDeployment resource consists of multiple SageMaker resources: Endpoint, EndpointConfig, and each Model. If you adopt a SageMaker endpoint in ACK, you need to adopt the Endpoint, EndpointConfig, and each Model separately. The Endpoint, EndpointConfig, and Model names can be found in status of the HostingDeployment resource (status.endpointName, status.endpointConfigName, and status.modelNames).

For a list of all supported SageMaker resources, refer to the [ACK API Reference](https://docs.aws.amazon.com/ckafka/latest/using/aws-controllers-k8s-sagemaker.html).

**Clean up old resources**

After the new SageMaker Operators for Kubernetes adopt your resources, it is time to uninstall old operators and clean up old resources.

**Step 1: Uninstall the old operator**

To uninstall the old operator, see Delete operators (p. 3339).

**Warning**

Uninstall the old operator before deleting any old resources.

**Step 2: Remove finalizers and delete old resources**

**Warning**

Before deleting old resources, be sure that you have uninstalled the old operator.
After uninstalling the old operator, you must explicitly remove the finalizers to delete old operator resources. The following sample script shows how to delete all training jobs managed by the old operator in a given namespace. You can use a similar pattern to delete additional resources once they are adopted by the new operator.

**Note**
You must use full resource names to get resources. For example, use `kubectl get trainingjobs.sagemaker.aws.amazon.com` instead of `kubectl get trainingjob`.

```
namespace=sagemaker_namespace
training_jobs=$(kubectl get trainingjobs.sagemaker.aws.amazon.com -n $namespace -ojson | jq -r '.items | .[] | .metadata.name')
for job in $training_jobs
do
echo "Deleting $job resource in $namespace namespace"
kubectl patch trainingjobs.sagemaker.aws.amazon.com $job -n $namespace -p '{"metadata": {"finalizers":null}}' --type=merge
kubectl delete trainingjobs.sagemaker.aws.amazon.com $job -n $namespace
done
```

**Tutorials**
For more in-depth guides on installing and using the new SageMaker Operator for Kubernetes, see the following tutorials:

- Machine Learning with the ACK SageMaker Controller
- Scale SageMaker Workloads with Application Auto Scaling

**SageMaker Components for Kubeflow Pipelines**

This document outlines how to use SageMaker Components for Kubeflow Pipelines (KFP). With these pipeline components, you can create and monitor native SageMaker training, tuning, endpoint deployment, and batch transform jobs from your Kubeflow Pipelines. By running Kubeflow Pipeline jobs on SageMaker, you move data processing and training jobs from the Kubernetes cluster to SageMaker's machine learning-optimized managed service. This document assumes prior knowledge of Kubernetes and Kubeflow.

**Contents**

- What is Kubeflow Pipelines? (p. 3370)
- Kubeflow Pipeline components (p. 3371)
- IAM permissions (p. 3372)
- Converting Pipelines to use SageMaker (p. 3373)
- Using SageMaker Components (p. 3373)

**What is Kubeflow Pipelines?**

Kubeflow Pipelines (KFP) is a platform for building and deploying portable, scalable machine learning (ML) workflows based on Docker containers. The Kubeflow Pipelines platform consists of the following:

- A user interface (UI) for managing and tracking experiments, jobs, and runs.
- An engine (Argo) for scheduling multi-step ML workflows.
- A AWS SDK for Python (Boto3) SDK for defining and manipulating pipelines and components.
• Notebooks for interacting with the system using the SDK.

A pipeline is a description of an ML workflow expressed as a directed acyclic graph as shown in the following diagram. Every step in the workflow is expressed as a Kubeflow Pipeline component, which is an AWS SDK for Python (Boto3) module.

If your data has been preprocessed, the standard pipeline can take a subset of the data and run hyperparameter optimization of your model. The pipeline then trains a model with the full dataset using the optimal hyperparameters. This model is used for both batch inference and endpoint creation.

For more information on Kubeflow Pipelines, see the Kubeflow Pipelines documentation.

### Kubeflow Pipeline components

A Kubeflow Pipeline component is a set of code used to execute one step of a Kubeflow pipeline. Components are represented by a AWS SDK for Python (Boto3) module built into a Docker image. These components make it fast and easy to write pipelines for experimentation and production environments without having to interact with the underlying Kubernetes infrastructure.

### SageMaker Components for Kubeflow Pipelines versions

SageMaker Components for Kubeflow Pipelines come in two versions. Each version leverages a different backend to create and manage resources on SageMaker.

- The SageMaker Components for Kubeflow Pipelines version 1 (v1.x or below) use Boto3 (AWS SDK for AWS SDK for Python (Boto3)) as backend.
- The version 2 (v2.0.0-alpha2 and above) of SageMaker Components for Kubeflow Pipelines use SageMaker Operator for Kubernetes (ACK).

AWS introduced ACK to facilitate a Kubernetes-native way of managing AWS Cloud resources. ACK includes a set of AWS service-specific controllers, one of which is the SageMaker controller. The SageMaker controller makes it easier for machine learning developers and data scientists using Kubernetes as their control plane to train, tune, and deploy machine learning (ML) models in SageMaker. For more information, see SageMaker Operators for Kubernetes

Both versions of the SageMaker Components for Kubeflow Pipelines are supported. However, the version 2 provides some additional advantages. In particular, it offers:

1. A consistent experience to manage your SageMaker resources from any application; whether you are using Kubeflow pipelines, or Kubernetes CLI (kubectl) or other Kubeflow applications such as Notebooks.
2. The flexibility to manage and monitor your SageMaker resources outside of the Kubeflow pipeline workflow.
3. Zero setup time to use the components if you deployed the full Kubeflow on AWS release since the SageMaker Operator is part of its deployment.

### What do SageMaker Components for Kubeflow Pipelines provide?

SageMaker Components for Kubeflow Pipelines offer an alternative to launching your compute-intensive jobs from SageMaker. The components integrate SageMaker with the portability and orchestration of Kubeflow Pipelines. Using the SageMaker Components for Kubeflow Pipelines (KFP), you can create and monitor your SageMaker resources as part of a Kubeflow Pipelines workflow. Each of the jobs in your pipelines runs on SageMaker instead of the local Kubernetes cluster. The job parameters, status, logs, and outputs from SageMaker are still accessible from the Kubeflow Pipelines UI.
The following SageMaker components have been created to integrate six key SageMaker features into your ML workflows. You can create a Kubeflow Pipeline built entirely using these components, or integrate individual components into your workflow as needed. Alternatively, you can find all SageMaker Components for Kubeflow Pipelines in GitHub.

There is no additional charge for using SageMaker Components for Kubeflow Pipelines. You incur charges for any SageMaker resources you use through these components.

Training components

Processing

The Processing component enables you to submit processing jobs to SageMaker directly from a Kubeflow Pipelines workflow. For more information, see SageMaker Processing Kubeflow Pipeline component version 1.

Training

The Training component allows you to submit SageMaker Training jobs directly from a Kubeflow Pipelines workflow. For more information, see SageMaker Training Kubeflow Pipelines component version 2. For information about Version 1 of the Training component see SageMaker Training Kubeflow Pipelines component version 1.

Hyperparameter Optimization

The Hyperparameter Optimization component enables you to submit hyperparameter tuning jobs to SageMaker directly from a Kubeflow Pipelines workflow. For more information, see SageMaker hyperparameter optimization Kubeflow Pipeline component version 1.

Inference components

Hosting Deploy

The Deploy component enables you to deploy a model in SageMaker Hosting from a Kubeflow Pipelines workflow. For more information, see SageMaker Hosting Services - Create Endpoint Kubeflow Pipeline component version 1.

Batch Transform component

The Batch Transform component enables you to run inference jobs for an entire dataset in SageMaker from a Kubeflow Pipelines workflow. For more information, see SageMaker Batch Transform Kubeflow Pipeline component version 1.

Ground Truth components

Ground Truth The Ground Truth component enables you to submit SageMaker Ground Truth labeling jobs directly from a Kubeflow Pipelines workflow. For more information, see SageMaker Ground Truth Kubeflow Pipelines component version 1.

Workteam

The Workteam component enables you to create SageMaker private workteam jobs directly from a Kubeflow Pipelines workflow. For more information, see SageMaker create private workteam Kubeflow Pipelines component version 1.

IAM permissions

Deploying Kubeflow Pipelines with SageMaker components requires the following three levels of IAM permissions:
• An IAM user/role to access your AWS account (your_credentials). Note: You don’t need this at all if
you already have access to KFP web UI and have your input data in Amazon S3, or if you already have
an Amazon Elastic Kubernetes Service (Amazon EKS) cluster with KFP.

You use this user/role from your gateway node, which can be your local machine or a remote
instance, to:
• Create an Amazon EKS cluster and install KFP
• Create IAM roles/users
• Create Amazon S3 buckets for your sample input data

The IAM user/role needs the following permissions:
• CloudWatchLogsFullAccess
• AWSCloudFormationFullAccess
• IAMFullAccess
• AmazonS3FullAccess
• AmazonEC2FullAccess
• AmazonEKSAdminPolicy (Create this policy using the schema from Amazon EKS Identity-Based
Policy Examples)

• An IAM role used by pipeline pods (kfp-example-pod-role) or the SageMaker Operator for Kubernetes
controller pod to access SageMaker. This permission is used to create and monitor SageMaker jobs.
Note: You can limit permissions to the KFP and controller pods by creating and attaching your own
custom policy.

The role needs the following permission:
• AmazonSageMakerFullAccess

• An IAM role used by SageMaker jobs to access resources such as Amazon S3 and Amazon ECR etc. (kfp-
example-sagemaker-execution-role).

Your SageMaker jobs use this role to:
• Access SageMaker resources
• Input Data from Amazon S3
• Store your output model to Amazon S3

The role needs the following permissions:
• AmazonSageMakerFullAccess
• AmazonS3FullAccess

These are all the IAM users/roles you need to run KFP components for SageMaker.

When you have run the components and have created the SageMaker endpoint, you also need a role with
the sagemaker:InvokeEndpoint permission to query inference endpoints.

Converting Pipelines to use SageMaker

You can convert an existing pipeline to use SageMaker by porting your generic AWS SDK for Python
(Boto3) processing containers and training containers. If you are using SageMaker for inference, you also
need to attach IAM permissions to your cluster and convert an artifact to a model.

Using SageMaker Components

In this tutorial, you run a pipeline using SageMaker Components for Kubeflow Pipelines to train a
classification model using Kmeans with the MNIST dataset. This workflow uses Kubeflow pipelines as the
orchestrator and SageMaker to execute each step of the workflow. For the full code for this and other
pipeline examples, see the Sample SageMaker Kubeflow Pipelines. For information on the components
used, see the KubeFlow Pipelines GitHub repository.
• Install Kubeflow Pipelines (p. 3374)
• Run Kubeflow Pipelines (p. 3381)

Install Kubeflow Pipelines

To use Kubeflow Pipelines (KFP), you need an Amazon Elastic Kubernetes Service (Amazon EKS) cluster and a gateway node to interact with that cluster. The following sections show the steps needed to set up these resources.

Topics
• Choose an installation option (p. 3374)
• Configure your pipeline permissions to access SageMaker (p. 3376)
• Access the KFP UI (p. 3378)

Choose an installation option

Kubeflow Pipelines offer two installation options. Select the option that applies to your use case:

1. Full Kubeflow on AWS Deployment (p. 3374)
   To use other Kubeflow components in addition to Kubeflow Pipelines, choose the full AWS Distribution of Kubeflow deployment.
2. Standalone Kubeflow Pipelines Deployment (p. 3374)
   To use the Kubeflow Pipelines without the other components of Kubeflow, install Kubeflow pipelines standalone.

Full Kubeflow on AWS Deployment

To install the full release of Kubeflow on AWS, follow one of the deployment guides

Standalone Kubeflow Pipelines Deployment

Set up a gateway node

A gateway node is used to create an Amazon EKS cluster and access the Kubeflow Pipelines UI. Use your local machine or an Amazon EC2 instance as your gateway node. If you want to use a new Amazon EC2 instance, create one with the latest Ubuntu 18.04 DLAMI version from the AWS console using the steps in Launching and Configuring a DLAMI.

Complete the following steps to set up your gateway node. Depending on your environment, you may have certain requirements already configured.

1. If you don't have an existing Amazon EKS cluster, create a user named your_credentials using the steps in Creating an IAM User in Your AWS Account. If you have an existing Amazon EKS cluster, use the credentials of the IAM role or user that has access to it.
2. Add the following permissions to your user using the steps in Changing Permissions for an IAM User:
   • CloudWatchLogsFullAccess
   • AWSCloudFormationFullAccess
   • IAMFullAccess
   • AmazonS3FullAccess
   • AmazonEC2FullAccess
   • AmazonEKSAdminPolicy (Create this policy using the schema from Amazon EKS Identity-Based Policy Examples)
3. Install the following on your gateway node to access the Amazon EKS cluster and KFP UI.
   - **AWS CLI.** If you are using an IAM user, configure your Access Key ID, Secret Access Key and preferred AWS Region by running: `aws configure`
   - **aws-iam-authenticator** version 0.1.31 and above
   - **eksctl** version above 0.15.
   - **kubectl** (The version needs to match your Kubernetes version within one minor version)

4. Install boto3.
   ```
   pip install boto3
   ```

### Set up an Amazon EKS cluster

Run the following steps from the command line of your gateway node to set up an Amazon EKS cluster:

1. If you do not have an existing Amazon EKS cluster, complete the following substeps. If you already have an Amazon EKS cluster, skip this step.
   a. Run the following from your command line to create an Amazon EKS cluster with version 1.17 or above. Replace `<your-cluster-name>` with any name for your cluster.
      ```
      eksctl create cluster --name <your-cluster-name> --region us-east-1 --auto-kubeconfig --timeout=50m --managed --nodes=1
      ```
   b. When cluster creation is complete, verify that you have access to the cluster using the following command.
      ```
      kubectl get nodes
      ```

2. Verify that the current kubectl context is the cluster you want to use with the following command. The current context is marked with an asterisk (*) in the output.
   ```
   kubectl config get-contexts
   ```
   ```
   CURRENT NAME     CLUSTER
   * <username>@<clusternname>.us-east-1.eksctl.io  <clusternname>.us-east-1.eksctl.io
   ```

3. If the desired cluster is not configured as your current default, update the default with the following command.
   ```
   aws eks update-kubeconfig --name <clusternname> --region us-east-1
   ```

### Install Kubeflow Pipelines

Run the following steps from the terminal of your gateway node to install Kubeflow Pipelines on your cluster.

1. Install all cert-manager components:
   ```
   kubectl apply -f https://github.com/cert-manager/cert-manager/releases/download/v1.9.1/cert-manager.yaml
   ```

2. Install the Kubeflow pipelines:
   ```
   export PIPELINE_VERSION=2.0.0-alpha.5
   ```
kubectl apply -k "github.com/kubeflow/pipelines/manifests/kustomize/env/cert-manager/cluster-scoped-resources?ref=$KFP_VERSION"

kubectl wait --for condition=established --timeout=60s crd/applications.app.k8s.io

kubectl apply -k "github.com/kubeflow/pipelines/manifests/kustomize/env/cert-manager/dev?ref=$KFP_VERSION"

3. Verify that the Kubeflow Pipelines service and other related resources are running.

```
kubectl -n kubeflow get all | grep pipeline
```

Your output should look like the following.

<table>
<thead>
<tr>
<th>Pod Name</th>
<th>Status</th>
<th>Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>pod/ml-pipeline-6b88c67994-kdtjv</td>
<td>1/1 Running</td>
<td>0d</td>
</tr>
<tr>
<td>pod/ml-pipeline-persistenceagent-64d74dfdbf-66stkl</td>
<td>1/1 Running</td>
<td>0d</td>
</tr>
<tr>
<td>pod/ml-pipeline-scheduledworkflow-65bdf46db7-5x9qj</td>
<td>1/1 Running</td>
<td>0d</td>
</tr>
<tr>
<td>pod/ml-pipeline-ui-66cc4cfff6-cmsdb</td>
<td>1/1 Running</td>
<td>0d</td>
</tr>
<tr>
<td>pod/ml-pipeline-viewer-crd-6db65cc4-wqlzj</td>
<td>1/1 Running</td>
<td>0d</td>
</tr>
<tr>
<td>pod/ml-pipeline-visualizationserver-9c47576f4-bqmx4</td>
<td>1/1 Running</td>
<td>0d</td>
</tr>
<tr>
<td>service/ml-pipeline</td>
<td>ClusterIP 10.100.170.170 &lt;none&gt;</td>
<td></td>
</tr>
<tr>
<td>8888/TCP, 8887/TCP</td>
<td>2d</td>
<td></td>
</tr>
<tr>
<td>service/ml-pipeline-ui</td>
<td>ClusterIP 10.100.38.71 &lt;none&gt;</td>
<td></td>
</tr>
<tr>
<td>80/TCP</td>
<td>2d</td>
<td></td>
</tr>
<tr>
<td>service/ml-pipeline-visualizationserver</td>
<td>ClusterIP 10.100.61.47 &lt;none&gt;</td>
<td></td>
</tr>
<tr>
<td>8888/TCP</td>
<td>2d</td>
<td></td>
</tr>
<tr>
<td>deployment.apps/ml-pipeline</td>
<td>1/1 1 1 2d</td>
<td></td>
</tr>
<tr>
<td>deployment.apps/ml-pipeline-persistenceagent</td>
<td>1/1 1 1 2d</td>
<td></td>
</tr>
<tr>
<td>deployment.apps/ml-pipeline-scheduledworkflow</td>
<td>1/1 1 1 2d</td>
<td></td>
</tr>
<tr>
<td>deployment.apps/ml-pipeline-ui</td>
<td>1/1 1 1 2d</td>
<td></td>
</tr>
<tr>
<td>deployment.apps/ml-pipeline-viewer-crd</td>
<td>1/1 1 1 2d</td>
<td></td>
</tr>
<tr>
<td>deployment.apps/ml-pipeline-visualizationserver</td>
<td>1/1 1 1 2d</td>
<td></td>
</tr>
<tr>
<td>replicaset.apps/ml-pipeline-6b88c67994</td>
<td>1 1 1</td>
<td></td>
</tr>
<tr>
<td>replicaset.apps/ml-pipeline-persistenceagent-64d74dfdbf</td>
<td>1 1 1</td>
<td></td>
</tr>
<tr>
<td>replicaset.apps/ml-pipeline-scheduledworkflow-65bdf46db7</td>
<td>1 1 1</td>
<td></td>
</tr>
<tr>
<td>replicaset.apps/ml-pipeline-ui-66cc4cfff6</td>
<td>1 1 1</td>
<td></td>
</tr>
<tr>
<td>replicaset.apps/ml-pipeline-viewer-crd-6db65cc4</td>
<td>1 1 1</td>
<td></td>
</tr>
<tr>
<td>replicaset.apps/ml-pipeline-visualizationserver-9c47576f4</td>
<td>1 1 1</td>
<td></td>
</tr>
</tbody>
</table>

**Configure your pipeline permissions to access SageMaker**

In this section, you create IAM users/roles and permissions to be used by Kubeflow Pipeline pods to access SageMaker services.

**Configuration for SageMaker components version 2**

To run SageMaker Components version 2 for Kubeflow Pipelines, you need to install the SageMaker Operator for Kubernetes and configure RBAC permissions for the Kubeflow Pipeline pods to create SageMaker custom resources in your Kubernetes cluster from the pipeline pods.
**Important**
Follow this section if you are using Kubeflow pipelines standalone deployment. These steps are preconfigured if you are using AWS distribution of Kubeflow version 1.6.0-aws-b1.0.0 or above.


   Follow the Setup section of [Machine Learning with ACK SageMaker Controller tutorial](#) to install the SageMaker Controller.

2. Configure RBAC permissions for the service account used by Kubeflow pipeline pods. In Kubeflow pipeline standalone deployment, the pipeline runs are executed in the namespace `kubeflow` using the pipeline-runner service account.

   a. Create a `RoleBinding` that grants service account access to manage sagemaker custom resources.

   ```
cat > manage_sagemaker_cr.yaml <<EOF
apiVersion: rbac.authorization.k8s.io/v1
kind: RoleBinding
metadata:
  name: manage-sagemaker-cr
  namespace: kubeflow
subjects:
- kind: ServiceAccount
  name: pipeline-runner
  namespace: kubeflow
roleRef:
  kind: ClusterRole
  name: ack-sagemaker-controller
  apiGroup: rbac.authorization.k8s.io
EOF

kubectl apply -f manage_sagemaker_cr.yaml
```

   b. Make sure that the rolebinding was created by running:

   ```
kubectl get rolebinding manage-sagemaker-cr -n kubeflow -o yaml
```

**Configuration for SageMaker components version 1**

To run SageMaker Components version 1 for Kubeflow Pipelines, the Kubeflow Pipeline pods need access to SageMaker.

**Important**
Follow this section if you are using full Kubeflow or standalone deployment.

To grant SageMaker access to the service account used by Kubeflow pipeline pods, follow those steps:
1. Export your cluster name (e.g., `my-cluster-name`) and cluster region (e.g., `us-east-1`).

```bash
export CLUSTER_NAME=my-cluster-name
export CLUSTER_REGION=us-east-1
```

2. Export the namespace and service account name according to your installation.

- For the full Kubeflow on AWS installation, export your profile namespace (e.g., `kubeflow-user-example-com`) and `default-editor` as the service account.

```bash
export NAMESPACE=kubeflow-user-example-com
export KUBEFLOW_PIPELINE_POD_SERVICE_ACCOUNT=default-editor
```

- For the standalone Pipelines deployment, export `kubeflow` as the namespace and `pipeline-runner` as the service account.

```bash
export NAMESPACE=kubeflow
export KUBEFLOW_PIPELINE_POD_SERVICE_ACCOUNT=pipeline-runner
```

3. Enable OIDC support on the Amazon EKS cluster with the following command.

```bash
eksctl utils associate-iam-oidc-provider --cluster ${CLUSTER_NAME} --region ${CLUSTER_REGION} --approve
```

4. Create a KFP execution role for the pods to access AWS services.

```bash
eksctl create iamserviceaccount
  --name ${KUBEFLOW_PIPELINE_POD_SERVICE_ACCOUNT}
  --namespace ${NAMESPACE} --cluster ${CLUSTER_NAME}
  --region ${CLUSTER_REGION}
  --attach-policy-arn arn:aws:iam::aws:policy/AmazonSageMakerFullAccess
  --attach-policy-arn arn:aws:iam::aws:policy/CloudWatchLogsFullAccess
  --override-existing-serviceaccounts
  --approve
```

Once you are finished configuring your pipeline permissions to access SageMaker Components version 1, follow the SageMaker components for Kubeflow pipelines guide on the Kubeflow on AWS documentation.

**Access the KFP UI**

The Kubeflow Pipelines UI is used for managing and tracking experiments, jobs, and runs on your cluster. For instructions on how to access the Kubeflow Pipelines UI from your gateway node, follow the steps that apply to your deployment option in this section.

**Full Kubeflow on AWS Deployment**

Follow the instructions on the Kubeflow on AWS website to connect to the Kubeflow dashboard and navigate to the pipelines tab.
Standalone Kubeflow Pipelines Deployment

Use port forwarding to access the Kubeflow Pipelines UI from your gateway node by following those steps.

Set up port forwarding to the KFP UI service

Run the following from the command line of your gateway node:

1. Verify that the KFP UI service is running using the following command:

```
kubectl -n kubeflow get service ml-pipeline-ui
```

<table>
<thead>
<tr>
<th>NAME</th>
<th>TYPE</th>
<th>CLUSTER-IP</th>
<th>EXTERNAL-IP</th>
<th>PORT(S)</th>
<th>AGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>ml-pipeline-ui</td>
<td>ClusterIP</td>
<td>10.100.38.71</td>
<td>&lt;none&gt;</td>
<td>80/TCP</td>
<td>2d22h</td>
</tr>
</tbody>
</table>

2. Run the following command to set up port forwarding to the KFP UI service. This forwards the KFP UI to port 8080 on your gateway node and allows you to access the KFP UI from your browser.

```
kubectl port-forward -n kubeflow service/ml-pipeline-ui 8080:80
```

The port forward from your remote machine drops if there is no activity. Run this command again if your dashboard is unable to get logs or updates. If the commands return an error, ensure that there is no process already running on the port you are trying to use.

Access the KFP UI service

Your method of accessing the KFP UI depends on your gateway node type.

- Local machine as the gateway node
  1. Access the dashboard in your browser as follows:

```
http://localhost:8080
```

  2. Choose **Pipelines** to access the pipelines UI.

- Amazon EC2 instance as the gateway node
  1. You need to set up an SSH tunnel on your Amazon EC2 instance to access the Kubeflow dashboard from your local machine's browser.

     From a new terminal session in your local machine, run the following. Replace `<public-DNS-of-gateway-node>` with the IP address of your instance found on the Amazon EC2 console. You can also use the public DNS. Replace `<path_to_key>` with the path to the pem key used to access the gateway node.

```
public_DNS_address=<public-DNS-of-gateway-node>
key=<path_to_key>

on Ubuntu:
ssh -i $(key) -L 9000:localhost:8080 ubuntu@$public_DNS_address

or on Amazon Linux:
ssh -i $(key) -L 9000:localhost:8080 ec2-user@$public_DNS_address
```

  2. Access the dashboard in your browser.

```
http://localhost:9000
```
3. Choose **Pipelines** to access the KFP UI.

(Optional) Add access to additional IAM users or roles

If you use an intuitive IDE like Jupyter or want other people in your organization to use the cluster you set up, you can also give them access. The following steps run through this workflow using SageMaker notebooks. An SageMaker notebook instance is a fully managed Amazon EC2 compute instance that runs the Jupyter Notebook App. You use the notebook instance to create and manage Jupyter notebooks to create ML workflows. You can define, compile, deploy, and run your pipeline using the KFP AWS SDK for Python (Boto3) SDK or CLI. If you’re not using an SageMaker notebook to run Jupyter, you need to install the **AWS CLI** and the latest version of **kubectl**.

1. Follow the steps in Create an SageMaker Notebook Instance to create a SageMaker notebook instance if you do not already have one. Give the IAM role for this instance the **S3FullAccess** permission.

2. Amazon EKS clusters use IAM users and roles to control access to the cluster. The rules are implemented in a config map named `aws-auth`. Only the user/role that has access to the cluster will be able to edit this config map. Run the following from the command line of your gateway node to get the IAM role of the notebook instance you created. Replace `<instance-name>` with the name of your instance.

   ```bash
   aws sagemaker describe-notebook-instance --notebook-instance-name <instance-name> --region <region> --output text --query 'RoleArn'
   ```

   This command outputs the IAM role ARN in the `arn:aws:iam::<account-id>:role/<role-name>` format. Take note of this ARN.

3. Run the following to attach the policies the IAM role. Replace `<role-name>` with the `<role-name>` in your ARN.

   ```bash
   aws iam attach-role-policy --role-name <role-name> --policy-arn arn:aws:iam::aws:policy/AmazonSageMakerFullAccess
   aws iam attach-role-policy --role-name <role-name> --policy-arn arn:aws:iam::aws:policy/AmazonEKSWorkerNodePolicy
   aws iam attach-role-policy --role-name <role-name> --policy-arn arn:aws:iam::aws:policy/AmazonS3FullAccess
   ```

4. eksctl provides commands to read and edit the `aws-auth` config map. system:masters is one of the default user groups. You add the user to this group. The system:masters group has super user permissions to the cluster. You can also create a group with more restrictive permissions or you can bind permissions directly to users. Replace `<IAM-Role-arn>` with the ARN of the IAM role. `<your_username>` can be any unique username.

   ```bash
   eksctl create iamidentitymapping \
   --cluster <cluster-name> \
   --arn <IAM-Role-arn> \
   --group system:masters \
   --username <your-username> \
   --region <region>
   ```

5. Open the Jupyter notebook on your SageMaker instance and run the following to verify that it has access to the cluster.

   ```bash
   aws eks --region <region> update-kubeconfig --name <cluster-name>
   kubectl -n kubeflow get all | grep pipeline
   ```
Run Kubeflow Pipelines

Now that the setup of your gateway node and Amazon EKS cluster is complete, you can create your classification pipeline. To create your pipeline, you need to define and compile it. You then deploy it and use it to run workflows. You can define your pipeline in AWS SDK for Python (Boto3) and use the KFP dashboard, KFP CLI, or AWS SDK for Python (Boto3) SDK to compile, deploy, and run your workflows. The full code for the MNIST classification pipeline example is available in the Kubeflow Github repository. To use it, clone the example AWS SDK for Python (Boto3) files to your gateway node.

To run the classification pipeline example, follow the first section then continue with the steps that apply to your deployment option.

Create a SageMaker execution role

The kfp-example-sagemaker-execution-role IAM role is used by SageMaker jobs to access AWS resources. For more information, see the IAM Permissions section. You provide this role as an input parameter when running the pipeline.

Run the following to create the role. Note the ARN that is returned in your output.

```
SAGEMAKER_EXECUTION_ROLE_NAME=kfp-example-sagemaker-execution-role


aws iam create-role --role-name ${SAGEMAKER_EXECUTION_ROLE_NAME} --assume-role-policy-document "$TRUST"

aws iam attach-role-policy --role-name ${SAGEMAKER_EXECUTION_ROLE_NAME} --policy-arn arn:aws:iam::aws:policy/AmazonSageMakerFullAccess

aws iam attach-role-policy --role-name ${SAGEMAKER_EXECUTION_ROLE_NAME} --policy-arn arn:aws:iam::aws:policy/AmazonS3FullAccess

aws iam get-role --role-name ${SAGEMAKER_EXECUTION_ROLE_NAME} --output text --query 'Role.Arn'
```

Full Kubeflow on AWS Deployment

Follow the instructions of the SageMaker Training Pipeline tutorial for MNIST Classification with K-Means.

Standalone Kubeflow Pipelines Deployment

Prepare datasets

To run the pipelines, you need to upload the data extraction pre-processing script to an Amazon S3 bucket. This bucket and all resources for this example must be located in the us-east-1 Amazon Region. If you don’t have a bucket, create one using the steps in Creating a bucket.

From the mnist-kmeans-sagemaker folder of the Kubeflow repository you cloned on your gateway node, run the following command to upload the kmeans_preprocessing.py file to your Amazon S3 bucket. Change <bucket-name> to the name of the Amazon S3 bucket you created.

```
aws s3 cp mnist-kmeans-sagemaker/kmeans_preprocessing.py s3://<bucket-name>/mnist_kmeans_example/processing_code/kmeans_preprocessing.py
```

Compile and deploy your pipeline

After defining the pipeline in AWS SDK for Python (Boto3), you must compile the pipeline to an intermediate representation before you can submit it to the Kubeflow Pipelines service. The intermediate representation is a workflow specification in the form of a YAML file compressed into a tar.gz file. You need the KFP SDK to compile your pipeline.
Install KFP SDK

Run the following from the command line of your gateway node:

1. Install the KFP SDK following the instructions in the Kubeflow pipelines documentation.
2. Verify that the KFP SDK is installed with the following command:
   ```shell
   pip show kfp
   ```
3. Verify that `dsl-compile` has been installed correctly as follows:
   ```shell
   which dsl-compile
   ```

Compile your pipeline

You have three options to interact with Kubeflow Pipelines: KFP UI, KFP CLI, or the KFP SDK. The following sections illustrate the workflow using the KFP UI and CLI.

Complete the following from your gateway node to compile your pipeline.

1. Modify your AWS SDK for Python (Boto3) file with your Amazon S3 bucket name and IAM role ARN.
2. Use the `dsl-compile` command from the command line to compile your pipeline as follows.
   ```shell
   dsl-compile --py <path-to-python-file> --output <path-to-output>
   ```

Upload and run the pipeline using the KFP CLI

Complete the following steps from the command line of your gateway node. KFP organizes runs of your pipeline as experiments. You have the option to specify an experiment name. If you do not specify one, the run will be listed under Default experiment.

1. Upload your pipeline as follows:
   ```shell
   kfp pipeline upload --pipeline-name <pipeline-name> <path-to-output-tar.gz>
   ```
   Your output should look like the following. Take note of the ID.
   
   Pipeline 29c3ff21-49f5-4dfe-94f6-618c0e2420fe has been submitted
   Pipeline Details
   ------------------
   ID 29c3ff21-49f5-4dfe-94f6-618c0e2420fe
   Name sm-pipeline
   Description
   Uploaded at 2020-04-30T22:39:00+00:00
   ...
   ...

2. Create a run using the following command. The KFP CLI run command currently does not support specifying input parameters while creating the run. You need to update your parameters in the AWS SDK for Python (Boto3) pipeline file before compiling. Replace `<experiment-name>` and `<job-name>` with any names. Replace `<pipeline-id>` with the ID of your submitted pipeline. Replace `<your-role-arn>` with the ARN of kfp-example-pod-role. Replace `<your-bucket-name>` with the name of the Amazon S3 bucket you created.
You can also directly submit a run using the compiled pipeline package created as the output of the dsl-compile command.

```
kfp run submit --experiment-name <experiment-name> --run-name <job-name> --pipeline-id <pipeline-id> role_arn="<your-role-arn>" bucket_name="<your-bucket-name>"
```

Your output should look like the following:

```
Creating experiment aws.
Run 95084a2c-f18d-4b77-a9da-eba00bf01e63 is submitted
+--------------------------------------+--------+----------+---------------------------
<table>
<thead>
<tr>
<th>run id</th>
<th>name</th>
<th>status</th>
<th>created at</th>
</tr>
</thead>
</table>
+-------------------------+---------+----------+---------------------------|
| 95084a2c-f18d-4b77-a9da-eba00bf01e63 | sm-job  |          | 2020-04-30T20:36:41+00:00 |
+-------------------------+---------+----------+---------------------------|
```

3. Navigate to the UI to check the progress of the job.

### Upload and run the pipeline using the KFP UI

1. On the left panel, choose the **Pipelines** tab.
2. In the upper-right corner, choose **+UploadPipeline**.
3. Enter the pipeline name and description.
4. Choose **Upload a file** and enter the path to the tar.gz file you created using the CLI or with the AWS SDK for Python (Boto3) SDK.
5. On the left panel, choose the **Pipelines** tab.
6. Find the pipeline you created.
7. Choose **+CreateRun**.
8. Enter your input parameters.
9. Choose **Run**.

### Run predictions

Once your classification pipeline is deployed, you can run classification predictions against the endpoint that was created by the Deploy component. Use the KFP UI to check the output artifacts for `sagemaker-deploy-model-endpoint_name`. Download the .tgz file to extract the endpoint name or check the SageMaker console in the region you used.

### Configure permissions to run predictions

If you want to run predictions from your gateway node, skip this section.

1. To use any other machine to run predictions, assign the `sagemaker:InvokeEndpoint` permission to the IAM role or IAM user used by the client machine. This permission is used to run predictions.
2. On your gateway node, run the following to create a policy file:
3. Attach the policy to the client node's IAM role or IAM user.

4. If your client machine has an IAM role attached, run the following. Replace `<your-instance-IAM-role>` with the name of the client node's IAM role. Replace `<path-to-sagemaker-invoke-json>` with the path to the policy file you created.

```
aws iam put-role-policy --role-name <your-instance-IAM-role> --policy-name sagemaker-invoke-for-worker --policy-document file://<path-to-sagemaker-invoke-json>
```

5. If your client machine has IAM user credentials configured, run the following. Replace `<your_IAM_user_name>` with the name of the client node's IAM user. Replace `<path-to-sagemaker-invoke-json>` with the path to the policy file you created.

```
aws iam put-user-policy --user-name <your_IAM_user_name> --policy-name sagemaker-invoke-for-worker --policy-document file://<path-to-sagemaker-invoke-json>
```

### Run predictions

1. Create a AWS SDK for Python (Boto3) file from your client machine named `mnist-predictions.py` with the following content. Replace the `ENDPOINT_NAME` variable. This script loads the MNIST dataset, then creates a CSV from those digits and sends it to the endpoint for prediction. It then outputs the results.

```python
import boto3
import gzip
import io
import json
import numpy
import pickle

ENDPOINT_NAME='<endpoint-name>
region = boto3.Session().region_name

# S3 bucket where the original mnist data is downloaded and stored
downloaded_data_bucket = f"jumpstart-cache-prod-{region}"
downloaded_data_prefix = "1p-notebooks-datasets/mnist"

# Download the dataset
s3 = boto3.client("s3")
s3.download_file_object(downloaded_data_bucket, f"{downloaded_data_prefix}/mnist.pkl.gz", "mnist.pkl.gz")

# Load the dataset
with gzip.open('mnist.pkl.gz', 'rb') as f:
    train_set, valid_set, test_set = pickle.load(f, encoding='latin1')
```
# Simple function to create a csv from our numpy array

def np2csv(arr):
    csv = io.BytesIO()
    numpy.savetxt(csv, arr, delimiter=',', fmt='%g')
    return csv.getvalue().decode().rstrip()

runtime = boto3.Session(region).client('sagemaker-runtime')

payload = np2csv(train_set[0][30:31])

response = runtime.invoke_endpoint(EndpointName=ENDPOINT_NAME,
                                   ContentType='text/csv',
                                   Body=payload)

result = json.loads(response['Body'].read().decode())

print(result)

2. Run the AWS SDK for Python (Boto3) file as follows:

   python mnist-predictions.py

View results and logs

When the pipeline is running, you can choose any component to check execution details, such as inputs and outputs. This lists the names of created resources.

If the KFP request is successfully processed and an SageMaker job is created, the component logs in the KFP UI provide a link to the job created in SageMaker. The CloudWatch logs are also provided if the job is successfully created.

If you run too many pipeline jobs on the same cluster, you may see an error message that indicates you do not have enough pods available. To fix this, log in to your gateway node and delete the pods created by the pipelines you are not using as follows:

   kubectl get pods -n kubeflow
   kubectl delete pods -n kubeflow <name-of-pipeline-pod>

Cleanup

When you're finished with your pipeline, you need to clean up your resources.

1. From the KFP dashboard, terminate your pipeline runs if they do not exit properly by choosing Terminate.

2. If the Terminate option doesn't work, log in to your gateway node and manually terminate all the pods created by your pipeline run as follows:

   kubectl get pods -n kubeflow
   kubectl delete pods -n kubeflow <name-of-pipeline-pod>

3. Using your AWS account, log in to the SageMaker service. Manually stop all training, batch transform, and HPO jobs. Delete models, data buckets, and endpoints to avoid incurring any additional costs. Terminating the pipeline runs does not stop the jobs in SageMaker.

Amazon SageMaker Workflows FAQ

Use the following FAQ items to find answers to commonly asked questions about MLOps workflows.
Q. Do I need to use the SageMaker Python SDK to create a SageMaker pipeline?

No, the SageMaker Python SDK is not required to create a SageMaker pipeline. You can also use boto3 or AWS CloudFormation. Creating a pipeline requires a pipeline definition, which is a JSON object that defines each step of the pipeline. The SageMaker SDK offers a simple way to construct the pipeline definition, which you can use with any of the APIs previously mentioned to create the pipeline itself. Without using the SDK, users have to write the raw JSON definition to create the pipeline without any of the error checks provided by the SageMaker Python SDK. To see the schema for the pipeline JSON definition, see SageMaker Pipeline Definition JSON Schema. The following code sample shows an example of a SageMaker pipeline definition JSON object:

```json
{"Version": '2020-12-01',
'Metadata': {},
'Parameters': [{"Name": 'ProcessingInstanceType',
'Type': 'String',
'DefaultValue': 'ml.m5.xlarge'},
{"Name": 'ProcessingInstanceCount', 'Type': 'Integer', 'DefaultValue': 1},
{"Name": 'TrainingInstanceType',
'Type': 'String',
'DefaultValue': 'ml.m5.xlarge'},
{"Name": 'ModelApprovalStatus',
'Type': 'String',
'DefaultValue': 'PendingManualApproval'},
{"Name": 'ProcessedData',
'Type': 'String',
'DefaultValue': 'S3_URL'},
{"Name": 'InputDataUrl',
'Type': 'String',
'DefaultValue': 'S3_URL'},
'PipelineExperimentConfig': {'ExperimentName': {'Get': 'Execution.PipelineName'},
'TrialName': {'Get': 'Execution.PipelineExecutionId'}},
'Steps': [{"Name": 'ReadTrainDataFromFS',
'Type': 'Processing',
'Arguments': {'ProcessingResources': {'ClusterConfig': {'InstanceType': 'ml.m5.xlarge',
'InstanceCount': 2,
'VolumeSizeInGB': 30}},
'AppSpecification': {'ImageUri': 'IMAGE_URI',
'ContainerArguments': []},
'RoleArn': 'ROLE',
'ProcessingInputs': [],
'ProcessingOutputConfig': {'Outputs': []},
'StoppingCondition': {'MaxRuntimeInSeconds': 86400},
'CacheConfig': {'Enabled': True, 'ExpireAfter': '30d'}},
...
...
...}
```

Q. Why do I see a repack step in my SageMaker pipeline?

Model repacking happens when the pipeline needs to include a custom script in the compressed model file (model.tar.gz) to be uploaded to Amazon S3 and used to deploy a model to a SageMaker endpoint. When SageMaker pipeline trains a model and registers it to the model registry, it introduces a repack step if the trained model output from the training job needs to include a custom inference script. The repack step uncompressed the model, adds a new script, and recompresses the model. Running the pipeline adds the repack step as a training job.
Q. Can I use SageMaker Experiments with SageMaker Pipelines?

Yes. SageMaker Pipelines is natively integrated with SageMaker Experiments. You can use `PipelineExperimentConfig` when creating a pipeline and set your own SageMaker Experiment name. Each run of the pipeline creates a trial, and each step in the pipeline corresponds to a `TrialComponent` within the trial. If no trial name is specified in the experiment config, the pipeline execution ID is used as the trial name.

```python
pipeline = Pipeline(
    name=pipeline_name,
    parameters=[...],
    steps=[...],
    sagemaker_session=sagemaker_session,
    pipeline_experiment_config=PipelineExperimentConfig(
        ExecutionVariables.PIPELINE_NAME,
        ExecutionVariables.PIPELINE_EXECUTION_ID
    )
)
```

Q. SageMaker Project templates have a model deploy repository that uses CloudFormation (CFN) to create an endpoint. Are there ways to deploy the model without using CloudFormation?

You can customize the deploy repository in the project template to deploy the model from the model registry any way you like. The template uses CloudFormation to create a real-time endpoint, as an example. You can update the deployment to use the SageMaker SDK, boto3, or any other API that can create endpoints instead of CFN. If you need to update the CodeBuild steps as part of the deployment pipeline, you can create a custom template.

Q. How do we pass the model file Amazon S3 URL from the train step to the model register step in a SageMaker pipeline at run time?

You can reference the model location as a property of the training step, as shown in the end-to-end example `CustomerChurn pipeline` in Github.

Q. If I am extending a prebuilt container to train an estimator or for a `ProcessingStep` on SageMaker Pipelines, is it necessary to copy the script to the container in the Dockerfile?

No, you can either copy the script to the container or pass it via the `entry_point` argument (of your estimator entity) or `code` argument (of your processor entity), as demonstrated in the following code sample.

```python
step_process = ProcessingStep(
    name="PreprocessAbaloneData",
    processor=sklearn_processor,
    inputs=[
        ProcessingInput(
            input_name='dataset',
            source=..., destination="/opt/ml/processing/code",
        )
    ],
    outputs=[
```

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Q. What's the recommended way to manage dependencies for different SageMaker Pipelines steps?

You can use a SageMaker Projects template to implement image-building CI/CD. With this template, you can automate the CI/CD of images that are built and pushed to Amazon ECR. Changes in the container files in your project's source control repositories initiate the ML pipeline and deploy the latest version for your container. For more information, see the blog Create Amazon SageMaker projects with image building CI/CD pipelines.

Q. How do I provide SageMaker Project access to specific user profiles in Amazon SageMaker Studio?

Since SageMaker Projects is backed by AWS Service Catalog, you must add each role that requires access to SageMaker Projects to the Amazon SageMaker Solutions and ML Ops products Portfolio in the service catalog. You can do this on the Groups, roles, and users tab, as shown in the following image. If each user profile in Studio has a different role, you should add each of those roles to the service catalog. You can also do this while creating a user profile in Studio.
Q. Where do I see the properties associated with each SageMaker pipeline step so that I can use them in subsequent steps?

Each step in the pipeline uses the underlying SageMaker APIs for the corresponding jobs. For example, TrainingStep invokes the CreateTrainingJob API and the step properties correspond to the response from DescribeTrainingJob. The response output can be found in the API reference link for DescribeTrainingJob. You can follow the same procedure to get the properties for TransformStep, ProcessingStep, TuningStep, and CreateModelStep. For more information about pipeline steps, see Pipeline Steps.

Q. What’s the best way to reproduce my model in SageMaker?

SageMaker’s Lineage Tracking service works in the backend to track all the metadata associated with your model training and deployment workflows. This includes your training jobs, datasets used, pipelines, endpoints, and the actual models. You can query the lineage service at any point to find the exact artifacts used to train a model. Using those artifacts, you can recreate the same ML workflow to reproduce the model as long as you have access to the exact dataset that was used. A trial component tracks the training job. This trial component has all the parameters used as part of the training job. If you don’t need to rerun the entire workflow, you can reproduce the training job to derive the same model.
Using Amazon Augmented AI for Human Review

When you use AI applications such as Amazon Rekognition, Amazon Textract, or your custom machine learning (ML) models, you can use Amazon Augmented AI to get human review of low-confidence predictions or random prediction samples.

What is Amazon Augmented AI?

Amazon Augmented AI (Amazon A2I) is a service that brings human review of ML predictions to all developers by removing the heavy lifting associated with building human review systems or managing large numbers of human reviewers.

Many ML applications require humans to review low-confidence predictions to ensure the results are correct. For example, extracting information from scanned mortgage application forms can require human review due to low-quality scans or poor handwriting. Building human review systems can be time-consuming and expensive because it involves implementing complex processes or workflows, writing custom software to manage review tasks and results, and managing large groups of reviewers.

Amazon A2I streamlines building and managing human reviews for ML applications. Amazon A2I provides built-in human review workflows for common ML use cases, such as content moderation and text extraction from documents. You can also create your own workflows for ML models built on SageMaker or any other tools. Using Amazon A2I, you can allow human reviewers to step in when a model is unable to make a high-confidence prediction or to audit its predictions on an ongoing basis.

Amazon A2I Use Case Examples

The following examples demonstrate how you can use Amazon A2I to integrate a human review loop into your ML application. For each of these examples, you can find a Jupyter Notebook that demonstrates that workflow in Use Cases and Examples Using Amazon A2I (p. 3411).

- **Use Amazon A2I with Amazon Textract** – Have humans review important key-value pairs in single-page documents or have Amazon Textract randomly sample and send documents from your dataset to humans for review.

- **Use Amazon A2I with Amazon Rekognition** – Have humans review unsafe images for explicit adult or violent content if Amazon Rekognition returns a low-confidence score, or have Amazon Rekognition randomly sample and send images from your dataset to humans for review.

- **Use Amazon A2I to review real-time ML inferences** – Use Amazon A2I to review real-time, low-confidence inferences made by a model deployed to a SageMaker hosted endpoint and incrementally train your model using Amazon A2I output data.

- **Use Amazon A2I with Amazon Comprehend** – Have humans review Amazon Comprehend inferences about text data such as sentiment analysis, text syntax, and entity detection.

- **Use Amazon A2I with Amazon Transcribe** – Have humans review Amazon Transcribe transcriptions of video or audio files. Use the results of transcription human review loops to create a custom vocabulary and improve future transcriptions of similar video or audio content.

- **Use Amazon A2I with Amazon Translate** – Have humans review low-confidence translations returned from Amazon Translate.
- **Use Amazon A2I to review tabular data** – Use Amazon A2I to integrate a human review loop into an ML application that uses tabular data.

---

**Core Components of Amazon A2I**

Review the following terms to familiarize yourself with the core components of Amazon A2I.

**Task Types**

The AI/ML workflow into which you integrate Amazon A2I defines an **Amazon A2I task type**.
Amazon A2I supports:

- **Two built-in task types**: Amazon Textract key-value pair extraction and Amazon Rekognition image moderation.

- **A custom task type**: Use a custom task type to integrate a human review loop into any machine learning workflow. You can use a custom task type to integrate Amazon A2I with other AWS services like Amazon Comprehend, Amazon Transcribe, and Amazon Translate, as well as your own custom machine learning workflows. To learn more, see Use Cases and Examples Using Amazon A2I (p. 3411).

Select a tab in the following table to see diagrams that illustrate how Amazon A2I works with each task type. Select the task type page using the links in the preceding list to learn more about that task type.

**Amazon Textract – Key-value pair extraction**

This image depicts the Amazon A2I built-in workflow with Amazon Textract. On the left, the resources that are required to create an Amazon Textract human review workflow are depicted: an Amazon S3 bucket, activation conditions, a worker task template, and a work team. These resources are used to create a human review workflow, or flow definition. An arrow points right to the next step in the workflow: using Amazon Textract to configure a human loop with the human review workflow. A second arrow points right from this step to the step in which activation conditions specified in the human review workflow are met. This initiates the creation of a human loop. On the right of the image, the human loop is depicted in three steps: 1) the worker UI and tools are generated and the task is made available to workers, 2) workers review input data, and finally, 3) results are saved in Amazon S3.

**Amazon Rekognition – Image moderation**

This image depicts the Amazon A2I built-in workflow with Amazon Rekognition. On the left, the resources that are required to create an Amazon Rekognition human review workflow are depicted: an Amazon S3 bucket, activation conditions, a worker task template, and a work team. These resources are used to create a human review workflow, or flow definition. An arrow points right to the next step in the workflow: using Amazon Rekognition to configure a human loop with the human review workflow. A second arrow points right from this step to the step in which activation conditions specified in the human review workflow are met. This initiates the creation of a human loop. On the right of the image, the human loop is depicted in three steps: 1) the worker UI and tools are generated and the task is made available to workers, 2) workers review input data, and finally, 3) results are saved in Amazon S3.
Custom Task Type

The following image depicts the Amazon A2I custom workflow. A custom ML model is used to generate predictions. The client application filters these predictions using user-defined criteria and determines if a human review is required. If so, these predictions are sent to Amazon A2I for human review. Amazon A2I collects the results of human review in Amazon S3, which can access by the client application. If the filter determines that no human review is needed, predictions can be fed directly to the client application.

Human Review Workflow (Flow Definition)

You use a human review workflow to specify your human work team, to set up your worker UI using a worker task template, and to provide information about how workers should complete the review task.

For built-in task types, you also use the human review workflow to identify the conditions under which a human loop is initiated. For example, Amazon Rekognition can perform image content moderation using machine learning. You can use the human review workflow to specify that an image is sent to a human for content moderation review if Amazon Rekognition's confidence is too low.

You can use a human review workflow to create multiple human loops.
You can create a flow definition in the SageMaker console or with the SageMaker API. To learn more about both of these options, see Create a Human Review Workflow (p. 3419).

Work Team

A work team is a group of human workers to whom you send your human review tasks.

When you create a human review workflow, you specify a single work team.

Your work team can come from the Amazon Mechanical Turk workforce, a vendor-managed workforce, or your own private workforce. When you use the private workforce, you can create multiple work teams. Each work team can be used in multiple human review workflows. To learn how to create a workforce and work teams, see Create and Manage Workforces (p. 694).

Worker Task Template and Human Task UI

You use a worker task template to create a worker UI (a human task UI) for your human review tasks.

The human task UI displays your input data, such as documents or images, and instructions to workers. It also provides interactive tools that the worker uses to complete your tasks.

For built-in task types, you must use the Amazon A2I worker task template provided for that task type.

Human Loops

A human loop is used to create a single human review job. For each human review job, you can choose the number of workers that are sent a task to review a single data object. For example, if you set the number of workers per object to 3 for an image classification labeling job, three workers classify each input image. Increasing the number of workers per object can improve label accuracy.

A human loop is created using a human review workflow as follows:

- For built-in task types, the conditions specified in the human review workflow determine when the human loop is created.
- Human review tasks are sent to the work team specified in the human review workflow.
- The worker task template specified in the human review workflow is used to render the human task UI.

When do human loops get created?

When you use one of the built-in task types, the corresponding AWS service creates and starts a human loop on your behalf when the conditions specified in your human review workflow are met. For example:

- When you use Augmented AI with Amazon Textract, you can integrate Amazon A2I into a document review task using the API operation AnalyzeDocument. A human loop is created every time Amazon Textract returns inferences about key-value pairs that meet the conditions you specify in your human review workflow.
- When you use Augmented AI with Amazon Rekognition, you can integrate Amazon A2I into an image moderation task using the API operation DetectModerationLabels. A human loop is created every time Amazon Rekognition returns inferences about image content that meet the conditions you specify in your human review workflow.

When using a custom task type, you start a human loop using the Amazon Augmented AI Runtime API. When you call StartHumanLoop in your custom application, a task is sent to human reviewers.

To learn how to create and start a human loop, see Create and Start a Human Loop (p. 3438).
To generate these resources and create a human review workflow, Amazon A2I integrates multiple APIs, including the Amazon Augmented AI Runtime Model, the SageMaker APIs, and APIs associated with your task type. To learn more, see Use APIs in Amazon Augmented AI (p. 3474).

**Note**
AWS Region availability may differ when you use Augmented AI with other AWS services, such as Amazon Textract. Create Augmented AI resources in the same AWS Region that you use to interact with those AWS services. For AWS Region availability for all services, see the Region Table.

**Prerequisites to Using Augmented AI**

Amazon A2I uses resources in IAM, SageMaker, and Amazon S3 to create and run your human review workflows. You can create some of these resources in the Amazon A2I console when you create a human review workflow. To learn how, see Tutorial: Get Started in the Amazon A2I Console (p. 3395).

To use Amazon A2I, you need the following resources:

- One or more Amazon S3 buckets in the same AWS Region as the workflow for your input and output data. To create a bucket, follow the instructions in Create a Bucket in the Amazon Simple Storage Service Console User Guide.
- An IAM role with required permissions to create a human review workflow and an IAM user or role with permission to access Augmented AI. For more information, see Permissions and Security in Amazon Augmented AI (p. 3466).
- A public, private, or vendor workforce for your human review workflows. If you plan to use a private workforce, you need to set one up ahead of time in the same AWS Region as your Amazon A2I workflow. To learn more about these workforce types, see Create and Manage Workforces (p. 694).

**Important**
To learn about the compliance programs that cover Amazon Augmented AI at this time, see AWS Services in Scope by Compliance Program. If you use Amazon Augmented AI in conjunction with other AWS services (such as Amazon Rekognition and Amazon Textract), note that Amazon Augmented AI may not be in scope for the same compliance programs as those other services. You are responsible for how you use Amazon Augmented AI, including understanding how the service processes or stores customer data and any impact on the compliance of your data environment. You should discuss your workload objectives and goals with your AWS account team; they can help you evaluate whether the service is a good fit for your proposed use case and architecture.

**Tutorial: Get Started in the Amazon A2I Console**

The following tutorial shows you how to get started using Amazon A2I in the Amazon A2I console.

The tutorial gives you the option to use Augmented AI with Amazon Textract for document review or Amazon Rekognition for image content review.

**Prerequisites**

To get started using Amazon A2I, complete the following prerequisites.

- Create an Amazon S3 bucket in the same AWS Region as the workflow for your input and output data. For example, if you are using Amazon A2I with Amazon Textract in us-east-1, create your bucket in us-east-1. To create a bucket, follow the instructions in Create a Bucket in the Amazon Simple Storage Service Console User Guide.
- Do one of the following:
• If you want to complete the tutorial using Amazon Textract, download the sample document and place it in your Amazon S3 bucket.
• If you want to complete the tutorial using Amazon Rekognition, download this image and place it in your Amazon S3 bucket.

**Note**
The Amazon A2I console is embedded in the SageMaker console.

**Step 1: Create a Work Team**

First, create a work team in the Amazon A2I console and add yourself as a worker so that you can preview the worker review task.

**Important**
This tutorial uses a private work team. The Amazon A2I private workforce is configured in the Ground Truth area of the SageMaker console and is shared between Amazon A2I and Ground Truth.

**To create a private workforce using worker emails**

2. In the navigation pane, choose **Labeling workforces** under **Ground Truth**.
3. Choose **Private**, then choose **Create private team**.
4. Choose **Invite new workers by email**.
5. For this tutorial, enter your email and any others that you want to be able to preview the human task UI. You can paste or type a list of up to 50 email addresses, separated by commas, into the email addresses box.
6. Enter an organization name and contact email.
7. Optionally, choose an Amazon SNS topic to which to subscribe the team so workers are notified by email when new Ground Truth labeling jobs become available. Amazon SNS notifications are supported by Ground Truth and are not supported by Augmented AI. If you subscribe workers to Amazon SNS notifications, they only receive notifications about Ground Truth labeling jobs. They do not receive notifications about Augmented AI tasks.
8. Choose **Create private team**.

If you add yourself to a private work team, you receive an email from no-reply@verificationemail.com with login information. Use the link in this email to reset your password and log in to your worker portal. This is where your human review tasks appear when you create a human loop.

**Step 2: Create a Human Review Workflow**

In this step, you create a human review workflow. Each human review workflow is created for a specific task type. This tutorial allows you to choose between the built-in task types: Amazon Rekognition and Amazon Textract.

**To create a human review workflow:**

1. Open the Augmented AI console at https://console.aws.amazon.com/a2i to access the **Human review workflows** page.
2. Select **Create human review workflow**.
3. In **Workflow settings**, enter a workflow **Name**, **S3 bucket**, and the **IAM role** that you created for this tutorial, with the AWS managed policy AmazonAugmentedAIIntegratedAPIAccess attached.
4. For **Task type**, select **Textract – Key-value pair extraction** or **Rekognition – Image moderation**.
5. Select the task type that you chose from the following table for instructions for that task type.

Amazon Textract – Key-value pair extraction

1. Select **Trigger a human review for specific form keys based on the form key confidence score or when specific form keys are missing**.

2. For **Key name**, enter **Mail Address**.

3. Set the identification confidence threshold between 0 and 99.

4. Set the qualification confidence threshold between 0 and 99.

5. Select **Trigger a human review for all form keys identified by Amazon Textract with confidence scores in a specific range**.

6. Set the identification confidence threshold between 0 and 90.

7. Set the qualification confidence threshold between 0 and 90.

This initiates a human review if Amazon Textract returns a confidence score that is less than 99 for **Mail Address** and its key, or if it returns a confidence score less than 90 for any key value pair detected in the document.

The following image shows the Amazon Textract form extraction - Conditions for invoking human review section of the Amazon A2I console. In the image, the check boxes for the two types of triggers explained in the proceeding paragraph are checked, and **Mail Address** is used as a **Key name** for the first trigger. The identification confidence threshold is defined using confidence scores for key-value pairs detect within the form and is set between 0 and 99. The qualification confidence threshold is defined using confidence scores for text contained within keys and values in a form and is set between 0 and 99.
1. Select **Trigger human review for labels identified by Amazon Rekognition based on label confidence score**.

2. Set the **Threshold** between 0 and 98.

This initiates a human review if Amazon Rekognition returns a confidence score that is less than 98 for an image moderation job.

The following image shows how you can select the **Trigger human review for labels identified by Amazon Rekognition based on label confidence score** option and enter a **Threshold** between 0 and 98 in the Amazon A2I console.
6. Under **Worker task template creation**, select **Create from a default template**.

7. Enter a **Template name**.

8. In **Task description** field, enter the following text:

   **Read the instructions carefully and complete the task.**

9. Under **Workers**, select **Private**.

10. Select the private team that you created.

11. Choose **Create**.

Once your human review workflow is created, it appears in the table on the **Human review workflows** page. When the **Status** is **Active**, copy and save the Workflow ARN. You need it for the next step.

### Step 3: Start a Human Loop

You must use an API operation to start a human loop. There are a variety of language-specific SDKs that you can use to interact with these API operations. To see documentation for each of these SDKs, refer to the **See Also** section in the API documentation, as shown in the following image.

For this tutorial, you use one of the following APIs:

- If you chose the Amazon Textract task type, you use the **AnalyzeDocument** operation.

- If you chose the Amazon Rekognition task type, you use the **DetectModerationLabels** operation.
You can interact with these APIs using a SageMaker notebook instance (recommended for new users) or the AWS Command Line Interface (AWS CLI). Choose one of the following to learn more about these options:

- To learn more about and set up a notebook instance, see Use Amazon SageMaker Notebook Instances (p. 291).
- To learn more about and get started using the AWS CLI, see What Is the AWS Command Line Interface? in the AWS Command Line Interface User Guide.

Select your task type in the following table to see example requests for Amazon Textract and Amazon Rekognition using the AWS SDK for Python (Boto3).

Amazon Textract – Key-value pair extraction

The following example uses the AWS SDK for Python (Boto3) to call `analyze_document` in us-west-2. Replace the italicized red text with your resources. Include the `DataAttributes` parameter if you are using the Amazon Mechanical Turk workforce. For more information, see the `analyze_document` documentation in the AWS SDK for Python (Boto) API Reference.

```python
response = client.analyze_document(
    Document={
        "S3Object": {
            "Bucket": "AWSDOC-EXAMPLE-BUCKET",
            "Name": "document-name.pdf"
        }
    },
    HumanLoopConfig={
        "HumanLoopName": "human-loop-name",
        "DataAttributes": {
            "ContentClassifiers": [
                "FreeOfPersonallyIdentifiableInformation",
                "FreeOfAdultContent"
            ]
        },
        "FeatureTypes": ["TABLES", "FORMS"]
    }
)
```

Amazon Rekognition – Image moderation

The following example uses the AWS SDK for Python (Boto3) to call `detect_moderation_labels` in us-west-2. Replace the italicized red text with your resources. Include the `DataAttributes` parameter if you are using the Amazon Mechanical Turk workforce. For more information, see the `detect_moderation_labels` documentation in the AWS SDK for Python (Boto) API Reference.

```python
response = client.detect_moderation_labels(
    Image={
        "S3Object": {
            "Bucket": "AWSDOC-EXAMPLE-BUCKET",
            "Name": "image-name.png"
        }
    },
    HumanLoopConfig={
        "HumanLoopName": "human-loop-name",
        "DataAttributes": {
            "ContentClassifiers": [
                "FreeOfPersonallyIdentifiableInformation",
                "FreeOfAdultContent"
            ]
        }
    }
)
```
Step 4: View Human Loop Status in Console

When you start a human loop, you can view its status in the Amazon A2I console.

To view your human loop status

1. Open the Augmented AI console at https://console.aws.amazon.com/a2i to access the Human review workflows page.
2. Select the human review workflow that you used to start your human loop.
3. In the Human loops section, you can see your human loop. View its status in the Status column.

Step 5: Download Output Data

Your output data is stored in the Amazon S3 bucket you specified when you created a human review workflow.

To view your Amazon A2I output data

1. Open the Amazon S3 console.
2. Select the Amazon S3 bucket you specified when you created your human review workflow in step 2 of this example.
3. Starting with the folder that is named after your human review workflow, navigate to your output data by selecting the folder with the following naming convention:

   s3://output-bucket-specified-in-human-review-workflow/human-review-workflow-name/YYYY/MM/DD/hh/mm/ss/human-loop-name/output.json

4. Select output.json and choose Download.

Tutorial: Get Started Using the Amazon A2I API

This tutorial explains the API operations you can use to get started using Amazon A2I.

To use a Jupyter Notebook to run these operations, select a Jupyter Notebook from Use Cases and Examples Using Amazon A2I (p. 3411) and use Use SageMaker Notebook Instance with Amazon A2I Jupyter Notebook (p. 3413) to learn how to use it in a SageMaker notebook instance.

To learn more about the API operations you can use with Amazon A2I, see Use APIs in Amazon Augmented AI (p. 3474).

Create a Private Work Team

You can create a private work team and add yourself as a worker so that you can preview Amazon A2I.

If you are not familiar with Amazon Cognito, we recommend that you use the SageMaker console to create a private workforce and add yourself as a private worker. For instructions, see Step 1: Create a Work Team (p. 3396).

If you are familiar with Amazon Cognito, you can use the following instructions to create a private work team using the SageMaker API. After you create a work team, note the work team ARN (WorkteamArn).

To learn more about the private workforce and other available configurations, see Use a Private Workforce (p. 699).
Create a private workforce

If you have not created a private workforce, you can do so using an Amazon Cognito user pool. Make sure that you have added yourself to this user pool. You can create a private work team using the AWS SDK for Python (Boto3) `create_workforce` function. For other language-specific SDKs, refer to the list in `CreateWorkforce`.

```python
response = client.create_workforce(
    CognitoConfig={
        "UserPool": "Pool_ID",
        "ClientId": "app-client-id"
    },
    WorkforceName="workforce-name"
)
```

Create a private work team

After you have created a private workforce in the AWS Region to configure and start your human loop, you can create a private work team using the AWS SDK for Python (Boto3) `create_workteam` function. For other language-specific SDKs, refer to the list in `CreateWorkteam`.

```python
response = client.create_workteam(
    WorkteamName="work-team-name",
    WorkforceName="workforce-name",
    MemberDefinitions=[
        {
            "CognitoMemberDefinition": {
                "UserPool": "<aws-region>_ID",
                "UserGroup": "user-group",
                "ClientId": "app-client-id"
            },
        }
    ]
)
```

Access your work team ARN as follows:

```python
workteamArn = response["WorkteamArn"]
```

List private work teams in your account

If you have already created a private work team, you can list all work teams in a given AWS Region in your account using the AWS SDK for Python (Boto3) `list_workteams` function. For other language-specific SDKs, refer to the list in `ListWorkteams`.

```python
response = client.list_workteams()
```

If you have numerous work teams in your account, you may want to use `MaxResults`, `SortBy`, and `NameContains` to filter your results.

Create a Human Review Workflow

You can create a human review workflow using the Amazon A2I `CreateFlowDefinition` operation. Before you create your human review workflow, you need to create a human task UI. You can do this with the `CreateHumanTaskUi` operation.
If you are using Amazon A2I with the Amazon Textract or Amazon Rekognition integrations, you can specify activation conditions using a JSON.

**Create a Human Task UI**

If you are creating a human review workflow to be used with Amazon Textract or Amazon Rekognition integrations, you need to use and modify pre-made worker task template. For all custom integrations, you can use your own custom worker task template. Use the following table to learn how to create a human task UI using a worker task template for the two built-in integrations. Replace the template with your own to customize this request.

Amazon Textract – Key-value pair extraction

To learn more about this template, see Custom Template Example for Amazon Textract (p. 3449).

```html
template = r""
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
{% capture s3_uri %}http://s3.amazonaws.com/
{{ task.input.aiServiceRequest.document.s3Object.bucket }}/
{{ task.input.aiServiceRequest.document.s3Object.name }}{% endcapture %}
<crowd-form>
  <crowd-textract-analyze-document
    src="{{ s3_uri | grant_read_access }}"
    initial-value="{{ task.input.selectedAiServiceResponse.blocks }}"
    header="Review the key-value pairs listed on the right and correct them if they
do\n't match the following document."
    no-key-edit=""
    no-geometry-edit=""
    keys="{{ task.input.humanLoopContext.importantFormKeys }}"
    block-types='["KEY_VALUE_SET"]'>
    <short-instructions header="Instructions">
    <p>Click on a key-value block to highlight the corresponding key-value pair in
    the document.</p>
    <p>If it is a valid key-value pair, review the content for the value. If the
    content is incorrect, correct it.</p>
    <p>The text of the value is incorrect, correct it.</p>
    <p>A wrong value is identified, correct it.</p>
    <p>If it is not a valid key-value relationship, choose No.</p>
    <p>If you can’t find the key in the document, choose Key not found.</p>
    <p>If the content of a field is empty, choose Value is blank.</p>
    <p>Key and value displayed next or below to each other.</p>
    <p>Key and value displayed in one line.</p>
    <p>Key and value displayed in two lines.</p>
  </short-instructions>
  </crowd-textract-analyze-document>
</crowd-form>
```
Amazon Rekognition – Image moderation

To learn more about this template, see Custom Template Example for Amazon Rekognition (p. 3451).

template = r""
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
{% capture s3_uri %}http://s3.amazonaws.com/{{ task.input.aiServiceRequest.image.s3Object.bucket }}/\n{{ task.input.aiServiceRequest.image.s3Object.name }}{% endcapture %}

<crowd-form>
<crowd-rekognition-detect-moderation-labels
  categories='[%
    {% for label in task.input.selectedAiServiceResponse.moderationLabels %}
    {
      name: "{{ label.name }}",
      parentName: "{{ label.parentName }}",
    },
    {% endfor %}
  ]'
  src="{{ s3_uri | grant_read_access }}"
  header="Review the image and choose all applicable categories."
>
  <short-instructions header="Instructions">
    <style>
      .instructions {
        white-space: pre-wrap;
      }
    </style>
    <p class="instructions">Review the image and choose all applicable categories. If no categories apply, choose None.</p>
  </short-instructions>
  <b>Nudity</b>
  Visuals depicting nude male or female person or persons

  <b>Partial Nudity</b>
  Visuals depicting covered up nudity, for example using hands or pose

  <b>Revealing Clothes</b>
  Visuals depicting revealing clothes and poses

  <b>Physical Violence</b>
  Visuals depicting violent physical assault, such as kicking or punching

  <b>Weapon Violence</b>
  Visuals depicting violence using weapons like firearms or blades, such as shooting

  <b>Weapons</b>
  Visuals depicting weapons like firearms and blades
</full-instructions>
</crowd-form>
Custom Integration

The following is an example template that can be used in a custom integration. This template is used in this notebook, demonstrating a custom integration with Amazon Comprehend.

```r
<crowd-rekognition-detect-moderation-labels>
</crowd-form>
```

Using the template specified above, you can create a template using the AWS SDK for Python (Boto3) `create_human_task_ui` function. For other language-specific SDKs, refer to the list in CreateHumanTaskUi.

```python
def create_template:
    template = r""
    <script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
    <crowd-form>
        <crowd-classifier
            name="sentiment"
            categories='["Positive", "Negative", "Neutral", "Mixed"]'
            initial-value="{{ task.input.initialValue }}"
            header="What sentiment does this text convey?"
        >
        <classification-target>
            {{ task.input.taskObject }}
        </classification-target>
        <full-instructions header="Sentiment Analysis Instructions">
            <p><strong>Positive</strong> sentiment include: joy, excitement, delight</p>
            <p><strong>Negative</strong> sentiment include: anger, sarcasm, anxiety</p>
            <p><strong>Neutral</strong>: neither positive or negative, such as stating a fact</p>
            <p><strong>Mixed</strong>: when the sentiment is mixed</p>
        </full-instructions>
        <short-instructions>
            Choose the primary sentiment that is expressed by the text.
        </short-instructions>
    </crowd-classifier>
""
```

This response element contains the human task UI ARN. Save this as follows:

```python
humanTaskUiArn = response['HumanTaskUiArn']
```

Create JSON to specify activation conditions

For Amazon Textract and Amazon Rekognition built-in integrations, you can save activation conditions in a JSON object and use this in your CreateFlowDefinition request.
Next, select a tab to see example activation conditions you can use for these built-in integrations. For additional information about activation condition options, see JSON Schema for Human Loop Activation Conditions in Amazon Augmented AI (p. 3425).

Amazon Textract – Key-value pair extraction

This example specifies conditions for specific keys (such as Mail address) in the document. If Amazon Textract's confidence falls outside of the thresholds set here, the document is sent to a human for review, with the specific keys that initiated the human loop prompted to the worker.

```python
import json

humanLoopActivationConditions = json.dumps(
{
    "Conditions": [
        {
            "Or": [
                {
                    "ConditionType": "ImportantFormKeyConfidenceCheck",
                    "ConditionParameters": {
                        "ImportantFormKey": "Mail address",
                        "ImportantFormKeyAliases": ["Mail Address:","Mail address:"],
                        "KeyValueBlockConfidenceLessThan": 100,
                        "WordBlockConfidenceLessThan": 100
                    }
                },
                {
                    "ConditionType": "MissingImportantFormKey",
                    "ConditionParameters": {
                        "ImportantFormKey": "Mail address",
                        "ImportantFormKeyAliases": ["Mail Address:","Mail address:","Mailing Add:","Mailing Addresses"]
                    }
                }
            ],
            "ConditionType": "ImportantFormKeyConfidenceCheck",
            "ConditionParameters": {
                "ImportantFormKey": "Phone Number",
                "ImportantFormKeyAliases": ["Phone number:","Phone No.:"],
                "KeyValueBlockConfidenceLessThan": 100,
                "WordBlockConfidenceLessThan": 100
            }
        },
        {
            "ConditionType": "ImportantFormKeyConfidenceCheck",
            "ConditionParameters": {
                "ImportantFormKey": "*",
                "KeyValueBlockConfidenceLessThan": 100,
                "WordBlockConfidenceLessThan": 100
            }
        },
        {
            "ConditionType": "ImportantFormKeyConfidenceCheck",
            "ConditionParameters": {
                "ImportantFormKey": "*",
                "KeyValueBlockConfidenceGreaterThan": 0,
                "WordBlockConfidenceGreaterThan": 0
            }
        }
    ]
})
```
Amazon Rekognition – Image moderation

The human loop activation conditions used here are tailored towards Amazon Rekognition content moderation; they are based on the confidence thresholds for the Suggestive and Female Swimwear Or Underwear moderation labels.

```python
import json

humanLoopActivationConditions = json.dumps(
    {
        "Conditions": [
            {
                "Or": [
                    {
                        "ConditionType": "ModerationLabelConfidenceCheck",
                        "ConditionParameters": {
                            "ModerationLabelName": "Suggestive",
                            "ConfidenceLessThan": 98
                        }
                    },
                    {
                        "ConditionType": "ModerationLabelConfidenceCheck",
                        "ConditionParameters": {
                            "ModerationLabelName": "Female Swimwear Or Underwear",
                            "ConfidenceGreaterThan": 98
                        }
                    }
                ]
            }
        ]
    }
)
```

Create a human review workflow

This section gives an example of the `create_flow_definition` AWS SDK for Python (Boto3) request using the resources created in the previous sections. For other language-specific SDKs, refer to the list in `CreateFlowDefinition`. Use the tabs in the following table to see the requests to create a human review workflow for Amazon Textract and Amazon Rekognition built-in integrations.

**Amazon Textract – Key-value pair extraction**

If you use the built-in integration with Amazon Textract, you must specify "AWS/Textract/AnalyzeDocument/Forms/V1" for "AwsManagedHumanLoopRequestSource" in `HumanLoopRequestSource`.

```python
response = client.create_flow_definition(
    FlowDefinitionName="human-review-workflow-name",
    HumanLoopRequestSource={
        "AwsManagedHumanLoopRequestSource": "AWS/Textract/AnalyzeDocument/Forms/V1"
    },
    HumanLoopActivationConfig={
        "HumanLoopActivationConditionsConfig": {
            "HumanLoopActivationConditions": humanLoopActivationConditions
        }
    }
)
```
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Amazon Rekognition – Image moderation

If you use the built-in integration with Amazon Rekognition, you must specify "AWS/Rekognition/DetectModerationLabels/Image/V3" for "AwsManagedHumanLoopRequestSource" in HumanLoopRequestSource.

response = client.create_flow_definition(
    FlowDefinitionName="human-review-workflow-name",
    HumanLoopRequestSource={
        "AwsManagedHumanLoopRequestSource": "AWS/Rekognition/DetectModerationLabels/Image/V3"
    },
    HumanLoopActivationConfig={
        "HumanLoopActivationConditionsConfig": {
            "humanLoopActivationConditions": humanLoopActivationConditions
        }
    },
    HumanLoopConfig={
        "workteamArn": workteamArn,
        "humanTaskUiArn": humanTaskUiArn,
        "taskTitle": "Image content moderation",
        "taskDescription": "Review the image and instructions. Complete the task",
        "taskCount": 1,
        "TaskExpirationBehavior": "EXPIRE_TASK",
        "TaskAvailabilityLifetimeInSeconds": 43200,
        "TaskTimeLimitInSeconds": 3600,
        "TaskKeywords": [
            "content moderation",
        ],
    },
    OutputConfig={
        "S3OutputPath": "s3://DOC-EXAMPLE-BUCKET/prefix/",
    },
    RoleArn="arn:aws:iam::<account-number>:role/<role-name>",
    Tags=[
        {
            "Key": "string",
            "Value": "string"
        }
    ]
)
Custom Integration

If you use a custom integration, exclude the following parameters: HumanLoopRequestSource, HumanLoopActivationConfig.

```python
response = client.create_flow_definition(
    FlowDefinitionName="human-review-workflow-name",
    HumanLoopConfig={
        "WorkteamArn": workteamArn,
        "HumanTaskUiArn": humanTaskUiArn,
        "TaskTitle": "Image content moderation",
        "TaskDescription": "Review the image and instructions. Complete the task",
        "TaskCount": 1,
        "TaskAvailabilityLifetimeInSeconds": 43200,
        "TaskTimeLimitInSeconds": 3600,
        "TaskKeywords": ["content moderation"],
    },
    OutputConfig={
        "S3OutputPath": "s3://DOC-EXAMPLE-BUCKET/prefix/",
    },
    RoleArn="arn:aws:iam::<account-number>:role/<role-name>",
    Tags=[
        {"Key": "string",
         "Value": "string"
        },
    ]
)
```

After you create a human review workflow, you can retrieve the flow definition ARN from the response:

```python
humanReviewWorkflowArn = response["FlowDefinitionArn"]
```

Create a Human Loop

The API operation you use to start a human loop depends on the Amazon A2I integration you use.

- If you use the Amazon Textract built-in integration, you use the `AnalyzeDocument` operation.
- If you use the Amazon Rekognition built-in integration, you use the `DetectModerationLabels` operation.
- If you use a custom integration, you use the `StartHumanLoop` operation.

Select your task type in the following table to see example requests for Amazon Textract and Amazon Rekognition using the AWS SDK for Python (Boto3).

Amazon Textract – Key-value pair extraction

The following example uses the AWS SDK for Python (Boto3) to call `analyze_document` in us-west-2. Replace the italicized red text with your resources. Include the `DataAttributes`
response = client.analyze_document(
    Document={"S3Object": {"Bucket": "AWSDOC-EXAMPLE-BUCKET", "Name": "document-name.pdf"},
                HumanLoopConfig={
            "HumanLoopName": "human-loop-name",
            "DataAttributes": {ContentClassifiers:
                                ["FreeOfPersonallyIdentifiableInformation"] | "FreeOfAdultContent")
                                }},
            FeatureTypes=["FORMS"]
)

Human loops are only created if Amazon Textract's confidence for document analysis task meets the activation conditions you specified in your human review workflow. You can check the response element to determine if a human loop has been created. To see everything included in this response, see HumanLoopActivationOutput.

if "HumanLoopArn" in analyzeDocumentResponse["HumanLoopActivationOutput"]:  
    # A human loop has been started!  
    print(f"A human loop has been started with ARN: {analyzeDocumentResponse["HumanLoopActivationOutput"]["HumanLoopArn"]}"

Amazon Rekognition – Image moderation

The following example uses the AWS SDK for Python (Boto3) to call detect_moderation_labels in us-west-2. Replace the italicized red text with your resources. Include the DataAttributes parameter if you are using the Amazon Mechanical Turk workforce. For more information, see the detect_moderation_labels documentation in the AWS SDK for Python (Boto) API Reference.

response = client.detect_moderation_labels(
    Image={"S3Object": {"Bucket": "AWSDOC-EXAMPLE-BUCKET", "Name": "image-name.png"},
            HumanLoopConfig={
            "HumanLoopName": "human-loop-name",
            "DataAttributes": {ContentClassifiers:
                                ["FreeOfPersonallyIdentifiableInformation"] | "FreeOfAdultContent")
                                }},
            )

Human loops are only created if Amazon Rekognition's confidence for an image moderation task meets the activation conditions you specified in your human review workflow. You can check the response element to determine if a human loop has been created. To see everything included in this response, see HumanLoopActivationOutput.

if "HumanLoopArn" in response["HumanLoopActivationOutput"]:  
    # A human loop has been started!  
    print(f"A human loop has been started with ARN: {response["HumanLoopActivationOutput"]["HumanLoopArn"]}

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Custom Integration

The following example uses the AWS SDK for Python (Boto3) to call `start_human_loop` in `us-west-2`. Replace the italicized red text with your resources. Include the `DataAttributes` parameter if you are using the Amazon Mechanical Turk workforce. For more information, see the `start_human_loop` documentation in the `AWS SDK for Python (Boto) API Reference`.

```python
response = client.start_human_loop(
    HumanLoopName= "human-loop-name",
    HumanLoopInput={"InputContent": inputContentJson},
    DataAttributes={"ContentClassifiers": ["FreeOfPersonallyIdentifiableInformation","FreeOfAdultContent"]}
)
```

This example stores input content in the variable `inputContentJson`. Assume that the input content contains two elements: a text blurb and sentiment (such as Positive, Negative, or Neutral), and it is formatted as follows:

```python
inputContent = {
    "initialValue": sentiment,
    "taskObject": blurb
}
```

The keys `initialValue` and `taskObject` must correspond to the keys used in the liquid elements of the worker task template. Refer to the custom template in `Create a Human Task UI (p. 3403)` to see an example.

To create `inputContentJson`, do the following:

```python
import json
inputContentJson = json.dumps(inputContent)
```

A human loop starts each time you call `start_human_loop`. To check the status of your human loop, use `describe_human_loop`:

```python
human_loop_info = a2i.describe_human_loop(HumanLoopName="human-loop-name")
print(f"HumanLoop Status: {resp["HumanLoopStatus"]}")
print(f"HumanLoop Output Destination: {resp["HumanLoopOutput"]}")
```

Use Cases and Examples Using Amazon A2I

You can use Amazon Augmented AI to incorporate a human review into your workflow for built-in task types, Amazon Textract and Amazon Rekognition, or your own custom tasks using a custom task type.

When you create a human review workflow using one of the built-in task types, you can specify conditions, such as confidence thresholds, that initiate a human review. The service (Amazon Rekognition or Amazon Textract) creates a human loop on your behalf when these conditions are met and supplies your input data directly to Amazon A2I to send to human reviewers. To learn more about the built-in task types, use the following:
• Use Amazon Augmented AI with Amazon Textract (p. 3413)
• Use Amazon Augmented AI with Amazon Rekognition (p. 3416)

When you use a custom task type, you create and start a human loop using the Amazon A2I Runtime API. Use the custom task type to incorporate a human review workflow with other AWS services or your own custom ML application.

• For more details, see Use Amazon Augmented AI with Custom Task Types (p. 3417)

The following table outlines a variety of Amazon A2I use cases that you can explore using SageMaker Jupyter Notebooks. To get started with a Jupyter Notebook, use the instructions in Use SageMaker Notebook Instance with Amazon A2I Jupyter Notebook (p. 3413). For more examples, see this GitHub repository.

<table>
<thead>
<tr>
<th>Use Case</th>
<th>Description</th>
<th>Task Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Use Amazon A2I with Amazon Textract</td>
<td>Have humans review single-page documents to review important form key-value pairs, or have Amazon Textract randomly sample and send documents from your dataset to humans for review.</td>
<td>Built-in</td>
</tr>
<tr>
<td>Use Amazon A2I with Amazon Rekognition</td>
<td>Have humans review unsafe images for explicit adult or violent content if Amazon Rekognition returns a low confidence score, or have Amazon Rekognition randomly sample and send images from your dataset to humans for review.</td>
<td>Built-in</td>
</tr>
<tr>
<td>Use Amazon A2I with Amazon Comprehend</td>
<td>Have humans review Amazon Comprehend inferences about text data such as sentiment analysis, text syntax, and entity detection.</td>
<td>Custom</td>
</tr>
<tr>
<td>Use Amazon A2I with Amazon Transcribe</td>
<td>Have humans review Amazon Transcribe transcriptions of video or audio files. Use the results of transcription human review loops to create a custom vocabulary and improve future transcriptions of similar video or audio content.</td>
<td>Custom</td>
</tr>
<tr>
<td>Use Amazon A2I with Amazon Translate</td>
<td>Have humans review low-confidence translations returned from Amazon Translate.</td>
<td>Custom</td>
</tr>
<tr>
<td>Use Amazon A2I to review real-time ML inferences</td>
<td>Use Amazon A2I to review real-time, low-confidence inferences made by a model deployed to a</td>
<td>Custom</td>
</tr>
</tbody>
</table>
Use Amazon A2I to review tabular data

<table>
<thead>
<tr>
<th>Use Case</th>
<th>Description</th>
<th>Task Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>SageMaker hosted endpoint and incrementally train your model using Amazon A2I output data.</td>
<td>Use Amazon A2I to integrate a human review loop into an ML application that uses tabular data.</td>
<td>Custom</td>
</tr>
</tbody>
</table>

### Use Amazon Augmented AI with Amazon Textract

Amazon Textract enables you to add document text detection and analysis to your applications. Amazon Augmented AI (Amazon A2I) directly integrates with Amazon Textract's `AnalyzeDocument` API operation. You can use `AnalyzeDocument` to analyze a document for relationships between detected items. When you add an Amazon A2I human review loop to a `AnalyzeDocument` request, Amazon A2I monitors the Amazon Textract results and sends a document to one or more human workers for review.

### Use Amazon Augmented AI with Amazon Rekognition

### Use Amazon Augmented AI with Custom Task Types

### Topics

- Use SageMaker Notebook Instance with Amazon A2I Jupyter Notebook (p. 3413)
- Use Amazon Augmented AI with Amazon Textract (p. 3413)
- Use Amazon Augmented AI with Amazon Rekognition (p. 3416)
- Use Amazon Augmented AI with Custom Task Types (p. 3417)

### Use SageMaker Notebook Instance with Amazon A2I Jupyter Notebook

For an end-to-end example that demonstrates how to integrate an Amazon A2I human review loop into a machine learning workflow, you can use a Jupyter Notebook from this GitHub Repository in a SageMaker notebook instance.

**To use an Amazon A2I custom task type sample notebook in an Amazon SageMaker notebook instance:**

1. If you do not have an active SageMaker notebook instance, create one by following the instructions in *Step 1: Create an Amazon SageMaker Notebook Instance* (p. 74).
2. When your notebook instance is active, choose **Open JupyterLab** to the right of the notebook instance's name. It may take a few moments for JupyterLab to load.
3. Choose the ![git clone](https://github.com/) icon to clone a GitHub repository into your workspace.
4. Enter the `amazon-a2i-sample-jupyter-notebooks` repository HTTPS URL.
5. Choose **Clone**.
6. Open the notebook that you would like to run.
7. Follow the instructions in the notebook to configure your human review workflow and human loop and run the cells.
8. To avoid incurring unnecessary charges, when you are done with the demo, stop and delete your notebook instance in addition to any Amazon S3 buckets, IAM roles, and CloudWatch Events resources created during the walkthrough.
review when the conditions specified in your flow definition are met. For example, if you want a human to review a specific key like Full name: and their associated input values, you can create an activation condition that starts a human review any time the Full name: key is detected or when the inference confidence for that key falls within a range that you specify.

The following image depicts the Amazon A2I built-in workflow with Amazon Textract. On the left, the resources that are required to create an Amazon Textract human review workflow are depicted: an Amazon S3 bucket, activation conditions, a worker task template, and a work team. These resources are used to create a human review workflow, or flow definition. An arrow points right to the next step in the workflow: using Amazon Textract to configure a human loop with the human review workflow. A second arrow points right from this step to the step in which activation conditions specified in the human review workflow are met. This initiates the creation of a human loop. On the right of the image, the human loop is depicted in three steps: 1) the worker UI and tools are generated and the task is made available to workers, 2) workers review input data, and finally, 3) results are saved in Amazon S3.

You can specify when Amazon Textract sends a task to a human worker for review when creating a human review workflow or flow definition by specifying activation conditions.

You can set the following activation conditions when using the Amazon Textract task type:

- Initiate a human review for specific form keys based on the form key confidence score.
- Initiate a human review when specific form keys are missing.
- Initiate human review for all form keys identified by Amazon Textract with confidence scores in a specified range.
- Randomly send a sample of forms to humans for review.

When your activation condition depends on form key confidence scores, you can use two types of prediction confidence to initiate human loops:

- **Identification confidence** – The confidence score for key-value pairs detected within a form.
- **Qualification confidence** – The confidence score for text contained within key and value in a form.

In the image in the following section, **Full Name: Jane Doe** is the key-value pair, **Full Name** is the key, and **Jane Doe** is the value.

You can set these activation conditions using the Amazon SageMaker console when you create a human review workflow, or by creating a JSON for human loop activation conditions and specifying this as input in the HumanLoopActivationConditions parameter of CreateFlowDefinition API operation.
learn how specify activation conditions in JSON format, see JSON Schema for Human Loop Activation Conditions in Amazon Augmented AI (p. 3425) and Use Human Loop Activation Conditions JSON Schema with Amazon Textract (p. 3427).

**Note**
When using Augmented AI with Amazon Textract, create Augmented AI resources in the same AWS Region you use to call AnalyzeDocument.

**Get Started: Integrate a Human Review into an Amazon Textract Analyze Document Job**

To integrate a human review into an Amazon Textract text detection and analysis job, you need to create a flow definition, and then use the Amazon Textract API to integrate that flow definition into your workflow. To learn how to create a flow definition using the SageMaker console or Augmented AI API, see the following topics:

- Create a Human Review Workflow (Console) (p. 3420)
- Create a Human Review Workflow (API) (p. 3422)

After you've created your flow definition, see Using Augmented AI with Amazon Textract to learn how to integrate your flow definition into your Amazon Textract task.

**End-to-End Example Using Amazon Textract and Amazon A2I**

For an end-to-end example that demonstrates how to use Amazon Textract with Amazon A2I using the console, see Tutorial: Get Started in the Amazon A2I Console (p. 3395).

To learn how to use the Amazon A2I API to create and start a human review, you can use Amazon Augmented AI (Amazon A2I) integration with Amazon Textract's Analyze Document [Example] in a SageMaker Notebook instance. To get started, see Use SageMaker Notebook Instance with Amazon A2I Jupyter Notebook (p. 3413).

**A2I Textract Worker Console Preview**

When they're assigned a review task in an Amazon Textract workflow, workers might see a user interface similar to the following:
You can customize this interface in the SageMaker console when you create your human review definition, or by creating and using a custom template. To learn more, see Create and Manage Worker Task Templates (p. 3446).

Use Amazon Augmented AI with Amazon Rekognition

Amazon Rekognition makes it easy to add image analysis to your applications. The Amazon Rekognition DetectModerationLabels API operation is directly integrated with Amazon A2I so that you can easily create a human loop to review unsafe images, such as explicit adult or violent content. You can use DetectModerationLabels to configure a human loop using a flow definition ARN. This enables Amazon A2I to analyze predictions made by Amazon Rekognition and send results to a human for review to ensure they meet the conditions set in your flow definition.

The following image depicts the Amazon A2I built-in workflow with Amazon Rekognition. On the left, the resources that are required to create an Amazon Rekognition human review workflow are depicted: and Amazon S3 bucket, activation conditions, a worker task template, and a work team. These resources are used to create a human review workflow, or flow definition. An arrow points right to the next step in the workflow: using Amazon Rekognition to configure a human loop with the human review workflow. A second arrow points right from this step to the step in which activation conditions specified in the human review workflow are met. This initiates the creation of a human loop. On the right of the image, the human loop is depicted in three steps: 1) the worker UI and tools are generated and the task is made available to workers, 2) workers review input data, and finally, 3) results are saved in Amazon S3.

You can set the following activation conditions when using the Amazon Rekognition task type:

- Initiate human review for labels identified by Amazon Rekognition based on the label confidence score.
- Randomly send a sample of images to humans for review.

You can set these activation conditions using the Amazon SageMaker console when you create a human review workflow, or by creating a JSON for human loop activation conditions and specifying this as input in the HumanLoopActivationConditions parameter of the CreateFlowDefinition API operation. To learn how specify activation conditions in JSON format, see JSON Schema for Human Loop Activation Conditions in Amazon Augmented AI (p. 3425) and Use Human Loop Activation Conditions JSON Schema with Amazon Rekognition (p. 3433).

Note
When using Augmented AI with Amazon Rekognition, create Augmented AI resources in the same AWS Region you use to call DetectModerationLabels.
Get Started: Integrate a Human Review into an Amazon Rekognition Image Moderation Job

To integrate a human review into an Amazon Rekognition, see the following topics:

- Create a Human Review Workflow (Console) (p. 3420)
- Create a Human Review Workflow (API) (p. 3422)

After you've created your flow definition, see Using Augmented AI with Amazon Rekognition to learn how to integrate your flow definition into your Amazon Rekognition task.

End-to-end Demo Using Amazon Rekognition and Amazon A2I

For an end-to-end example that demonstrates how to use Amazon Rekognition with Amazon A2I using the console, see Tutorial: Get Started in the Amazon A2I Console (p. 3395).

To learn how to use the Amazon A2I API to create and start a human review, you can use Amazon Augmented AI (Amazon A2I) integration with Amazon Rekognition [Example] in a SageMaker notebook instance. To get started, see Use SageMaker Notebook Instance with Amazon A2I Jupyter Notebook (p. 3413).

A2I Rekognition Worker Console Preview

When they're assigned a review task in an Amazon Rekognition workflow, workers might see a user interface similar to the following:

You can customize this interface in the SageMaker console when you create your human review definition, or by creating and using a custom template. To learn more, see Create and Manage Worker Task Templates (p. 3446).

Use Amazon Augmented AI with Custom Task Types

You can use Amazon Augmented AI (Amazon A2I) to incorporate a human review (human loop) into any machine learning workflow using the custom task type. This options gives you the most flexibility to customize the conditions under which your data objects are sent to humans for review, as well as the look and feel of your worker user interface.
When you use a custom task type, you create a custom human review workflow and specify the conditions under which a data object is sent for human review directly in your application.

The following image depicts the Amazon A2I custom workflow. A custom ML model is used to generate predictions. The client application filters these predictions using user-defined criteria and determines if a human review is required. If so, these predictions are sent to Amazon A2I for human review. Amazon A2I collects the results of human review in Amazon S3, which can access by the client application. If the filter determines that no human review is needed, predictions can be fed directly to the client application.

Use the procedures on this page to learn how to integrate Amazon A2I into any machine learning workflow using the custom task type.

Create a human loop using a flow definition, integrate it into your application, and monitor the results

1. Complete the Amazon A2I Prerequisites to Using Augmented AI (p. 3395). Note the following:
   - The path to the Amazon Simple Storage Service (Amazon S3) bucket or buckets where you store your input and output data.
   - The Amazon Resource Name (ARN) of an AWS Identity and Access Management (IAM) role with required permissions attached.
   - (Optional) The ARN of your private workforce, if you plan to use one.

2. Using HTML elements, create a custom worker template which Amazon A2I uses to generate your worker task UI. To learn how to create a custom template, see Create Custom Worker Task Templates (p. 3448).

3. Use the custom worker template from step 2 to generate a worker task template in the Amazon SageMaker console. To learn how, see Create a Worker Task Template (p. 3447).

In the next step, you create a flow definition:

- If you want to create a flow definition using the SageMaker API, note the ARN of this worker task template for the next step.
- If you are creating a flow definition using the console, your template automatically appears in Worker task template section when you choose Create human review workflow.

4. When creating your flow definition, provide the path to your S3 buckets, your IAM role ARN, and your worker template.

- To learn how to create a flow definition using the SageMaker CreateFlowDefinition API, see Create a Human Review Workflow (API) (p. 3422).
Create a Human Review Workflow

Use an Amazon Augmented AI (Amazon A2I) human review workflow, or flow definition, to specify the following:

- For the Amazon Textract and Amazon Rekognition built-in task types, the conditions under which your human loop is called
- The workforce to which your tasks are sent
- The set of instructions that your workforce receives, which is called a worker task template
- The configuration of your worker tasks, including the number of workers that receive a task and time limits to complete tasks
- Where your output data is stored

You can create a human review workflow in the SageMaker console or using the SageMaker CreateFlowDefinition operation. You can build a worker task template using the console for Amazon Textract and Amazon Rekognition task types while creating your flow definition.

Important

Human loop activation conditions, which initiate the human loop—for example, confidence thresholds—aren’t available for Amazon A2I custom task types. When using the console to create a flow definition for a custom task type, you can’t specify activation conditions. When using the Amazon A2I API to create a flow definition for a custom task type, you can’t set the HumanLoopActivationConditions attribute of the HumanLoopActivationConditionsConfig parameter. To control when human reviews are initiated, specify conditions under which StartHumanLoop is called in your custom application. In this case, every StartHumanLoop invocation results in a human review. For more information, see Use Amazon Augmented AI with Custom Task Types (p. 3417).

Prerequisites

To create a human review workflow definition, you must have completed the prerequisites described in Prerequisites to Using Augmented AI (p. 3395).
Create a Human Review Workflow (Console)

Use this procedure to create a Amazon Augmented AI (Amazon A2I) human review workflow using the SageMaker console. If you are new to Amazon A2I, we recommend that you create a private work team using people in your organization, and use this work team's ARN when creating your flow definition. To learn how to set up a private workforce and create a work team, see Create a Private Workforce (Amazon SageMaker Console) (p. 700). If you have already set up a private workforce, see Create a Work Team Using the SageMaker Console (p. 704) to learn how to add a work team to that workforce.

If you are using Amazon A2I with one of the built-in task types, you can create worker instructions using a default worker task template provided by Augmented AI while creating a human review workflow in the console. To see samples of the default templates provided by Augmented AI, see the built-in task types in Use Cases and Examples Using Amazon A2I (p. 3411).

To create flow definition (console)

2. In the navigation pane, under the Augmented AI section, choose Human review workflows and then choose Create human review workflow.
3. In Overview, do the following:
   a. For Name, enter a unique workflow name. The name must be lowercase, unique within the AWS Region in your account, and can have up to 63 characters. Valid characters include: a-z, 0-9, and - (hyphen).
   b. For S3 location for output, enter the S3 bucket where you want to store the human review results. The bucket must be located in the same AWS Region as the workflow.
   c. For IAM role, choose the role that has the required permissions. If you choose a built-in task type and want to preview your worker template in the console, provide a role with the type of policy described in Enable Worker Task Template Previews (p. 3470) attached.
4. For Task type, choose the task type that you want the human worker to perform.
5. If you chose the Amazon Rekognition or Amazon Textract task type, specify the conditions that invoke human review.
   - For Amazon Rekognition image moderation tasks, choose an inference confidence score threshold interval that initiates human review.
   - For Amazon Textract tasks, you can initiate a human review when specific form keys are missing or when form key detection confidence is low. You can also initiate a human review if, after evaluating all of the form keys in the text, confidence is lower than your required threshold for
any form key. Two variables specify your confidence thresholds: **Identification confidence** and **Qualification confidence**. To learn more about these variables, see Use Amazon Augmented AI with Amazon Textract (p. 3413).

- For both task types, you can randomly send a percentage of data objects (images or forms) and their labels to humans for review.

6. **Configure and specify your worker task template:**

   a. If you are using the Amazon Rekognition or Amazon Textract task type:

      - In the **Create template** section:

        - To create instructions for your workers using the Amazon A2I default template for Amazon Rekognition and Amazon Textract task types, choose **Build from a default template**.
        - If you choose **Build from a default template**, create your instructions under **Worker task design**:
          - Provide a **Template name** that is unique in the AWS Region you are in.
          - In the **Instructions** section, provide detailed instructions on how to complete your task. To help workers achieve greater accuracy, provide good and bad examples.
          - (Optional) In **Additional instructions**, provide your workers with additional information and instructions.

          For information on creating effective instructions, see Creating Good Worker Instructions (p. 3455).

        - To select a custom template that you've created, choose it from the **Template** menu and provide a **Task description** to briefly describe the task for your workers. To learn how to create a custom template, see Create a Worker Task Template (p. 3447).

   b. If you are using the custom task type:

      - In the **Worker task template** section, select your template from the list. All of the templates that you have created in the SageMaker console appear in this list. To learn how to create a template for custom task types, see Create and Manage Worker Task Templates (p. 3446).

7. **(Optional) Preview your worker template:**

   For Amazon Rekognition and Amazon Textract task types, you have the option to choose **See a sample worker task** to preview your worker task UI.

   If you are creating a flow definition for a custom task type, you can preview your worker task UI using the **RenderUiTemplate** operation. For more information, see Preview a Worker Task Template (p. 3455).

8. For **Workers**, choose a workforce type.

9. Choose **Create**.

**Next Steps**

After you've created a human review workflow, it appears in the console under **Human review workflows**. To see your flow definition's Amazon Resource Name (ARN) and configuration details, choose the workflow by selecting its name.

If you are using a built-in task type, you can use the flow definition ARN to start a human loop using that AWS service's API (for example, the Amazon Textract API). For custom task types, you can use the ARN to start a human loop using the Amazon Augmented AI Runtime API. To learn more about both options, see Create and Start a Human Loop (p. 3438).
Create a Human Review Workflow (API)

To create a flow definition using the SageMaker API, you use the CreateFlowDefinition operation. After you complete the Prerequisites to Using Augmented AI (p. 3395), use the following procedure to learn how to use this API operation.

For an overview of the CreateFlowDefinition operation, and details about each parameter, see CreateFlowDefinition.

To create a flow definition (API)

1. For FlowDefinitionName, enter a unique name. The name must be unique within the AWS Region in your account, and can have up to 63 characters. Valid characters include: a-z, 0-9, and - (hyphen).
2. For RoleArn, enter the ARN of the role that you configured to grant access to your data sources.
3. For HumanLoopConfig, enter information about the workers and what they should see. For information about each parameter in HumanLoopConfig, see HumanLoopConfig.
4. (Optional) If you are using a built-in task type, provide conditions that initiate a human loop in HumanLoopActivationConfig. To learn how to create the input required for the HumanLoopActivationConfig parameter, see JSON Schema for Human Loop Activation Conditions in Amazon Augmented AI (p. 3425). If you do not specify conditions here, when you provide a flow definition to the AWS service associated with a built-in task type (for example, Amazon Textract or Amazon Rekognition), that service sends every task to a human worker for review.

If you are using a custom task type, HumanLoopActivationConfig is disabled. To learn how to control when tasks are sent to human workers using a custom task type, see Use Amazon Augmented AI with Custom Task Types (p. 3417).

5. (Optional) If you are using a built-in task type, specify the integration source (for example, Amazon Rekognition or Amazon Textract) in the HumanLoopRequestSource parameter.
6. For OutputConfig, indicate where in Amazon Simple Storage Service (Amazon S3) to store the output of the human loop.
7. (Optional) Use Tags to enter key-value pairs to help you categorize and organize a flow definition. Each tag consists of a key and a value, both of which you define.

Amazon Textract – Key-value pair extraction

The following is an example of a request to create an Amazon Textract human review workflow (flow definition) using the AWS SDK for Python (Boto3). You must use 'AWS/Textract/AnalyzeDocument/Forms/V1' to create a Amazon Textract human loop. Only include PublicWorkforceTaskPrice if you are using the Mechanical Turk workforce.

```python
sagemaker_client = boto3.client('sagemaker', aws_region)
response = sagemaker_client.create_flow_definition(
    FlowDefinitionName='ExampleFlowDefinition',
    HumanLoopRequestSource={
        'AwsManagedHumanLoopRequestSource': 'AWS/Textract/AnalyzeDocument/Forms/V1'
    },
    HumanLoopActivationConfig={
        'HumanLoopActivationConditionsConfig': {
            'HumanLoopActivationConditions': '{...}'
        }
    },
    HumanLoopConfig={
```
Amazon Rekognition – Image moderation

The following is an example of a request to create an Amazon Rekognition human review workflow (flow definition) using the AWS SDK for Python (Boto3). You must use 'AWS/Rekognition/DetectModerationLabels/Image/V3' to create an Amazon Rekognition flow definition. Only include PublicWorkforceTaskPrice if you are using the Mechanical Turk workforce.

```python
sagemaker_client = boto3.client('sagemaker', aws_region)
response = sagemaker_client.create_flow_definition(
    FlowDefinitionName='ExampleFlowDefinition',
    HumanLoopRequestSource={
        'AwsManagedHumanLoopRequestSource': 'AWS/Rekognition/DetectModerationLabels/Image/V3'
    },
    HumanLoopActivationConfig={
        'HumanLoopActivationConditionsConfig': {
            'HumanLoopActivationConditions': ' [...]'
        }
    },
    HumanLoopConfig={
        'TaskTitle': 'Example task title',
        'TaskDescription': 'Example task description.',
        'TaskCount': 123,
        'TaskAvailabilityLifetimeInSeconds': 123,
        'TaskTimeLimitInSeconds': 123,
        'TaskKeywords': [
            'Keyword1', 'Keyword2'
        ],
        'PublicWorkforceTaskPrice': {
            'AmountInUsd': {
                'Dollars': 123,
                'Cents': 123,
                'TenthFractionsOfACent': 123
            }
        }
    },
    OutputConfig={
        'S3OutputPath': 's3://bucket/path/',
        'KmsKeyId': '1234abcd-12ab-34cd-56ef-1234567890ab'
    },
    RoleArn='arn:aws:iam::aws_account_number:role/role_name',
    Tags=[
        {
            'Key': 'KeyName',
            'Value': 'ValueName'
        }
    ]
)
```

Custom Workflow

The following is an example of a request to create a human review workflow (flow definition) for a custom integration. To create this type of human review workflow, omit HumanLoopRequestSource from the flow definition request. You only need to include PublicWorkforceTaskPrice if you are using the Mechanical Turk workforce.

```python
sagemaker_client = boto3.client('sagemaker', aws_region)
response = sagemaker_client.create_flow_definition(
    FlowDefinitionName='ExampleFlowDefinition',
    HumanLoopActivationConfig={
        'HumanLoopActivationConditionsConfig': {
            'HumanLoopActivationConditions': '{...}'
        }
    },
    HumanLoopConfig={
        'TaskTitle': 'Example task title',
        'TaskDescription': 'Example task description.',
        'TaskCount': 123,
        'TaskAvailabilityLifetimeInSeconds': 123,
        'TaskTimeLimitInSeconds': 123,
        'TaskKeywords': [
            'Keyword1', 'Keyword2'
        ],
        'PublicWorkforceTaskPrice': {
            'AmountInUsd': {
                'Dollars': 123,
                'Cents': 123,
                'TenthFractionsOfACent': 123
            }
        },
        'OutputConfig':{
            'S3OutputPath': 's3://bucket/path/',
            'KmsKeyId': '1234abcd-12ab-34cd-56ef-1234567890ab'
        },
        'RoleArn': 'arn:aws:iam::account_number:role/role_name',
        'Tags': [
            {
                'Key': 'KeyName',
                'Value': 'ValueName'
            }
        ]
    })
```

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Next Steps

The return value of a successful call of the CreateFlowDefinition API operation is a flow definition Amazon Resource Name (ARN).

If you are using a built-in task type, you can use the flow definition ARN to start a human loop using that AWS service's API (i.e. the Amazon Textract API). For custom task types, you can use the ARN to start a human loop using the Amazon Augmented AI Runtime API. To learn more about both of these options, see Create and Start a Human Loop (p. 3438).

JSON Schema for Human Loop Activation Conditions in Amazon Augmented AI

The HumanLoopActivationConditions is an input parameter of the CreateFlowDefinition API. This parameter is a JSON-formatted string. The JSON models the conditions under which a human loop is created when those conditions are evaluated against the response from an integrating AI service API (such as Rekognition.DetectModerationLabels or Textract.AnalyzeDocument). This response is referred to as an inference. For example, Amazon Rekognition sends an inference of a moderation label with an associated confidence score. In this example, the inference is the model's best estimate of the appropriate label for an image. For Amazon Textract, inference is made on the association between blocks of text (key-value pairs), such as the association between Name: and Sue in a form as well as content within a block of text, or word block, such as 'Name'.

The following is the schema for the JSON. At the top level, the HumanLoopActivationConditions has a JSON array, Conditions. Each member of this array is an independent condition that, if evaluated to true, results in Amazon A2I creating a human loop. Each such independent condition can be a simple condition or a complex condition. A simple condition has the following attributes:

- **ConditionType**: This attribute identifies the type of condition. Each AWS AI service API that integrates with Amazon A2I defines its own set of allowed ConditionTypes.
- **Rekognition DetectModerationLabels** – This API supports the ModerationLabelConfidenceCheck and Sampling ConditionType values.
- **Textract AnalyzeDocument** – This API supports the ImportantFormKeyConfidenceCheck, MissingImportantFormKey, and Sampling ConditionType values.
- **ConditionParameters** – This is a JSON object that parameterizes the condition. The set of allowed attributes of this object is dependent on the value of the ConditionType. Each ConditionType defines its own set of ConditionParameters.

A member of the Conditions array can model a complex condition. This is accomplished by logically connecting simple conditions using the And and Or logical operators and nesting the underlying simple conditions. Up to two levels of nesting are supported.

```json
{
    "$schema": "http://json-schema.org/draft-07/schema#",
    "definitions": {
        "Condition": {
            "type": "object",
            "properties": {
                "ConditionType": {
                    "type": "string"
                }
            }
        }
    }
}
```
"ConditionParameters": { "type": "object" },
"required": [ "ConditionType" ]},
"OrConditionArray": { "type": "object", "properties": { "Or": { "type": "array", "minItems": 2, "items": { "$ref": "#/definitions/ComplexCondition" } } } },
"AndConditionArray": { "type": "object", "properties": { "And": { "type": "array", "minItems": 2, "items": { "$ref": "#/definitions/ComplexCondition" } } } } },
"ComplexCondition": { "anyOf": [ { "$ref": "#/definitions/Condition" }, { "$ref": "#/definitions/OrConditionArray" }, { "$ref": "#/definitions/AndConditionArray" } ] } },
"type": "object",
"properties": { "Conditions": { "type": "array", "items": { "$ref": "#/definitions/ComplexCondition" } } } }

**Note**

Human loop activation conditions aren't available for human review workflows that are integrated with custom task types. The `HumanLoopActivationConditions` parameter is disabled for custom task types.

**Topics**
• **Use Human Loop Activation Conditions JSON Schema with Amazon Textract** (p. 3427)
• **Use Human Loop Activation Conditions JSON Schema with Amazon Rekognition** (p. 3433)

## Use Human Loop Activation Conditions JSON Schema with Amazon Textract

When used with Amazon A2I, the AnalyzeDocument operation supports the following inputs in the `ConditionType` parameter:

- **ImportantFormKeyConfidenceCheck** – Use this condition to create a human loop when inference confidence is within a specified range for document form keys and word blocks. A form key is any word in a document that is associated with an input. The input is called a value. Together, form keys and values are referred to as key-value pairs. A word block refers to the words that Amazon Textract recognizes inside of a detected block of text. To learn more about Amazon Textract document blocks, see [Documents and Block Objects](#) in the Amazon Textract Developer Guide.

- **MissingImportantFormKey** – Use this condition to create a human loop when Amazon Textract did not identify the key or its associated aliases within the document.

- **Sampling** – Use this condition to specify a percentage of forms to send to humans for review, regardless of inference confidence scores. Use this condition to do the following:
  - Audit your ML model by randomly sampling all forms analyzed by your model and sending a specified percentage to humans for review.
  - Using the `ImportantFormKeyConfidenceCheck` condition, randomly sample a percentage of the inferences that met the conditions specified in `ImportantFormKeyConfidenceCheck` to start a human loop and send only the specified percentage to humans for review.

**Note**

If you send the same request to AnalyzeDocument multiple times, the result of Sampling does not change for the inference of that input. For example, if you make an AnalyzeDocument request once, and Sampling doesn't initiate a human loop, subsequent requests to AnalyzeDocument with the same configuration do not initiate a human loop.

### ImportantFormKeyConfidenceCheck Inputs and Results

The `ImportantFormKeyConfidenceCheck` ConditionType supports the following ConditionParameters:

- **ImportantFormKey** – A string representing a key in a key-value pair detected by Amazon Textract that needs to be reviewed by human workers. If the value of this parameter is the special catch-all value (*), then all keys are considered to be matched to the condition. You can use this to model the case where any key-value pair satisfying certain confidence thresholds needs human review.

- **ImportantFormKeyAliases** – An array that represents alternate spellings or logical equivalents for the important form key.

- **KeyValueBlockConfidenceEquals**
- **KeyValueBlockConfidenceLessThan**
- **KeyValueBlockConfidenceLessThanEquals**
- **KeyValueBlockConfidenceGreaterThan**
- **KeyValueBlockConfidenceGreaterThanEquals**

- **WordBlockConfidenceEquals**
- **WordBlockConfidenceLessThan**
- **WordBlockConfidenceLessThanEquals**
• **WordBlockConfidenceGreaterThan**
• **WordBlockConfidenceGreaterThanEquals**

When you use the **ImportantFormKeyConfidenceCheck** ConditionType, Amazon A2I sends the key-value block and word block inferences of the key-value blocks and associated aliases that you specified in **ImportantFormKey** and **ImportantFormKeyAliases** for human review.

When creating a flow definition, if you use the default worker task template that is provided in the **Human review workflows** section of the Amazon SageMaker console, key-value and block inferences sent for human review by this activation condition are included in the worker UI. If you use a custom worker task template, you need to include the **{{ task.input.selectedAiServiceResponse.blocks }}** element to include initial-value input data (inferences) from Amazon Textract. For an example of a custom template that uses this input element, see **Custom Template Example for Amazon Textract** (p. 3449).

**MissingImportantFormKey** Inputs and Results

The **MissingImportantFormKey** ConditionType supports the following ConditionParameters:

• **ImportantFormKey** – A string representing a key in a key-value pair detected by Amazon Textract that needs to be reviewed by human workers.
• **ImportantFormKeyAliases** – An array that represents alternate spellings or logical equivalents for the important form key.

When you use the **MissingImportantFormKey** ConditionType, if the key in **ImportantFormKey** or aliases in **ImportantFormKeyAliases** are not included in the Amazon Textract inference, that form is sent to human for review and no predicted key-value pairs are included. For example, if Amazon Textract only identified **Address** and **Phone** in a form, but was missing the **ImportantFormKey Name** (in the **MissingImportantFormKey** condition type) that form would be sent to humans for review without any of the form keys detected (Address and Phone).

If you use the default worker task template that is provided in the SageMaker console, a task is created asking workers to identify the key in **ImportantFormKey** and associated value. If you use a custom worker task template, you need to include the **<task.input.humanLoopContext>** custom HTML element to configure this task.

**Sampling Inputs and Results**

The **Sampling** ConditionType supports the **RandomSamplingPercentage** ConditionParameters. The input for **RandomSamplingPercentage** must be a real number between 0.01 and 100. This number represents the percentage of data that qualifies for a human review and is sent to humans for review. If you use the **Sampling** condition without any other conditions, this number represents the percentage of all resulting inferences made by the **AnalyzeDocument** operation from a single request that is sent to humans for review.

If you specify the **Sampling** condition without any other condition type, all key-value and block inferences are sent to workers for review.

When creating a flow definition, if you use the default worker task template that is provided in the **Human review workflows** section of the SageMaker console, all key-value and block inferences sent for human review by this activation condition are included in the worker UI. If you use a custom worker task template, you need to include the **{{ task.input.selectedAiServiceResponse.blocks }}** element to include initial-value input data (inferences) from Amazon Textract. For an example of a custom template that uses this input element, see **Custom Template Example for Amazon Textract** (p. 3449).
Examples

While only one condition needs to evaluate to true to initiate a human loop, Amazon A2I evaluates all conditions for each object analyzed by Amazon Textract. The human reviewers are asked to review the important form keys for all the conditions that evaluated to true.

Example 1: Detect important form keys with confidence scores in a specified range that initiate a human loop

The following example shows a HumanLoopActivationConditions JSON that initiates a human loop if any one of the following three conditions is met:

- The Amazon Textract AnalyzeDocument API returns a key-value pair whose key is one of Employee Name, Name, or EmployeeName, with the confidence of the key-value block being less than 60 and the confidences of each of the word blocks making up the key and value being less than 85.
- The Amazon Textract AnalyzeDocument API returns a key-value pair whose key is one of Pay Date, PayDate, DateOfPay, or pay-date, with the confidence of the key-value block being less than 65 and the confidences of each of the word blocks making up the key and value being less than 85.
- The Amazon Textract AnalyzeDocument API returns a key-value pair whose key is one of Gross Pay, GrossPay, or GrossAmount, with the confidence of the key-value block being less than 60 and the confidences of each of the word blocks making up the key and value being less than 85.

```json
{
    "Conditions": [
    {
        "ConditionType": "ImportantFormKeyConfidenceCheck",
        "ConditionParameters": {
            "ImportantFormKey": "Employee Name",
            "ImportantFormKeyAliases": [
                "Name",
                "EmployeeName"
            ],
            "KeyValueBlockConfidenceLessThan": 60,
            "WordBlockConfidenceLessThan": 85
        }
    },
    {
        "ConditionType": "ImportantFormKeyConfidenceCheck",
        "ConditionParameters": {
            "ImportantFormKey": "Pay Date",
            "ImportantFormKeyAliases": [
                "PayDate",
                "DateOfPay",
                "pay-date"
            ],
            "KeyValueBlockConfidenceLessThan": 65,
            "WordBlockConfidenceLessThan": 85
        }
    },
    {
        "ConditionType": "ImportantFormKeyConfidenceCheck",
        "ConditionParameters": {
            "ImportantFormKey": "Gross Pay",
            "ImportantFormKeyAliases": [
                "GrossPay",
                "GrossAmount"
            ],
            "KeyValueBlockConfidenceLessThan": 60,
            "WordBlockConfidenceLessThan": 85
        }
    }
}
```
Example 2: Use `ImportantFormKeyConfidenceCheck`  
In the following example, if Amazon Textract detects a key-value pair whose confidence for the key-value block is less than 60 and is less than 90 for any underlying word blocks, it creates a human loop. The human reviewers are asked to review all the form key-value pairs that matched the confidence value comparisons.

```json
{
  "Conditions": [
    {
      "ConditionType": "ImportantFormKeyConfidenceCheck",
      "ConditionParameters": {
        "ImportantFormKey": "*",
        "KeyValueBlockConfidenceLessThan": 60,
        "WordBlockConfidenceLessThan": 90
      }
    }
  ]
}
```

Example 3: Use Sampling  
In the following example, 5% of inferences resulting from an Amazon Textract `AnalyzeDocument` request are sent to human workers for review. All detected key-value pairs returned by Amazon Textract are sent to workers for review.

```json
{
  "Conditions": [
    {
      "ConditionType": "Sampling",
      "ConditionParameters": {
        "RandomSamplingPercentage": 5
      }
    }
  ]
}
```

Example 4: Use `MissingImportantFormKey`  
In the following example, if Mailing Address or its alias, Mailing Address:, is missing from keys detected by Amazon Textract, a human review is initiated. When using the default worker task template, the worker UI asks workers to identify the key Mailing Address or Mailing Address: and its associated value.

```json
{
  "ConditionType": "MissingImportantFormKey",
  "ConditionParameters": {
    "ImportantFormKey": "Mailing Address",
    "ImportantFormKeyAliases": ["Mailing Address:"]
  }
}
```

Example 5: Use Sampling and `ImportantFormKeyConfidenceCheck` with the And operator  
In this example, 5% of key-value pairs detected by Amazon Textract whose key is one of Pay Date, PayDate, DateOfPay, or pay-date, with the confidence of the key-value block less than 65 and the confidences of each of the word blocks making up the key and value less than 85, are sent to workers for review.

```json
{
  "ConditionType": "Sampling and ImportantFormKeyConfidenceCheck with the And operator",
  "ConditionParameters": {
    "ConditionType": "ImportantFormKeyConfidenceCheck",
    "ConditionParameters": {
      "ImportantFormKey": "Pay Date",
      "KeyValueBlockConfidenceLessThan": 65,
      "WordBlockConfidenceLessThan": 85
    }
  }
}
```
Example 6: Use Sampling and ImportantFormKeyConfidenceCheck with the And operator

Use this example to configure your human review workflow to always send low confidence inferences of a specified key-value pair for human review and sample high confidence inference of a key-value pair at a specified rate.

In the following example, a human review is initiated in one of the following ways:

- Key-value pairs detected whose key is one of Pay Date, PayDate, DateOfPay, or pay-date, with key-value and word block confidences less than 60, are sent for human review. Only the Pay Date form key (and its aliases) and associated values are sent to workers to review.
- 5% of key-value pairs detected whose key is one of Pay Date, PayDate, DateOfPay, or pay-date, with key-value and word block confidences greater than 90, are sent for human review. Only the Pay Date form key (and its aliases) and associated values are sent to workers to review.

```json
{
  "Conditions": [
    {
      "And": [
        {
          "ConditionType": "Sampling",
          "ConditionParameters": {
            "RandomSamplingPercentage": 5
          }
        },
        {
          "ConditionType": "ImportantFormKeyConfidenceCheck",
          "ConditionParameters": {
            "ImportantFormKey": "Pay Date",
            "ImportantFormKeyAliases": [
              "PayDate",
              "DateOfPay",
              "pay-date"
            ],
            "KeyValueBlockConfidenceLessThan": 65,
            "WordBlockConfidenceLessThan": 85
          }
        }
      ]
    }
  ]
}
```
"And": [
  {
    "ConditionType": "Sampling",
    "ConditionParameters": {
      "RandomSamplingPercentage": 5
    }
  },
  {
    "ConditionType": "ImportantFormKeyConfidenceCheck",
    "ConditionParameters": {
      "ImportantFormKey": "Pay Date",
      "ImportantFormKeyAliases": [
        "PayDate",
        "DateOfPay",
        "pay-date"
      ],
      "KeyValueBlockConfidenceLessThan": 90,
      "WordBlockConfidenceGreaterThan": 90
    }
  }
]

Example 7: Use Sampling and ImportantFormKeyConfidenceCheck with the Or operator

In the following example, the Amazon Textract AnalyzeDocument operation returns a key-value pair whose key is one of Pay Date, PayDate, DateOfPay, or pay-date, with the confidence of the key-value block less than 65 and the confidences of each of the word blocks making up the key and value less than 85. Additionally, 5% of all other forms initiate a human loop. For each form randomly chosen, all key-value pairs detected for that form are sent to humans for review.

{
  "Conditions": [
    "Or": [
      {
        "ConditionType": "Sampling",
        "ConditionParameters": {
          "RandomSamplingPercentage": 5
        }
      },
      {
        "ConditionType": "ImportantFormKeyConfidenceCheck",
        "ConditionParameters": {
          "ImportantFormKey": "Pay Date",
          "ImportantFormKeyAliases": [
            "PayDate",
            "DateOfPay",
            "pay-date"
          ],
          "KeyValueBlockConfidenceLessThan": 65,
          "WordBlockConfidenceGreaterThan": 85
        }
      }
    ]
  ]
}
Use Human Loop Activation Conditions JSON Schema with Amazon Rekognition

When used with Amazon A2I, the Amazon Rekognition DetectModerationLabels operation supports the following inputs in the ConditionType parameters:

- **ModerationLabelConfidenceCheck** – Use this condition type to create a human loop when inference confidence is low for one or more specified labels.
- **Sampling** – Use this condition to specify a percentage of all inferences to send to humans for review. Use this condition to do the following:
  - Audit your ML model by randomly sampling all of your model's inferences and sending a specified percentage to humans for review.
  - Using the ModerationLabelConfidenceCheck condition, randomly sample a percentage of the inferences that met the conditions specified in ModerationLabelConfidenceCheck to start a human loop and send only the specified percentage to humans for review.

**Note**

If you send the same request to DetectModerationLabels multiple times, the result of Sampling does not change for the inference of that input. For example, if you make a DetectModerationLabels request once, and Sampling does not initiate a human loop, subsequent requests to DetectModerationLabels with the same configuration don't initiate a human loop.

When creating a flow definition, if you use the default worker task template that is provided in the Human review workflows section of the Amazon SageMaker console, inferences sent for human review by these activation conditions are included in the worker UI when a worker opens your task. If you use a custom worker task template, you need to include the `<task.input.selectedAiServiceResponse.blocks>` custom HTML element to access these inferences. For an example of a custom template that uses this HTML element, see Custom Template Example for Amazon Rekognition (p. 3451).

**ModerationLabelConfidenceCheck Inputs**

For the ModerationLabelConfidenceCheck ConditionType, the following ConditionParameters are supported:

- **ModerationLabelName** – The exact (case-sensitive) name of a ModerationLabel detected by the Amazon Rekognition DetectModerationLabels operation. You can specify the special catch-all value (*) to denote any moderation label.
- **ConfidenceEquals**
- **ConfidenceLessThan**
- **ConfidenceLessThanEquals**
- **ConfidenceGreaterThan**
- **ConfidenceGreaterThanEquals**

When you use the ModerationLabelConfidenceCheck ConditionType, Amazon A2I sends label inferences for the labels that you specified in ModerationLabelName for human review.

**Sampling Inputs**

The Sampling ConditionType supports the RandomSamplingPercentage ConditionParameters. The input for the RandomSamplingPercentage parameter should be real number between 0.01 and
100. This number represents the percentage of inferences that qualifies for a human review that are sent to humans for review. If you use the Sampling condition without any other conditions, this number represents the percentage of all inferences that result from a single DetectModerationLabel request that are sent to humans for review.

**Examples**

**Example 1: Use ModerationLabelConfidenceCheck with the And operator**

The following example of a HumanLoopActivationConditions condition initiates a human loop when one or more of the following conditions are met:

- Amazon Rekognition detects the Graphic Male Nudity moderation label with a confidence between 90 and 99.
- Amazon Rekognition detects the Graphic Female Nudity moderation label with a confidence between 80 and 99.

Note the use of the Or and And logical operators to model this logic.

Although only one of the two conditions under the Or operator needs to evaluate to true for a human loop to be created, Amazon Augmented AI evaluates all conditions. Human reviewers are asked to review the moderation labels for all the conditions that evaluated to true.

```json
{
  "Conditions": [[
    "Or": [[
      "And": [[
        "ConditionType": "ModerationLabelConfidenceCheck",
        "ConditionParameters": {
          "ModerationLabelName": "Graphic Male Nudity",
          "ConfidenceLessThanEquals": 99
        }
      ],
      [[
        "ConditionType": "ModerationLabelConfidenceCheck",
        "ConditionParameters": {
          "ModerationLabelName": "Graphic Female Nudity",
          "ConfidenceLessThanEquals": 99
        }
      ]]
    ],
    "And": [[
      "ConditionType": "ModerationLabelConfidenceCheck",
      "ConditionParameters": {
        "ModerationLabelName": "Graphic Female Nudity",
        "ConfidenceGreaterThanEquals": 80
      }
    ]]
  ]]
}
```
Example 2: Use ModerationLabelConfidenceCheck with the catch-all value (*)

In the following example, if any moderation label with a confidence greater than or equal to 75 is detected, a human loop is initiated. Human reviewers are asked to review all moderation labels with confidence scores greater than or equal to 75.

```json
{
    "Conditions": [
        {
            "ConditionType": "ModerationLabelConfidenceCheck",
            "ConditionParameters": {
                "ModerationLabelName": "*",
                "ConfidenceGreaterThanEquals": 75
            }
        }
    ]
}
```

Example 3: Use Sampling

In the following example, 5% of Amazon Rekognition inferences from a DetectModerationLabels request are sent to human workers. When using the default worker task template provided in the SageMaker console, all moderation labels returned by Amazon Rekognition are sent to workers for review.

```json
{
    "Conditions": [
        {
            "ConditionType": "Sampling",
            "ConditionParameters": {
                "RandomSamplingPercentage": 5
            }
        }
    ]
}
```

Example 4: Use Sampling and ModerationLabelConfidenceCheck with the And operator

In this example, 5% of Amazon Rekognition inferences of the Graphic Male Nudity moderation label with a confidence greater than 50 are sent workers for review. When using the default worker task template provided in the SageMaker console, only the inferences of the Graphic Male Nudity label are sent to workers for review.

```json
{
    "Conditions": [
        {
            "And": [
                {
                    "ConditionType": "Sampling",
                    "ConditionParameters": {
                        "RandomSamplingPercentage": 5
                    }
                },
                {
                    "ConditionType": "ModerationLabelConfidenceCheck",
                    "ConditionParameters": {
                        "ModerationLabelName": "Graphic Male Nudity",
                        "ConfidenceGreaterThan": 50
                    }
                }
            ]
        }
    ]
}
```
Example 5: Use Sampling and ModerationLabelConfidenceCheck with the And operator

Use this example to configure your human review workflow to always send low-confidence inferences of a specified label for human review and sample high-confidence inferences of a label at a specified rate.

In the following example, a human review is initiated in one of the following ways:

- Inferences for the Graphic Male Nudity moderation label the with confidence scores less than 60 are always sent for human review. Only the Graphic Male Nudity label is sent to workers to review.
- 5% of all inferences for the Graphic Male Nudity moderation label the with confidence scores greater than 90 are sent for human review. Only the Graphic Male Nudity label is sent to workers to review.

```json
{
  "Conditions": [
    {
      "Or": [
        {
          "ConditionType": "ModerationLabelConfidenceCheck",
          "ConditionParameters": {
            "ModerationLabelName": "Graphic Male Nudity",
            "ConfidenceLessThan": 60
          }
        },
        {
          "And": [
            {
              "ConditionType": "Sampling",
              "ConditionParameters": {
                "RandomSamplingPercentage": 5
              }
            },
            {
              "ConditionType": "ModerationLabelConfidenceCheck",
              "ConditionParameters": {
                "ModerationLabelName": "Graphic Male Nudity",
                "ConfidenceGreaterThan": 90
              }
            }
          ]
        }
      ],
    }
  ]
}
```

Example 6: Use Sampling and ModerationLabelConfidenceCheck with the Or operator

In the following example, a human loop is created if the Amazon Rekognition inference response contains the 'Graphic Male Nudity' label with inference confidence greater than 50. Additionally, 5% of all other inferences initiate a human loop.

```json
{
  "Conditions": [
    {
      "Or": [
        {
          "ConditionType": "ModerationLabelConfidenceCheck",
          "ConditionParameters": {
            "ModerationLabelName": "Graphic Male Nudity",
            "ConfidenceGreaterThan": 50
          }
        },
        {
          "ConditionType": "Sampling",
          "ConditionParameters": {
            "RandomSamplingPercentage": 5
          }
        }
      ]
    }
  ]
}
```
Delete a Human Review Workflow

When you delete a human review workflow or you delete your AWS account while a human loop is in process, your human review workflow status changes to Deleting. Amazon A2I automatically stops and deletes all associated human loops if workers have not started tasks created by those human loops. If human workers are already working on a task, that task continues to be available until it is completed or expires. As long as workers are still working on a task, your human review workflow's status is Deleting. If these tasks are completed, the results are stored in the Amazon S3 bucket specified in your flow definition.

Deleting a flow definition does not remove any worker answers from your S3 bucket. If the tasks are completed, but you deleted your AWS account, the results are stored in the Augmented AI service bucket for 30 days and then permanently deleted.

After all human loops have been deleted, the human review workflow is permanently deleted. When a human review workflow has been deleted, you can reuse its name to create a new human review workflow.

You might want to delete a human review workflow for any of the following reasons:

• You have sent data to a set of human reviewers and you want to delete all non-started human loops because you do not want those workers to work on those tasks any longer.
• The worker task template used to generate your worker UI does not render correctly or is not functioning as expected.

After you delete a human review workflow, the following changes occur:

• The human review workflow no longer appears on the Human review workflows page in the Augmented AI area of the Amazon SageMaker console.
• When you use the human review workflow name as input to the API operations DescribeFlowDefinition or DeleteFlowDefinition, Augmented AI returns a ResourceNotFoundException error.
• When you use ListFlowDefinitions, deleted human review workflows aren’t included in the results.
• When you use the human review workflow ARN as input to the Augmented AI Runtime API operation ListHumanLoops, Augmented AI returns a ResourceNotFoundException.
Delete a Flow Definition Using the Console or the SageMaker API

You can delete a human review workflow on the **Human review workflows** page in the Augmented AI area of the SageMaker console or by using the SageMaker API.

Flow definitions can only be deleted if their status is **Active**.

**Delete a human review workflow (console)**

1. Navigate to the Augmented AI console at [https://console.aws.amazon.com/a2i/](https://console.aws.amazon.com/a2i/).
2. In the navigation pane, under the **Augmented AI** section, choose **Human review workflows**.
3. Select the hyperlinked name of the human review workflow that you want to delete.
4. On the **Summary** page of your human review workflow, choose **Delete**.
5. In the dialog box asking you to confirm that you want to delete your human review workflow, choose **Delete**.

You're automatically redirected to the **Human review workflows** page. While your human review workflow is being deleted, the status **Deleting** appears in the status column for that workflow. After it's deleted, it doesn't appear in the list of workflows on this page.

**Delete a human review workflow (API)**

You can delete a human review workflow (flow definition) using the SageMaker **DeleteFlowDefinition** API operation. This API operation is supported through the **AWS CLI** and a **variety of language specific SDKs**. The following table shows example requests using SDK for Python (Boto3) and the AWS CLI to delete the human review workflow, **example-flow-definition**.

**AWS SDK for Python (Boto3)**

The following request example uses the SDK for Python (Boto3) to delete the human review workflow. For more information, see **delete_flow_definition** in the [AWS SDK for Python (Boto) API Reference](https://boto3.amazonaws.com/v1/documentation/api/latest/reference/services/sagemaker.html#SageMaker.Client.delete_flow_definition).

```python
import boto3

sagemaker_client = boto3.client('sagemaker')
response = sagemaker_client.delete_flow_definition(FlowDefinitionName='example-flow-definition')
```

**AWS CLI**

The following request example uses the AWS CLI to delete the human review workflow. For more information, see **delete-flow-definition** in the [AWS CLI Command Reference](https://awscli.amazonaws.com/v2/documentation/api/latest/reference/sagemaker/delete-flow-definition.html).

```
$ aws sagemaker delete-flow-definition --flow-definition-name 'example-flow-definition'
```

If the action is successful, Augmented AI sends back an HTTP 200 response with an empty HTTP body.

**Create and Start a Human Loop**

A **human loop** starts your human review workflow and sends data review tasks to human workers. When you use one of the Amazon A2I built-in task types, the corresponding AWS service creates and
starts a human loop on your behalf when the conditions specified in your flow definition are met. If no conditions are specified in your flow definition, a human loop is created for each object. When using Amazon A2I for a custom task, a human loop starts when your application calls \texttt{StartHumanLoop}.

Use the following instructions to configure a human loop with Amazon Rekognition or Amazon Textract built-in task types and custom task types.

**Prerequisites**

To create and start a human loop, you must attach the \texttt{AmazonAugmentedAIFullAccess} policy to the AWS Identity and Access Management (IAM) user or role that configures or starts the human loop. This is the identity that you use to configure the human loop using \texttt{HumanLoopConfig} for built-in task types. For custom task types, this is the identity that you use to call \texttt{StartHumanLoop}.

Additionally, when using a built-in task type, your IAM user or role must have permission to invoke API operations of the AWS service associated with your task type. For example, if you are using Amazon Rekognition with Augmented AI, you must attach permissions required to call \texttt{DetectModerationLabels}. For examples of identity-based policies you can use to grant these permissions, see \textit{Amazon Rekognition Identity-Based Policy Examples} and \textit{Amazon Textract Identity-Based Policy Examples}. You can also use the more general policy \texttt{AmazonAugmentedAIIntegratedAPIAccess} to grant these permissions. For more information, see \textit{Create an IAM User With Permissions to Invoke Amazon A2I, Amazon Textract, and Amazon Rekognition API Operations} (p. 3469).

To create and start a human loop, you need a flow definition ARN. To learn how to create a flow definition (or human review workflow), see \textit{Create a Human Review Workflow} (p. 3419).

**Important**

Amazon A2I requires all S3 buckets that contain human loop input image data to have a CORS policy attached. To learn more about this change, see \textit{CORS Permission Requirement} (p. 3467).

**Create and Start a Human Loop for a Built-in Task Type**

To start a human loop using a built-in task type, use the corresponding service's API to provide your input data and to configure the human loop. For Amazon Textract, you use the \texttt{AnalyzeDocument} API operation. For Amazon Rekognition, you use the \texttt{DetectModerationLabels} API operation. You can use the AWS CLI or a language-specific SDK to create requests using these API operations.

**Important**

When you create a human loop using a built-in task type, you can use \texttt{DataAttributes} to specify a set of \texttt{ContentClassifiers} related to the input provided to the \texttt{StartHumanLoop} operation. Use content classifiers to declare that your content is free of personally identifiable information or adult content.

To use Amazon Mechanical Turk, ensure your data is free of personally identifiable information, including protected health information under HIPAA. Include the \texttt{FreeOfPersonallyIdentifiableInformation} content classifier. If you do not use this content classifier, SageMaker does not send your task to Mechanical Turk. If your data is free of adult content, also include the \texttt{'FreeOfAdultContent'} classifier. If you do not use these content classifiers, SageMaker may restrict the Mechanical Turk workers that can view your task.

After you start your ML job using your built-in task type's AWS service API, Amazon A2I monitors the inference results of that service. For example, when running a job with Amazon Rekognition, Amazon A2I checks the inference confidence score for each image and compares it to the confidence thresholds specified in your flow definition. If the conditions to start a human review task are satisfied, or if you didn't specify conditions in your flow definition, a human review task is sent to workers.
Create an Amazon Textract Human Loop

Amazon A2I integrates with Amazon Textract so that you can configure and start a human loop using the Amazon Textract API. To send a document file to Amazon Textract for document analysis, you use the Amazon Textract AnalyzeDocument API operation. To add a human loop to this document analysis job, you must configure the parameter HumanLoopConfig.

When you configure your human loop, the flow definition you specify in FlowDefinitionArn of HumanLoopConfig must be located in the same AWS Region as the bucket identified in Bucket of the Document parameter.

The following table shows examples of how to use this operation with the AWS CLI and AWS SDK for Python (Boto3).

**AWS SDK for Python (Boto3)**

The following request example uses the SDK for Python (Boto3). For more information, see analyze_document in the AWS SDK for Python (Boto) API Reference.

```python
import boto3
textract = boto3.client('textract', aws_region)

response = textract.analyze_document(
    Document={'S3Object': {'Bucket': bucket_name, 'Name': document_name}},
    FeatureTypes=['TABLES', "FORMS"],
    HumanLoopConfig={
        'FlowDefinitionArn': 'arn:aws:sagemaker:',
        aws_region': aws_account_number:
flows-definition/flow_def_name',
        'HumanLoopName': human_loop_name',
        'DataAttributes': {'ContentClassifiers':
            ['FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent']}
    } )
```

**AWS CLI**

The following request example uses the AWS CLI. For more information, see analyze-document in the AWS CLI Command Reference.

```bash
$ aws textract analyze-document \
    --document '"S3Object":{"Bucket":"bucket_name","Name":"document_name"}}' \
    --human-loop-config
    HumanLoopName="human_loop_name",FlowDefinitionArn="arn:aws:sagemaker:',
    aws-region:aws_account_number:flow-definition/flow_def_name",DataAttributes={"ContentClassifiers=["FreeOfPersonallyIdentifiableInformation", "FreeOfAdultContent"]}" \
    --feature-types ['"TABLES", "FORMS"]'
```

```bash
$ aws textract analyze-document \
    --document '"S3Object":{"Bucket":"bucket_name","Name":"document_name"}}' \
    --human-loop-config
    '{"HumanLoopName":"human_loop_name","FlowDefinitionArn":arn:aws:sagemaker:',
    aws-region:aws_account_number:flow-definition/flow_def_name","DataAttributes": ["ContentClassifiers":
        ["FreeOfPersonallyIdentifiableInformation","FreeOfAdultContent"]],"FeatureTypes": ['"TABLES", "FORMS"]'
```
After you run AnalyzeDocument with a human loop configured, Amazon A2I monitors the results from AnalyzeDocument and checks it against the flow definition’s activation conditions. If the Amazon Textract inference confidence score for one or more key-value pairs meets the conditions for review, Amazon A2I starts a human review loop and includes the HumanLoopActivationOutput object in the AnalyzeDocument response.

Create an Amazon Rekognition Human Loop

Amazon A2I integrates with Amazon Rekognition so that you can configure and start a human loop using the Amazon Rekognition API. To send images to Amazon Rekognition for content moderation, you use the Amazon Rekognition DetectModerationLabels API operation. To configure a human loop, set the HumanLoopConfig parameter when you configure DetectModerationLabels.

When you configure your human loop, the flow definition you specify in FlowDefinitionArn of HumanLoopConfig must be located in the same AWS Region as the S3 bucket identified in Bucket of the Image parameter.

The following table shows examples of how to use this operation with the AWS CLI and AWS SDK for Python (Boto3).

AWS SDK for Python (Boto3)

The following request example uses the SDK for Python (Boto3). For more information, see detect_moderation_labels in the AWS SDK for Python (Boto) API Reference.

```
import boto3
rekognition = boto3.client("rekognition", aws_region)
response = rekognition.detect_moderation_labels( \
  Image={'S3Object': {'Bucket': bucket_name, 'Name': image_name}}, \
  HumanLoopConfig={ \
    'HumanLoopName': human_loop_name, \
    'FlowDefinitionArn': \
    "arn:aws:sagemaker:aws_region:aws_account_number:flow-definition/flow_def_name" \
    'DataAttributes': {'ContentClassifiers': ['FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent']} 
  })
```

AWS CLI

The following request example uses the AWS CLI. For more information, see detect-moderation-labels in the AWS CLI Command Reference.

```
$ aws rekognition detect-moderation-labels \
  --image "S3Object={Bucket='bucket_name',Name='image_name'}" \
  --human-loop-config HumanLoopName="human_loop_name",FlowDefinitionArn="arn:aws:sagemaker:aws_region:aws_account_number:flow-definition/flow_def_name",DataAttributes='{"ContentClassifiers=['FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent']"'
```

```
$ aws rekognition detect-moderation-labels \
  --image "S3Object={Bucket='bucket_name',Name='image_name'}" \
  --human-loop-config "{"HumanLoopName": "human_loop_name", "FlowDefinitionArn": "arn:aws:sagemaker:aws_region:aws_account_number:flow-definition/flow_def_name", "DataAttributes": {"ContentClassifiers": ["FreeOfPersonallyIdentifiableInformation", "FreeOfAdultContent"]}}"
```
After you run DetectModerationLabels with a human loop configured, Amazon A2I monitors the results from DetectModerationLabels and checks it against the flow definition's activation conditions. If the Amazon Rekognition inference confidence score for an image meets the conditions for review, Amazon A2I starts a human review loop and includes the response element HumanLoopActivationOutput in the DetectModerationLabels response.

Create and Start a Human Loop for a Custom Task Type

To configure a human loop for a custom human review task, use the StartHumanLoop operation within your application. This section provides an example of a human loop request using the AWS SDK for Python (Boto3) and the AWS Command Line Interface (AWS CLI). For documentation on other language-specific SDKs that support StartHumanLoop, use the See Also section of StartHumanLoop in the Amazon Augmented AI Runtime API documentation. Refer to Use Cases and Examples Using Amazon A2I (p. 3411) to see examples that demonstrate how to use Amazon A2I with a custom task type.

Prerequisites

To complete this procedure, you need:

- Input data formatted as a string representation of a JSON-formatted file
- The Amazon Resource Name (ARN) of your flow definition

To configure the human loop

1. For DataAttributes, specify a set of ContentClassifiers related to the input provided to the StartHumanLoop operation. Use content classifiers to declare that your content is free of personally identifiable information or adult content.

   To use Amazon Mechanical Turk, ensure your data is free of personally identifiable information, including protected health information under HIPAA, and include the FreeOfPersonallyIdentifiableInformation content classifier. If you do not use this content classifier, SageMaker does not send your task to Mechanical Turk. If your data is free of adult content, also include the 'FreeOfAdultContent' classifier. If you do not use these content classifiers, SageMaker may restrict the Mechanical Turk workers that can view your task.

2. For FlowDefinitionArn, enter the Amazon Resource Name (ARN) of your flow definition.

3. For HumanLoopInput, enter your input data as a string representation of a JSON-formatted file. Structure your input data and custom worker task template so that your input data is properly displayed to human workers when you start your human loop. See Preview a Worker Task Template (p. 3455) to learn how to preview your custom worker task template.

4. For HumanLoopName, enter a name for the human loop. The name must be unique within the Region in your account and can have up to 63 characters. Valid characters are a-z, 0-9, and - (hyphen).

To start a human loop

- To start a human loop, submit a request similar to the following examples using your preferred language-specific SDK.

AWS SDK for Python (Boto3)

The following request example uses the SDK for Python (Boto3). For more information, see Boto 3 Augmented AI Runtime in the AWS SDK for Python (Boto) API Reference.
import boto3

a2i_runtime_client = boto3.client('sagemaker-a2i-runtime')

response = a2i_runtime_client.start_human_loop(
    HumanLoopName='human_loop_name',
    HumanLoopInput={
        'InputContent': '{"InputContent": "{\"prompt\":\"What is the answer?\"}\"}
    },
    DataAttributes={
        'ContentClassifiers': [
            'FreeOfPersonallyIdentifiableInformation', 'FreeOfAdultContent',
        ]
    }
)

AWS CLI

The following request example uses the AWS CLI. For more information, see start-human-loop in the AWS CLI Command Reference.

```
$ aws sagemaker-a2i-runtime start-human-loop
    --flow-definition-arn 'arn:aws:sagemaker:aws-region:xyz:flow-definition/flow_def_name' \ 
    --human-loop-name 'human_loop_name' \ 
    --human-loop-input '{"InputContent": "{\"prompt\":\"What is the answer?\"}\"}' \ 
    --data-attributes ContentClassifiers='FreeOfPersonallyIdentifiableInformation', "FreeOfAdultContent"
```

When you successfully start a human loop by invoking StartHumanLoop directly, the response includes a HumanLoopARN and a HumanLoopActivationResults object which is set to NULL. You can use this the human loop name to monitor and manage your human loop.

**Next Steps:**

After starting a human loop, you can manage and monitor it with the Amazon Augmented AI Runtime API and Amazon CloudWatch Events. To learn more, see Monitor and Manage Your Human Loop (p. 3456).

**Delete a Human Loop**

When you delete a human loop, the status changes to Deleting. When the human loop is deleted, the associated human review task is no longer available to workers. You might want to delete a human loop in one of the following circumstances:

- The worker task template used to generate your worker user interface does not render correctly or is not functioning as expected.
- A single data object was accidentally sent to workers multiple times.
- You no longer need a data object reviewed by a human.

If the status of a human loop is InProgress, you must stop the human loop before deleting it. When you stop a human loop, the status changes to Stopping while it is being stopped. When the status changes to Stopped, you can delete the human loop.
If human workers are already working on a task when you stop the associated human loop, that task continues to be available until it is completed or expires. As long as workers are still working on a task, your human loop's status is Stopping. If these tasks are completed, the results are stored in the Amazon S3 bucket URI specified in your human review workflow. If the worker leaves the task without submitting work, it is stopped and the worker can't return to the task. If no worker has started working on the task, it is stopped immediately.

If you delete the AWS account used to create the human loop, it is stopped and deleted automatically.

**Human Loop Data Retention and Deletion**

When a human worker completes a human review task, the results are stored in the Amazon S3 output bucket you specified in the human review workflow used to create the human loop. Deleting or stopping a human loop does not remove any worker answers from your S3 bucket.

Additionally, Amazon A2I temporarily stores human loop input and output data internally for the following reasons:

- If you configure your human loops so that a single data object is sent to multiple workers for review, Amazon A2I does not write output data to your S3 bucket until all workers have completed the review task. Amazon A2I stores partial answers—answers from individual workers—internally so that it can write full results to your S3 bucket.
- If you report a low-quality human review result, Amazon A2I can investigate and respond to your issue.
- If you lose access to or delete the output S3 bucket specified in the human review workflow used to create a human loop, and the task has already been sent to one or more workers, Amazon A2I needs a place to temporarily store human review results.

Amazon A2I deletes this data internally 30 days after a human loop's status changes to one of the following: Deleted, Stopped, or Completed. In other words, data is deleted 30 days after the human loop has been completed, stopped, or deleted. Additionally, this data is deleted after 30 days if you close the AWS account used to create associated human loops.

**Stop and Delete a Flow Definition Using the Console or the Amazon A2I API**

You can stop and delete a human loop in the Augmented AI console or by using the SageMaker API. When the human loop has been deleted, the status changes to Deleted.

**Delete a human loop (console)**

1. Navigate to the Augmented AI console at https://console.aws.amazon.com/a2i/.
2. In the navigation pane, under the Augmented AI section, choose Human review workflows.
3. Choose the hyperlinked name of the human review workflow you used to create the human loop you want to delete.
4. In the Human loops section at the bottom of the page, select the human loop you want to stop and delete.
5. If the human loop status is Completed, Stopped, or Failed, select Delete.

   If the human loop Status is InProgress, select Stop. When the status changes to Stopped, select Delete.
Delete a human loop (API)

1. Check the status of your human loop using the Augmented AI Runtime API operation `DescribeHumanLoop`. See examples using this operation in the following table.

AWS SDK for Python (Boto3)

The following example uses the SDK for Python (Boto3) to describe the human loop named `example-human-loop`. For more information, see `describe_human_loop` in the AWS SDK for Python (Boto) API Reference.

```python
import boto3
a2i_runtime_client = boto3.client('sagemaker-a2i-runtime')
response = a2i_runtime_client.describe_human_loop(HumanLoopName='example-human-loop')
human_loop_status = response['HumanLoopStatus']
print(f'example-human-loop status is: {human_loop_status}')
```

AWS CLI

The following example uses the AWS CLI to describe the human loop named `example-human-loop`. For more information, see `describe-human-loop` in the AWS CLI Command Reference.

```bash
$ aws sagemaker-a2i-runtime describe-human-loop --human-loop-name 'example-human-loop'
```

2. If the flow definition status is Completed, Stopped, or Failed, delete the flow definition using the Augmented AI Runtime API operation `DeleteHumanLoop`.

AWS SDK for Python (Boto3)

The following example uses the SDK for Python (Boto3) to delete the human loop named `example-human-loop`. For more information, see `delete_human_loop` in the AWS SDK for Python (Boto) API Reference.

```python
import boto3
a2i_runtime_client = boto3.client('sagemaker-a2i-runtime')
response = a2i_runtime_client.delete_human_loop(HumanLoopName='example-human-loop')
```

AWS CLI

The following example uses the AWS CLI to delete the human loop named `example-human-loop`. For more information, see `delete-human-loop` in the AWS CLI Command Reference.

```bash
$ aws sagemaker-a2i-runtime delete-human-loop --human-loop-name 'example-human-loop'
```

If the human loop status is InProgress, stop the human loop using `StopHumanLoop` and then use `DeleteHumanLoop` to delete it.

AWS SDK for Python (Boto3)

The following example uses the SDK for Python (Boto3) to describe the human loop named `example-human-loop`. For more information, see `stop_human_loop` in the AWS SDK for Python (Boto) API Reference.

```python
import boto3
a2i_runtime_client = boto3.client('sagemaker-a2i-runtime')
response = a2i_runtime_client.stop_human_loop(HumanLoopName='example-human-loop')
```
**Create and Manage Worker Task Templates**

You can create a task user interface for your workers by creating a *worker task template*. A worker task template is an HTML file that is used to display your input data and instructions to help workers complete your task.

For Amazon Rekognition or Amazon Textract task types, you can customize a pre-made worker task template using a graphical user interface (GUI) and avoid interacting with HTML code. For this option, use the instructions in [Create a Human Review Workflow (Console) (p. 3420)](p.3420) to create a human review workflow and customize your worker task template in the Amazon SageMaker console. Once you create a template using these instructions, it appears on the worker task templates page of the Augmented AI console.

If you are creating a human review workflow for a custom task type, you must create a *custom worker task template* using HTML code. For more information, see [Create Custom Worker Task Templates (p. 3448)](p.3448).

If you create your template using HTML, you must use this template to generate an Amazon A2I human task UI Amazon Resource Name (ARN) in the Amazon A2I console. This ARN has the following format: arn:aws:sagemaker:<aws-region>:<aws-account-number>:human-task-ui/<template-name>. This ARN is associated with a worker task template resource that you can use in one or more human review workflows (flow definitions).

Generate a human task UI ARN using a worker task template by following the instructions found in [Create a Worker Task Template (p. 3447)](p.3447) or by using the CreateHumanTaskUi API operation.

**Topics**
- Create and Delete Worker Task Templates (p. 3446)
- Create Custom Worker Task Templates (p. 3448)
- Creating Good Worker Instructions (p. 3455)

---

**Create and Delete Worker Task Templates**

You can use a worker template to customize the interface and instructions that your workers see when working on your tasks. Use the instructions on this page to create a worker task template in the Augmented AI area of the Amazon SageMaker console. A starter template is provided for Amazon Textract and Amazon Rekognition tasks. To learn how to customize your template using HTML crowd elements, see [Create Custom Worker Task Templates (p. 3448)](p.3448).

When you create a worker template in the worker task templates page of the Augmented AI area of the SageMaker console, a worker task template ARN is generated. Use this ARN as the input to
Create and Delete Worker Task Templates

HumanTaskUiArn when you create a flow definition using the API operation `CreateFlowDefinition`. You can choose this template when creating a human review workflow on the human review workflows page of the console.

If you are creating a worker task template resource for an Amazon Textract or Amazon Rekognition task type, you can preview the worker UI that is generated from your template on the worker task templates console page. You must attach the policy described in Enable Worker Task Template Previews (p. 3470) to the IAM role that you use to preview the template.

Create a Worker Task Template

You can create a worker task template using the SageMaker console and using the SageMaker API operation `CreateHumanTaskUi`.

Create a worker task template (console)

1. Open the Amazon A2I console at https://console.aws.amazon.com/a2i/.
2. Under Amazon Augmented AI in the left navigation pane, choose Worker task templates.
3. Choose Create template.
4. In Template name, enter a unique name.
5. (Optional) Enter an IAM role that grants Amazon A2I the permissions necessary to call services on your behalf.
6. In Template type, choose a template type from the dropdown list. If you are creating a template for a Textract-form extraction or Rekognition-image moderation task, choose the appropriate option.
7. Enter your custom template elements as follows:
   - If you selected the Amazon Textract or Amazon Rekognition task template, the Template editor autopopulates with a default template that you can customize.
   - If you are using a custom template, enter your predefined template in the editor.
8. (Optional) To complete this step, you must provide an IAM role ARN with permission to read Amazon S3 objects that get rendered on your user interface in Step 5.

You can only preview your template if you are creating templates for Amazon Textract or Amazon Rekognition.

Choose See preview to preview the interface and instructions that workers see. This is an interactive preview. After you complete the sample task and choose Submit, you see the resulting output from the task that you just performed.

If you are creating a worker task template for a custom task type, you can preview your worker task UI using `RenderUiTemplate`. For more information, see Preview a Worker Task Template (p. 3455).

9. When you're satisfied with your template, choose Create.

After you've created your template, you can select that template when you create a human review workflow in the console. Your template also appears in the Amazon Augmented AI section of the SageMaker console under Worker task templates. Choose your template to view its ARN. Use this ARN when using the `CreateFlowDefinition` API operation.

Create a worker task template using a worker task template (API)

To generate a worker task template using the SageMaker API operation `CreateHumanTaskUi`, specify a name for your UI in `HumanTaskUiName` and input your HTML template in Content under UiTemplate. Find documentation on language-specific SDKs that support this API operation in the See Also section of the `CreateHumanTaskUi`.
Delete a Worker Task Template

Once you have created a worker task template, you can delete it using the SageMaker console or the SageMaker API operation `DeleteHumanTaskUi`.

When you delete a worker task template, you are not able to use human review workflows (flow definitions) created using that template to start human loops. Any human loops that have already been created using the worker task template that you delete continue to be processed until completion and are not impacted.

Delete a worker task template (console)

1. Open the Amazon A2I console at `https://console.aws.amazon.com/a2i/`.
2. Under Amazon Augmented AI in the left navigation pane, choose `Worker task templates`.
3. Select the template that you want to delete.
4. Select `Delete`.
5. A modal appears to confirm your choice. Select `Delete`.

Delete a worker task template (API)

To delete a worker task template using the SageMaker API operation `DeleteHumanTaskUi`, specify a name of your UI in `HumanTaskUiName`.

Create Custom Worker Task Templates

*Crowd HTML Elements* are web components that provide a number of task widgets and design elements that you can tailor to the question you want to ask. You can use these crowd elements to create a custom worker template and integrate it with an Amazon Augmented AI (Amazon A2I) human review workflow to customize the worker console and instructions.

For a list of all HTML crowd elements available to Amazon A2I users, see `Crowd HTML Elements Reference` (p. 720). For examples of templates, see the AWS GitHub repository, which contains over 60 sample custom task templates.

Develop Templates Locally

When in the console to test how your template processes incoming data, you can test the look and feel of your template's HTML and custom elements in your browser by adding the following code to the top of your HTML file.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
```

This loads the necessary code to render the custom HTML elements. Use this code if you want to develop your template's look and feel in your preferred editor instead of in the console.

This code won't parse your variables. You might want to replace them with sample content while developing locally.

Use External Assets

Amazon Augmented AI custom templates enable you to embed external scripts and style sheets. For example, the following header embeds a `text/css` style sheet name `stylesheet` located at `https://www.example.com/my-enhancement-styles.css` into the custom template.
Example

```html
<script src="https://www.example.com/my-enhancement-script.js"></script>
<link rel="stylesheet" type="text/css" href="https://www.example.com/my-enhancement-styles.css">
```

If you encounter errors, ensure that your originating server is sending the correct MIME type and encoding headers with the assets.

For example, the MIME and encoding type for remote scripts is `application/javascript;CHARSET=UTF-8`.

The MIME and encoding type for remote stylesheets is `text/css;CHARSET=UTF-8`.

### Track Your Variables

When building a custom template, you must add variables to it to represent the pieces of data that might change from task to task, or worker to worker. If you're starting with one of the sample templates, you need to make sure you're aware of the variables it already uses.

For example, for a custom template that integrates an Augmented AI human review loop with a Amazon Textract text review task, `{{ task.input.selectedAiServiceResponse.blocks }}` is used for initial-value input data. For Amazon Augmented AI (Amazon A2I) integration with Amazon Rekognition, `{{ task.input.selectedAiServiceResponse.moderationLabels }}` is used. For a custom task type, you need to determine the input parameter for your task type.

Use `{{ task.input.customInputValuesForStartHumanLoop }}` where you specify `customInputValuesForStartHumanLoop`.

### Custom Template Example for Amazon Textract

All custom templates begin and end with the `<crowd-form> </crowd-form>` elements. Like standard HTML `<form>` elements, all of your form code should go between these elements.

For an Amazon Textract document analysis task, use the `<crowd-textract-analyze-document>` element. It uses the following attributes:

- `src` – Specifies the URL of the image file to be annotated.
- `initialValue` – Sets initial values for attributes found in the worker UI.
- `blockTypes (required)` – Determines the kind of analysis that the workers can do. Only `KEY_VALUE_SET` is currently supported.
- `keys (required)` – Specifies new keys and the associated text value that the worker can add.
- `no-key-edit (required)` – Prevents the workers from editing the keys of annotations passed through `initialValue`.
- `no-geometry-edit` – Prevents workers from editing the polygons of annotations passed through `initialValue`.

For children of the `<crowd-textract-analyze-document>` element, you must have two Regions. You can use arbitrary HTML and CSS elements in these Regions.

- `<full-instructions>` – Instructions that are available from the View full instructions link in the tool. You can leave this blank, but we recommend that you provide complete instructions to get better results.
- `<short-instructions>` – A brief description of the task that appears in the tool's sidebar. You can leave this blank, but we recommend that you provide complete instructions to get better results.
An Amazon Textract template would look similar to the following.

**Example**

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
{% capture s3_uri %}http://s3.amazonaws.com/{{ task.input.aiServiceRequest.document.s3Object.bucket }}/{{ task.input.aiServiceRequest.document.s3Object.name }}{% endcapture %}

<crowd-form>
  <crowd-textract-analyze-document
    src="{{ s3_uri | grant_read_access }}"
    initial-value="{{ task.input.selectedAiServiceResponse.blocks }}"
    header="Review the key-value pairs listed on the right and correct them if they don't match the following document."
    no-key-edit
    no-geometry-edit
    keys="{{ task.input.humanLoopContext.importantFormKeys }}"
    block-types="'KEY_VALUE_SET'"
  >
    <short-instructions header="Instructions">
      <style>
        .instructions {
          white-space: pre-wrap;
        }
        .instructionsImage {
          display: inline-block;
          max-width: 100%;
        }
      </style>
      <p class='instructions'>Choose a key-value block to highlight the corresponding key-value pair in the document.

      If it is a valid key-value pair, review the content for the value. If the content is incorrect, correct it.
      The text of the value is incorrect, correct it.
      <img class='instructionsImage' src="https://example-site/correct-value-text.png" />
      A wrong value is identified, correct it.
      <img class='instructionsImage' src="https://example-site/correct-value.png" />
      If it is not a valid key-value relationship, choose No.
      <img class='instructionsImage' src="https://example-site/not-a-key-value-pair.png" />
      If you can't find the key in the document, choose Key not found.
      <img class='instructionsImage' src="https://example-site/key-is-not-found.png" />
      If the content of a field is empty, choose Value is blank.
      <img class='instructionsImage' src="https://example-site/value-is-blank.png" />
      <b>Examples</b>
      Key and value are often displayed next to or below each other.
      Key and value displayed in one line.
      <img class='instructionsImage' src="https://example-site/sample-key-value-pair-1.png" />
      Key and value displayed in two lines.
      <img class='instructionsImage' src="https://example-site/sample-key-value-pair-2.png" />
      If the content of the value has multiple lines, enter all the text without a line break. Include all value text even if it extends beyond the highlight box.
      <img class='instructionsImage' src="https://assets.crowd.aws/images/a2i-console/multiple-lines.png" /></p>
    </short-instructions>
  </crowd-textract-analyze-document>
</crowd-form>
```
Custom Template Example for Amazon Rekognition

All custom templates begin and end with the `<crowd-form>` elements. Like standard HTML `<form>` elements, all of your form code should go between these elements. For an Amazon Rekognition custom task template, use the `<crowd-rekognition-detect-moderation-labels>` element. This element supports the following attributes:

- **categories** – An array of strings or an array of objects where each object has a name field.
  - If the categories come in as objects, the following applies:
    - The displayed categories are the value of the name field.
    - The returned answer contains the full objects of any selected categories.
  - If the categories come in as strings, the following applies:
    - The returned answer is an array of all the strings that were selected.

- **exclusion-category** – By setting this attribute, you create a button underneath the categories in the UI. When a user selects the button, all categories are deselected and disabled. If the worker selects the button again, you re-enable users to choose categories. If the worker submits the task by selecting Submit after you select the button, that task returns an empty array.

For children of the `<crowd-rekognition-detect-moderation-labels>` element, you must have two Regions.

- **full-instructions** – Instructions that are available from the View full instructions link in the tool. You can leave this blank, but we recommend that you provide complete instructions to get better results.
- **short-instructions** – Brief description of the task that appears in the tool's sidebar. You can leave this blank, but we recommend that you provide complete instructions to get better results.

A template using these elements would look similar to the following.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
{% capture s3_uri %}http://s3.amazonaws.com/
{{ task.input.aiServiceRequest.image.s3Object.bucket }}/
{{ task.input.aiServiceRequest.image.s3Object.name }}{% endcapture %}

<crowd-form>
  <crowd-rekognition-detect-moderation-labels
categories='[
    {% for label in task.input.selectedAiServiceResponse.moderationLabels %}
      { name: "{{ label.name }}",
        parentName: "{{ label.parentName }}",
      },
    {% endfor %}
  ]' src="{{ s3_uri | grant_read_access }}"
header="Review the image and choose all applicable categories."
  >
  <short-instructions header="Instructions">
    <style>
      .instructions {
        white-space: pre-wrap;
      }
    </style>
  </short-instructions>
</crowd-form>
```
Create Custom Worker Task Templates

Review the image and choose all applicable categories. If no categories apply, choose None.

- **Nudity**
  Visuals depicting nude male or female person or persons

- **Graphic Male Nudity**
  Visuals depicting full frontal male nudity, often close ups

- **Graphic Female Nudity**
  Visuals depicting full frontal female nudity, often close ups

- **Sexual Activity**
  Visuals depicting various types of explicit sexual activities and pornography

- **Illustrated Nudity or Sexual Activity**
  Visuals depicting animated or drawn sexual activity, nudity, or pornography

- **Adult Toys**
  Visuals depicting adult toys, often in a marketing context

- **Female Swimwear or Underwear**
  Visuals depicting female person wearing only swimwear or underwear

- **Male Swimwear Or Underwear**
  Visuals depicting male person wearing only swimwear or underwear

- **Partial Nudity**
  Visuals depicting covered up nudity, for example using hands or pose

- **Revealing Clothes**
  Visuals depicting revealing clothes and poses, such as deep cut dresses

- **Graphic Violence or Gore**
  Visuals depicting prominent blood or bloody injuries

- **Physical Violence**
  Visuals depicting violent physical assault, such as kicking or punching

- **Weapon Violence**
  Visuals depicting violence using weapons like firearms or blades, such as shooting

- **Weapons**
  Visuals depicting weapons like firearms and blades

- **Self Injury**
  Visuals depicting self-inflicted cutting on the body, typically in distinctive patterns using sharp objects

- **Emaciated Bodies**
  Visuals depicting extremely malnourished human bodies

- **Corpses**
  Visuals depicting human dead bodies

- **Hanging**
  Visuals depicting death by hanging
Add Automation with Liquid

The custom template system uses Liquid for automation. Liquid is an open-source inline markup language. For more information and documentation, see the Liquid homepage.

In Liquid, the text between single curly braces and percent symbols is an instruction or tag that performs an operation like control flow or iteration. Text between double curly braces is a variable or object that outputs its value. The following list includes two types of liquid tags that you may find useful to automate template input data processing. If you select one of the following tag-types, you are redirected to the Liquid documentation.

- Control flow: Includes programming logic operators like if/else, unless, and case/when.
- Iteration: Enables you to run blocks of code repeatedly using statements like for loops.

For example, the following code example demonstrates how you can use the Liquid for tag to create a for loop. This example loops through the moderationLabels returned from Amazon Rekognition and displays the moderationLabels attributes name and parentName for workers to review:

```liquid
{# for label in task.input.selectedAiServiceResponse.moderationLabels %}
    { name: &quot;{{ label.name }}&quot;, parentName: &quot;{{ label.parentName }}&quot; },
{# endfor %}
```

Use Variable Filters

In addition to the standard Liquid filters and actions, Amazon Augmented AI (Amazon A2I) offers additional filters. You apply filters by placing a pipe (|) character after the variable name, and then specifying a filter name. To chain filters, use the following format.

**Example**

```
{{ <content> | <filter> | <filter> }}
```

Autoescape and Explicit Escape

By default, inputs are HTML-escaped to prevent confusion between your variable text and HTML. You can explicitly add the escape filter to make it more obvious to someone reading the source of your template that escaping is being done.

escape_once

escape_once ensures that if you've already escaped your code, it doesn't get re-escaped again. For example, it ensures that &amp; doesn't become &amp;amp;.

skip_autoescape

skip_autoescape is useful when your content is meant to be used as HTML. For example, you might have a few paragraphs of text and some images in the full instructions for a bounding box.

**Note**

Use skip_autoescape sparingly. As a best practice for templates, avoid passing in functional code or markup with skip_autoescape unless you are absolutely sure that you have strict control over what's being passed. If you're passing user input, you could be opening your workers up to a cross-site scripting attack.
to_json

to_json encodes data that you provide to JavaScript Object Notation (JSON). If you provide an object, it serializes it.

grant_read_access

grant_read_access takes an Amazon Simple Storage Service (Amazon S3) URI and encodes it into an HTTPS URL with a short-lived access token for that resource. This makes it possible to display photo, audio, or video objects stored in S3 buckets that are not otherwise publicly accessible to workers.

Example Example of the to_json and grant_read_access filters

Input

| auto-escape: | {{ "Have you read 'James & the Giant Peach'?" }} |
| explicit escape: | {{ "Have you read 'James & the Giant Peach'?" | escape }} |
| explicit escape_once: | {{ "Have you read 'James & the Giant Peach'?" | escape_once }} |
| skip_autoescape: | {{ "Have you read 'James & the Giant Peach'?" | skip_autoescape }} |
| to_json: | {{ jsObject | to_json }} |
| grant_read_access: | {{ "s3://examplebucket/myphoto.png" | grant_read_access }} |

Example

Output

| auto-escape: | Have you read 'James & the Giant Peach'? |
| explicit escape: | Have you read 'James & the Giant Peach'? |
| explicit escape_once: | Have you read 'James & the Giant Peach'? |
| skip_autoescape: | Have you read 'James & the Giant Peach'? |
| to_json: | { "point_number": 8, "coords": [ 59, 76 ] } |
| grant_read_access: | https://s3.amazonaws.com/examplebucket/myphoto.png?access token and other params> |

Example Example of an automated classification template.

To automate this simple text classification sample, include the Liquid tag {{ task.input.source }}. This example uses the crowd-classifier (p. 734) element.

```html
<script src="https://assets.crowd.aws/crowd-html-elements.js"></script>
<crowd-form>
  <crowd-classifier
    name="tweetFeeling"
    categories="["positive", "negative", "neutral", "cannot determine"]"
    header="Which term best describes this tweet?"
  >
    <classification-target>
      {{ task.input.source }}
    </classification-target>

    <full-instructions header="Analyzing a sentiment">
      Try to determine the feeling the author of the tweet is trying to express.
      If none seems to match, choose "other."
    </full-instructions>

    <short-instructions>
      Pick the term that best describes the sentiment of the tweet.
    </short-instructions>
```
Preview a Worker Task Template

To preview a custom worker task template, use the SageMaker RenderUiTemplate operation. You can use the RenderUiTemplate operation with the AWS CLI or your preferred AWS SDK. For documentation on the supported language specific SDKs for this API operation, see the See Also section of the RenderUiTemplate.

Prerequisites

To preview your worker task template, the AWS Identity and Access Management (IAM) role Amazon Resource Name (ARN), or RoleArn, that you use must have permission to access to the S3 objects that are used by the template. To learn how to configure your role or user see Enable Worker Task Template Previews (p. 3470).

To preview your worker task template using the RenderUiTemplate operation:

1. Provide a RoleArn of the role with required policies attached to preview your custom template.
2. In the Input parameter of Task, provide a JSON object that contains values for the variables defined in the template. These are the variables that are substituted for the task.input source variable. For example, if you define a task.input.text variable in your template, you can supply the variable in the JSON object as text: sample text.
3. In the Content parameter of UiTemplate, insert your template.

Once you've configured RenderUiTemplate, use your preferred SDK or the AWS CLI to submit a request to render your template. If your request was successful, the response includes RenderedContent, a Liquid template that renders the HTML for the worker UI.

Important
To preview your template, you need an IAM role with permissions to read Amazon S3 objects that get rendered on your user interface. For a sample policy that you can attach to your IAM role to grant these permissions, see Enable Worker Task Template Previews (p. 3470).

Creating Good Worker Instructions

Creating good instructions for your human review jobs improves your worker's accuracy in completing their task. You can modify the default instructions that are provided in the console when creating a human review workflow, or you can use the console to create a custom worker template and include your instructions in this template. The instructions are shown to the worker on the UI page where they complete their labeling task.

Create Good Worker Instructions

There are three kinds of instructions in the Amazon Augmented AI console:

- **Task Description** – The description should provide a succinct explanation of the task.
- **Instructions** – These instructions are shown on the same webpage where workers complete a task. These instructions should provide an easy reference to show the worker the correct way to complete the task.
- **Additional Instructions** – These instructions are shown in a dialog box that appears when a worker chooses View full instructions. We recommend that you provide detailed instructions for completing the task, and include several examples showing edge cases and other difficult situations for labeling objects.
Add Example Images to Your Instructions

Images provide useful examples for your workers. To add a publicly accessible image to your instructions, do the following:

1. Place the cursor where the image should go in the instructions editor.
2. Choose the image icon in the editor toolbar.
3. Enter the URL of your image.

If your instruction image is in an S3 bucket that isn't publicly accessible, do the following:

- For the image URL, enter: `{{ 'https://s3.amazonaws.com/your-bucket-name/image-file-name' | grant_read_access }}`.

This renders the image URL with a short-lived, one-time access code that's appended so the worker's browser can display it. A broken image icon is displayed in the instructions editor, but previewing the tool displays the image in the rendered preview. See `grant_read_access` (p. 3454) for more information about the `grant_read_access` element.

Monitor and Manage Your Human Loop

Once you've started a human review loop, you can check the results of tasks sent to the loop and manage it using the Amazon Augmented AI Runtime API. Additionally, Amazon A2I integrates with Amazon EventBridge (also known as Amazon CloudWatch Events) to alert you when a human review loop status changes to Completed, Failed, or Stopped. This event delivery is guaranteed at least once, which means all events created when human loops finish are successfully delivered to EventBridge.

Use the procedures below to learn how to use the Amazon A2I Runtime API to monitor and manage your human loops. See `Use Amazon CloudWatch Events in Amazon Augmented AI` (p. 3471) to learn how Amazon A2I integrates with Amazon EventBridge.

**To check your output data:**

1. Check the results of your human loop by calling the `DescribeHumanLoop` operation. The result of this API operation contains information about the reason for and outcome of the loop activation.
2. Check the output data from your human loop in Amazon Simple Storage Service (Amazon S3). In the path to the data, `YYYY/MM/DD/hh/mm/ss` represents the human loop creation date with year (YYYY), month (MM), and day (DD), and the creation time with hour (hh), minute (mm), and second (ss).

   s3://customer-output-bucket-specified-in-flow-definition/flow-definition-name/YYYY/MM/DD/hh/mm/ss/human-loop-name/output.json

You can integrate this structure with AWS Glue or Amazon Athena to partition and analyze your output data. For more information, see `Managing Partitions for ETL Output in AWS Glue`.

To learn more about Amazon A2I output data format, see `Amazon A2I Output Data` (p. 3457).

**To stop and delete your human loop:**

1. Once a human loop has been started, you can stop your human loop by calling the `StopHumanLoop` operation using the `HumanLoopName`. If a human loop was successfully stopped, the server sends back an HTTP 200 response.
To delete a human loop for which the status equals Failed, Completed, or Stopped, use the `DeleteHumanLoop` operation.

**To list human loops:**

1. You can list all active human loops by calling the `ListHumanLoops` operation. You can filter human loops by the creation date of the loop using the `CreationTimeAfter` and `CreateTimeBefore` parameters.
2. If successful, `ListHumanLoops` returns `HumanLoopSummaries` and `NextToken` objects in the response element. `HumanLoopSummaries` contains information about a single human loop. For example, it lists a loop's status and, if applicable, its failure reason.

   Use the string returned in `NextToken` as an input in a subsequent call to `ListHumanLoops` to see the next page of human loops.

**Amazon A2I Output Data**

When your machine learning workflow sends Amazon A2I a data object, a human loop is created and human reviewers receive a task to review that data object. The output data from each human review task is stored in the Amazon Simple Storage Service (Amazon S3) output bucket you specify in your human review workflow. In the path to the data, `YYYY/MM/DD/hh/mm/ss` represents the human loop creation date with year (YYYY), month (MM), and day (DD), and the creation time with hour (hh), minute (mm), and second (ss).

![s3://customer-output-bucket-specified-in-flow-definition/flow-definition-name/YYYY/MM/DD/hh/mm/ss/human-loop-name/output.json](image-url)

The content of your output data depends on the type of task type (built-in or custom) and the type of workforce you use. Your output data always includes the response from the human worker. Additionally, output data may include metadata about the human loop, the human reviewer (worker), and the data object.

Use the following sections to learn more about Amazon A2I output data format for different task types and workforces.

**Output Data From Built-In Task Types**

Amazon A2I built-in task types include Amazon Textract and Amazon Rekognition. In addition to human responses, the output data from one of these tasks includes details about the reason the human loop was created and information about the integrated service used to create the human loop. Use the following table to learn more about the output data schema for all built-in task types. The value for each of these parameters depends on the service you use with Amazon A2I. Refer to the second table in this section for more information about these service-specific values.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value Type</th>
<th>Example Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>awsManagedHumanLoopRequestSource</code></td>
<td>String</td>
<td><code>AWS/Rekognition/DetectModerationLabels/Image/V3</code> or <code>AWS/Textract/AnalyzeDocument/Forms/V1</code></td>
<td>The API operation and associated AWS services that requested that Amazon A2I create the human loop. This is the API operation you use to configure your human loop.</td>
</tr>
<tr>
<td>Parameter</td>
<td>Value Type</td>
<td>Example Values</td>
<td>Description</td>
</tr>
<tr>
<td>---------------</td>
<td>-------------------</td>
<td>--------------------------------------------------------------------------------</td>
<td>------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>flowDefinitionArn</td>
<td>String</td>
<td><code>arn:aws:sagemaker:us-west-2:111122233333:flow-definition/flow-definition-name</code></td>
<td>The Amazon Resource Number (ARN) of the human review workflow (flow definition) used to create the human loop.</td>
</tr>
<tr>
<td>humanAnswers</td>
<td>List of JSON objects</td>
<td>```</td>
<td>A list of JSON objects that contain worker responses in answerContent. For human loop output data produced from Amazon Rekognition DetectModerationLabel review tasks, this parameter only contains positive responses. For example, if workers select <em>No content</em>, this response is not included.</td>
</tr>
<tr>
<td>humanLoopName</td>
<td>String</td>
<td>'human-loop-name'</td>
<td>The name of the human loop.</td>
</tr>
<tr>
<td>inputContent</td>
<td>JSON object</td>
<td>```</td>
<td>The input content the AWS service sent to Amazon A2I when it requested a human loop be created.</td>
</tr>
</tbody>
</table>

```json
{
   "aiServiceRequest": {...},
   "aiServiceResponse": {...},
   "humanTaskActivationConditionResults": {...},
   "selectedAiServiceResponse": {...}
}  ```
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value Type</th>
<th>Example Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>aiServiceRequest</td>
<td>JSON object</td>
<td>{</td>
<td>The original request sent to the AWS service integrated with Amazon A2I. For example, if you use Amazon Rekognition with Amazon A2I, this includes the request made through the API operation <code>DetectModerationLabels</code>. For Amazon Textract integrations, this includes the request made through <code>AnalyzeDocument</code>.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>or</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>{</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>&quot;image&quot;: {...},</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>&quot;humanLoopConfig&quot;: {...}</td>
<td></td>
</tr>
<tr>
<td>aiServiceResponse</td>
<td>JSON object</td>
<td>{</td>
<td>The full response from the AWS service. This is the data that is used to determine if a human review is required. This object may contain metadata about the data object that is not shared with human reviewers.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>or</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>{</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>&quot;blocks&quot;: [...],</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>&quot;documentMetadata&quot;: {}</td>
<td></td>
</tr>
<tr>
<td>selectedAiServiceResponse</td>
<td>JSON object</td>
<td>{</td>
<td>The subset of the aiServiceResponse that matches the activation conditions in <code>ActivationConditions</code>. All data objects listed in aiServiceResponse are listed in selectedAiServiceResponse when inferences are randomly sampled, or all inferences initiated activation conditions.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>or</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>{</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>&quot;blocks&quot;: [...],</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>&quot;documentMetadata&quot;: {}</td>
<td></td>
</tr>
</tbody>
</table>
Select a tab on the following table to learn about the task type–specific parameters and see an example output-data code block for each of the built-in task types.

### Amazon Textract Task Type Output Data

When you use the Amazon Textract built-in integration, you see `'AWS/Textract/AnalyzeDocument/Forms/V1'` as the value for `awsManagedHumanLoopRequestSource` in your output data.

The `answerContent` parameter contains a Block object that includes human responses for all blocks sent to Amazon A2I.

The `aiServiceResponse` parameter also includes a Block object with Amazon Textract's response to the original request sent using to `AnalyzeDocument`.

To learn more about the parameters you see in the block object, refer to `Block` in the Amazon Textract Developer Guide.

The following is an example of the output data from an Amazon A2I human review of Amazon Textract document analysis inferences.

```json
{
  "awsManagedHumanLoopRequestSource": "AWS/Textract/AnalyzeDocument/Forms/V1",
  "humanAnswers": [
    {
      "answerContent": {
        "AWS/Textract/AnalyzeDocument/Forms/V1": {
          "blocks": [...]
        }
      },
      "submissionTime": "2020-09-28T19:17:59.880Z",
```
"workerId": "111122223333",
"workerMetadata": {
  "identityData": {
    "identityProviderType": "Cognito",
    "sub": "c6aa8eb7-9944-42e9-a6b9-111122223333"
  }
},
"humanLoopName": "human-loop-name",
"inputContent": {
  "aiServiceRequest": {
    "document": {
      "s3Object": {
        "bucket": "DOC-EXAMPLE-BUCKET1",
        "name": "document-demo.jpg"
      }
    },
    "featureTypes": [
      "TABLES",
      "FORMS"
    ],
    "humanLoopConfig": {
      "dataAttributes": {
        "contentClassifiers": [
          "FreeOfPersonallyIdentifiableInformation"
        ]
      },
      "humanLoopName": "human-loop-name"
    }
  },
  "aiServiceResponse": {
    "blocks": [...],
    "documentMetadata": {
      "pages": 1
    }
  },
  "humanTaskActivationConditionResults": {
    "Conditions": [
      {
        "EvaluationResult": true,
        "Or": [
          {
            "ConditionParameters": {
              "ImportantFormKey": "Mail address",
              "ImportantFormKeyAliases": [
                "Mail Address:",
                "Mail address:",
                "Mailing Add:",
                "Mailing Addresses"
              ],
              "KeyValueBlockConfidenceLessThan": 100,
              "WordBlockConfidenceLessThan": 100
            },
            "ConditionType": "ImportantFormKeyConfidenceCheck",
            "EvaluationResult": true
          },
          {
            "ConditionParameters": {
              "ImportantFormKey": "Mail address",
              "ImportantFormKeyAliases": [
                "Mail Address:"
              ]
            },
            "ConditionType": "ImportantFormKeyConfidenceCheck",
            "EvaluationResult": true
          }
        ]
      }
    ]
  }
}
When you use the Amazon Textract built-in integration, you see the string 'AWS/Rekognition/DetectModerationLabels/Image/V3' as the value for awsManagedHumanLoopRequestSource in your output data.

The answerContent parameter contains a moderationLabels object that contains human responses for all moderation labels sent to Amazon A2I.

The aiServiceResponse parameter also includes a moderationLabels object with Amazon Rekognition's response to the original request sent to DetectModerationLabels.

To learn more about the parameters you see in the block object, refer to ModerationLabel in the Amazon Rekognition Developer Guide.

The following is an example of the output data from an Amazon A2I human review of Amazon Rekognition image moderation inferences.

```json
{
    "awsManagedHumanLoopRequestSource": "AWS/Rekognition/DetectModerationLabels/Image/V3",
    "humanAnswers": [
        {
            "answerContent": {
                "AWS/Rekognition/DetectModerationLabels/Image/V3": {
                    "moderationLabels": ...
                }
            },
            "submissionTime": "2020-09-28T19:22:35.508Z",
            "workerId": "ef7294f850a3d9d1",
            "workerMetadata": {
                "identityData": {
                    "identityProviderType": "Cognito",
                    "sub": "c6aa8eb7-9944-42e9-a6b9-111122223333"
                }
            }
        }
    ],
    "humanLoopName": "human-loop-name",
    "inputContent": {
        "aiServiceRequest": {
            "humanLoopConfig": {
                ...
            }
        }
    }
}
```
Output Data From Custom Task Types

When you add Amazon A2I to a custom human review workflow, you see the following parameters in the output data returned from human review tasks.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>flowDefinitionArn</td>
<td>String</td>
<td>The Amazon Resource Number (ARN) of the human review</td>
</tr>
<tr>
<td>humanLoopName</td>
<td></td>
<td></td>
</tr>
<tr>
<td>image</td>
<td></td>
<td></td>
</tr>
<tr>
<td>s3Object.bucket</td>
<td></td>
<td></td>
</tr>
<tr>
<td>s3Object.name</td>
<td></td>
<td></td>
</tr>
<tr>
<td>moderationLabels</td>
<td></td>
<td></td>
</tr>
<tr>
<td>moderationModelVersion</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EvaluationResult</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Or</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ConditionParameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ConfidenceLessThan</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ModerationLabelName</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ConditionType</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EvaluationResult</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ConditionParameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ConfidenceGreaterThan</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ModerationLabelName</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ConditionType</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EvaluationResult</td>
<td></td>
<td></td>
</tr>
<tr>
<td>moderationLabels</td>
<td></td>
<td></td>
</tr>
<tr>
<td>confidence</td>
<td></td>
<td></td>
</tr>
<tr>
<td>name</td>
<td></td>
<td></td>
</tr>
<tr>
<td>parentName</td>
<td></td>
<td></td>
</tr>
<tr>
<td>moderationModelVersion</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parameter</td>
<td>Value Type</td>
<td>Description</td>
</tr>
<tr>
<td>-------------------</td>
<td>------------------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>humanAnswers</td>
<td>List of JSON objects</td>
<td>A list of JSON objects that contain worker responses in answerContent. The value in this parameter is determined by the output received from your worker task template. If you are using a private workforce, worker metadata is included. To learn more, see Track Worker Activity (p. 3465).</td>
</tr>
<tr>
<td>humanLoopName</td>
<td>String</td>
<td>The name of the human loop.</td>
</tr>
<tr>
<td>inputContent</td>
<td>JSON Object</td>
<td>The input content sent to Amazon A2I in the request to StartHumanLoop.</td>
</tr>
</tbody>
</table>

The following is an example of output data from a custom integration with Amazon A2I and Amazon Transcribe. In this example, the inputContent consists of:

- A path to an .mp4 file in Amazon S3 and the video title
- The transcription returned from Amazon Transcribe (parsed from Amazon Transcribe output data)
- A start and end time used by the worker task template to clip the .mp4 file and show workers a relevant portion of the video

```json
{
    "humanAnswers": [
        {
            "answerContent": {
                "transcription": "use lambda to turn your notebook"
            },
            "submissionTime": "2020-06-18T17:08:26.246Z",
            "workerId": "ef7294f850a3d9d1",
            "workerMetadata": {
                "identityData": {
                    "identityProviderType": "Cognito",
                    "sub": "c6aa8eb7-9944-42e9-a6b9-111122223333"
                }
            }
        }
    ],
    "humanLoopName": "human-loop-name",
    "inputContent": {
        "audioPath": "s3://DOC-EXAMPLE-BUCKET1/a2i_transcribe_demo/Fully-Managed Notebook Instances with Amazon SageMaker - a Deep Dive.mp4",
        "end_time": 950.27,
        "original_words": "but definitely use Lambda to turn your ",
        "start_time": 948.51
    }
}
```
Track Worker Activity

Amazon A2I provides information that you can use to track individual workers in task output data. To identify the worker that worked on the human review task, use the following from the output data in Amazon S3:

- The `acceptanceTime` is the time that the worker accepted the task. The format of this date and time stamp is `YYYY-MM-DDTHH:MM:SS.mmmZ` for the year (YYYY), month (MM), day (DD), hour (HH), minute (MM), second (SS), and millisecond (mmm). The date and time are separated by a T.
- The `submissionTime` is the time that the worker submitted their annotations using the Submit button. The format of this date and time stamp is `YYYY-MM-DDTHH:MM:SS.mmmZ` for the year (YYYY), month (MM), day (DD), hour (HH), minute (MM), second (SS), and millisecond (mmm). The date and time are separated by a T.
- `timeSpentInSeconds` reports the total time, in seconds, that a worker actively worked on that task. This metric does not include time when a worker paused or took a break.
- The `workerId` is unique to each worker.
- If you use a private workforce, in workerMetadata, you see the following.
  - The `identityProviderType` is the service used to manage the private workforce.
  - The `issuer` is the Amazon Cognito user pool or OpenID Connect (OIDC) Identity Provider (IdP) issuer associated with the work team assigned to this human review task.
  - A unique sub identifier refers to the worker. If you create a workforce using Amazon Cognito, you can retrieve details about this worker (such as the name or user name) associated with this ID using Amazon Cognito. To learn how, see Managing and Searching for User Accounts in Amazon Cognito Developer Guide.

The following is an example of the output you may see if you use Amazon Cognito to create a private workforce. This is identified in the `identityProviderType`.

```json
"submissionTime": "2020-12-28T18:59:58.321Z",
"acceptanceTime": "2020-12-28T18:15:19.191Z",
"timeSpentInSeconds": 40.543,
"workerId": "a12b3cdefg4h5i67",
"workerMetadata": {
  "identityData": {
    "identityProviderType": "Cognito",
    "sub": "aaaaaaaa-bbbb-cccc-dddd-eeeeeeeeeeee"
  }
}
```

The following is an example of the output you may see if you use your own OIDC IdP to create a private workforce:

```json
"workerMetadata": {
  "identityData": {
    "identityProviderType": "Oidc",
    "issuer": "https://example-oidc-ipd.com/adfs",
    "sub": "aaaaaaaa-bbbb-cccc-dddd-eeeeeeeeeeee"
  }
}
```
Permissions and Security in Amazon Augmented AI

When using Amazon Augmented AI (Amazon A2I) to create a human review workflow for your ML/AI application, you create and configure resources in Amazon SageMaker such as a human workforce and worker task templates. To configure and start a human loop, you either integrate Amazon A2I with other AWS services such as Amazon Textract or Amazon Rekognition, or use the Amazon Augmented AI Runtime API. To create a human review workflow and start a human loop, you must attach certain policies to your AWS Identity and Access Management (IAM) role or user. Specifically:

• When you start a human loop using image input data on or after January 12th, 2020, you must add a CORS header policy to the Amazon S3 bucket that contains your input data. See CORS Permission Requirement (p. 3467) to learn more.

• When you create a flow definition, you need to provide a role that grants Amazon A2I permission to access Amazon S3 both for reading objects that are rendered in a human task UI and for writing the results of the human review. This role must also have a trust policy attached to give SageMaker permission to assume the role. This allows Amazon A2I to perform actions in accordance with permissions that you attach to the role. See Add Permissions to the IAM Role Used to Create a Flow Definition (p. 3467) for example policies that you can modify and attach to the role you use to create a flow definition. These are the policies that are attached to the IAM role that is created in the Human review workflows section of the Amazon A2I area of the SageMaker console.

• To create and start human loops, you either use an API operation from a built-in task type (such as DetectModerationLabel or AnalyzeDocument) or the Amazon A2I Runtime API operation StartHumanLoop in a custom ML application. You need to attach the AmazonAugmentedAIFullAccess managed policy to the IAM user that invokes these API operations to grant permission to these services to use Amazon A2I operations. To learn how, see Create an IAM User That Can Invoke Amazon A2I API Operations (p. 3469).

This policy does not grant permission to invoke the API operations of the AWS service associated with built-in task types. For example, AmazonAugmentedAIFullAccess does not grant permission to call the Amazon Rekognition DetectModerationLabel API operation or Amazon Textract AnalyzeDocument API operation. You can use the more general policy, AmazonAugmentedAIIntegratedAPIAccess, to grant these permissions. For more information, see Create an IAM User With Permissions to Invoke Amazon A2I, Amazon Textract, and Amazon Rekognition API Operations (p. 3469). This is a good option when you want to grant an IAM user broad permissions to use Amazon A2I and integrated AWS services' API operations.

If you want to configure more granular permissions, see Amazon Rekognition Identity-Based Policy Examples and Amazon Textract Identity-Based Policy Examples for identity-based policies you can use to grant permission to use these individual services.

• To preview your custom worker task UI template, you need an IAM role with permissions to read Amazon S3 objects that get rendered on your user interface. See a policy example in Enable Worker Task Template Previews (p. 3470).

Topics
• CORS Permission Requirement (p. 3467)
• Add Permissions to the IAM Role Used to Create a Flow Definition (p. 3467)
• Create an IAM User That Can Invoke Amazon A2I API Operations (p. 3469)
• Create an IAM User With Permissions to Invoke Amazon A2I, Amazon Textract, and Amazon Rekognition API Operations (p. 3469)
CORS Permission Requirement

Earlier in 2020, widely used browsers like Chrome and Firefox changed their default behavior for rotating images based on image metadata, referred to as **EXIF data**. Previously, images would always display in browsers exactly how they are stored on disk, which is typically unrotated. After the change, images now rotate according to a piece of image metadata called **orientation value**. This has important implications for the entire machine learning (ML) community. For example, if the EXIF orientation is not considered, applications that are used to annotate images may display images in unexpected orientations and result in incorrect labels.

Starting with Chrome 89, AWS can no longer automatically prevent the rotation of images because the web standards group W3C has decided that the ability to control rotation of images violates the web's Same-Origin Policy. Therefore, to ensure human workers annotate your input images in a predictable orientation when you submit requests to create a human loop, you must add a CORS header policy to the S3 buckets that contain your input images.

**Important**

If you do not add a CORS configuration to the S3 buckets that contains your input data, human review tasks for those input data objects fail.

You can add a CORS policy to an S3 bucket that contains input data in the Amazon S3 console. To set the required CORS headers on the S3 bucket that contains your input images in the S3 console, follow the directions detailed in How do I add cross-domain resource sharing with CORS?. Use the following CORS configuration code for the buckets that host your images. If you use the Amazon S3 console to add the policy to your bucket, you must use the JSON format.

**JSON**

```json
[
  "AllowedHeaders": [],
  "AllowedMethods": ["GET"],
  "AllowedOrigins": ["*"],
  "ExposedHeaders": []
]
```

**XML**

```xml
<CORSConfiguration>
  <CORSRule>
    <AllowedOrigin>*</AllowedOrigin>
    <AllowedMethod>GET</AllowedMethod>
  </CORSRule>
</CORSConfiguration>
```

**Add Permissions to the IAM Role Used to Create a Flow Definition**

To create a flow definition, attach the policies in this section to the role that you use when creating a human review workflow in the SageMaker console, or when using the CreateFlowDefinition API operation.
Add Permissions to the IAM Role
Used to Create a Flow Definition

• If you are using the console to create a human review workflow, enter the role Amazon Resource Name (ARN) in the IAM role field when creating a human review workflow in the console.

• When creating a flow definition using the API, attach these policies to the role that is passed to the RoleArn parameter of the CreateFlowDefinition operation.

When you create a human review workflow (flow definition), Amazon A2I invokes Amazon S3 to complete your task. To grant Amazon A2I permission to retrieve and store your files in your Amazon S3 bucket, create the following policy and attach it to your role. For example, if the images, documents, and other files that you are sending for human review are stored in an S3 bucket named my_input_bucket, and if you want the human reviews to be stored in a bucket named my_output_bucket, create the following policy.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["s3:GetObject"],
      "Resource": ["arn:aws:s3:::my_input_bucket/*"]
    },
    {
      "Effect": "Allow",
      "Action": ["s3:PutObject"],
      "Resource": ["arn:aws:s3:::my_output_bucket/*"]
    }
  ]
}
```

In addition, the IAM role must have the following trust policy to give SageMaker permission to assume the role. To learn more about IAM trust policies, see Resource-Based Policies section of Policies and Permissions in the AWS Identity and Access Management documentation.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "AllowSageMakerToAssumeRole",
      "Effect": "Allow",
      "Principal": {
        "Service": "sagemaker.amazonaws.com"
      },
      "Action": "sts:AssumeRole"
    }
  ]
}
```

For more information about creating and managing IAM roles and policies, see the following topics in the AWS Identity and Access Management User Guide:

• To create an IAM role, see Creating a Role to Delegate Permissions to an IAM User.
• To learn how to create IAM policies, see Creating IAM Policies.
Create an IAM User That Can Invoke Amazon A2I API Operations

To use Amazon A2I to create and start human loops for Amazon Rekognition, Amazon Textract, or the Amazon A2I runtime API, you must use an IAM user that has permissions to invoke Amazon A2I operations. To do this, use the IAM console to attach the `AmazonAugmentedAIFullAccess` managed policy to a new or existing IAM user.

This policy grants permission to an IAM user to invoke API operations from the SageMaker API for flow definition creation and management and the Amazon Augmented AI Runtime API for human loop creation and management. To learn more about these API operations, see Use APIs in Amazon Augmented AI.

`AmazonAugmentedAIFullAccess` does not grant permissions to use Amazon Rekognition or Amazon Textract API operations.

**Note**

You can also attach the `AmazonAugmentedAIFullAccess` policy to an IAM role that is used to create and start a human loop.

**To create the required IAM user**

2. Choose Users and choose an existing user, or create a new user by choosing Add user. To learn how to create a new user, see Creating an IAM User in Your AWS Account in the AWS Identity and Access Management User Guide.
   - If you chose to attach the policy to an existing user, choose Add permissions.
   - While creating a new user, follow the next step on the Set permissions page.
3. Choose Attach existing policies directly.
4. In the Search bar, enter AmazonAugmentedAIFullAccess and check the box next to that policy. To enable this IAM user to create a flow definition with the public work team, also attach the AmazonSageMakerMechanicalTurkAccess managed policy.
5. After attaching the policy or policies:
   a. If you are using an existing user, choose Next: Review, and then choose Add permissions.
   b. If you are creating a new user, choose Next: Tags and complete the process of creating your user.

For more information, see Adding and Removing IAM Identity Permissions in the AWS Identity and Access Management User Guide.

Create an IAM User With Permissions to Invoke Amazon A2I, Amazon Textract, and Amazon Rekognition API Operations

To create an IAM user that has permission to invoke the API operations used by the built-in task types (that is, DetectModerationLabels for Amazon Rekognition and AnalyzeDocument for Amazon...
To customize the interface and instructions that your workers see when working on your tasks, you create a worker task template. You can create the template using the `CreateHumanTaskUi` operation or the SageMaker console.

To preview your template, you need an IAM role with the following permissions to read Amazon S3 objects that get rendered on your user interface.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["s3:GetObject"],
      "Resource": ["arn:aws:s3:::my_input_bucket/*"]
    }
  ]
}
```
For Amazon Rekognition and Amazon Textract task types, you can preview your template using the Amazon Augmented AI section of the SageMaker console. For custom task types, you preview your template by invoking the `RenderUiTemplate` operation. To preview your template, follow the instructions for your task type:

- Amazon Rekognition and Amazon Textract task types – In the SageMaker console, use the role's Amazon Resource Name (ARN) in the procedure documented in Create a Worker Task Template (p. 3447).
- Custom task types – In the `RenderUiTemplate` operation, use the role's ARN in the `RoleArn` parameter.

**Using Amazon A2I with AWS KMS Encrypted Buckets**

If you specify an AWS Key Management Service (AWS KMS) customer managed key to encrypt output data in `OutputConfig` of CreateFlowDefinition, you must add an IAM policy similar to the following to that key. This policy gives the IAM execution role that you use to create your human loops permission to use this key to perform all of the actions listed in "Action". To learn more about these actions, see AWS KMS permissions in the AWS Key Management Service Developer Guide.

To use this policy, replace the IAM service-role ARN in "Principal" with the ARN of the execution role you use to create the human review workflow (flow definition). When you create a labeling job using CreateFlowDefinition, this is the ARN you specify for `RoleArn`. Note that you cannot provide a `KmsKeyId` when you create a flow definition in the console.

```json
{
   "Sid": "AllowUseOfKmsKey",
   "Effect": "Allow",
   "Principal": {
      "AWS": "arn:aws:iam::111122223333:role/service-role/example-role"
   },
   "Action": [
      "kms:Encrypt",
      "kms:Decrypt",
      "kms:ReEncrypt*",
      "kms:GenerateDataKey*",
      "kms:DescribeKey"
   ],
   "Resource": "**"
}
```

**Additional Permissions and Security Resources**

- the section called “Control Access to SageMaker Resources by Using Tags” (p. 3527).
- the section called “SageMaker Identity-Based Policies” (p. 3505)
- the section called “Control Creation of SageMaker Resources with Condition Keys” (p. 3518)
- the section called “Amazon SageMaker API Permissions Reference” (p. 3553)
- Security (p. 3493)

**Use Amazon CloudWatch Events in Amazon Augmented AI**

Amazon Augmented AI uses Amazon CloudWatch Events to alert you when a human review loop status changes to Completed, Failed, or Stopped. This event delivery is guaranteed at least once, which
means all events created when human loops finish are successfully delivered to CloudWatch Events (Amazon EventBridge). When a review loop changes to one of these states, Augmented AI sends an event to CloudWatch Events similar to the following.

```json
{
    "version":"0",
    "id":"12345678-1111-2222-3333-12345EXAMPLE",
    "detail-type":"SageMaker A2I HumanLoop Status Change",
    "source":"aws.sagemaker",
    "account":"111111111111",
    "time":"2019-11-14T17:49:25Z",
    "region":"us-east-1",
    "resources":[]
    "detail":{
        "creationTime":"2019-11-14T17:37:36.740Z",
        "failureCode":null,
        "failureReason":null,
        "flowDefinitionArn":"arn:aws:sagemaker:us-east-1:111111111111:flow-definition/flowdef-nov-12",
        "humanLoopName":"humanloop-nov-14-1",
        "humanLoopOutput":{
            "outputS3Uri":"s3://customer-output-bucket-specified-in-flow-definition/flowdef-nov-12/2019/11/14/17/37/36/humanloop-nov-14-1/output.json"
        },
        "humanLoopStatus":"Completed"
    }
}
```

The details in the JSON output include the following:

- **creationTime**: The timestamp when Augmented AI created the human loop.
- **failureCode**: A failure code denoting a specific type of failure.
- **failureReason**: The reason why a human loop has failed. The failure reason is only returned when the human review loop status is failed.
- **flowDefinitionArn**: The Amazon Resource Name (ARN) of the flow definition, or human review workflow.
- **humanLoopArn**: The Amazon Resource Name (ARN) of the human loop.
- **humanLoopName**: The name of the human loop.
- **humanLoopOutput**: An object containing information about the output of the human loop.
- **outputS3Uri**: The location of the Amazon S3 object where Augmented AI stores your human loop output.
Send Events from Your Human Loop to CloudWatch Events

The status of the human loop.

Send Events from Your Human Loop to CloudWatch Events

To configure a CloudWatch Events rule to get status updates, or events, for your Amazon A2I human loops, use the AWS Command Line Interface (AWS CLI) put-rule command. When using the put-rule command, specify the following to receive human loop statuses:

- "source": ["aws.sagemaker"]
- "detail-type": ["SageMaker A2I HumanLoop Status Change"]

To configure a CloudWatch Events rule to watch for all status changes, use the following command and replace the placeholder text. For example, replace "A2IHumanLoopStatusChanges" with a unique CloudWatch Events rule name and "arn:aws:iam::111122223333:role/MyRoleForThisRule" with the Amazon Resource Number (ARN) of an IAM role with an events.amazonaws.com trust policy attached. Replace region with the AWS Region in which you want to create the rule.

```bash
aws events put-rule --name "A2IHumanLoopStatusChanges"
   --event-pattern "{"source": ["aws.sagemaker"], "detail-type": ["SageMaker A2I HumanLoop Status Change"]}"
   --role-arn "arn:aws:iam::111122223333:role/MyRoleForThisRule"
   --region "region"
```

To learn more about the put-rule request, see Event Patterns in CloudWatch Events in the Amazon CloudWatch Events User Guide.

Set Up a Target to Process Events

To process events, you need to set up a target. For example, if you want to receive an email when a human loop status changes, use a procedure in Setting Up Amazon SNS Notifications in the Amazon CloudWatch User Guide to set up an Amazon SNS topic and subscribe your email to it. Once you have created a topic, you can use it to create a target.

To add a target to your CloudWatch Events rule

1. Open the CloudWatch console: https://console.aws.amazon.com/cloudwatch/home
2. In the navigation pane, choose Rules.
3. Choose the rule to which you want to add a target.
4. Choose Actions, and then choose Edit.
5. Under Targets, choose Add Target and choose the AWS service you want to act when a human loop status change event is detected.
6. Configure your target. For instructions, see the topic for configuring a target in the AWS documentation for that service.
7. Choose Configure details.
8. For Name, enter a name and, optionally, provide details about the purpose of the rule in Description.
9. Make sure that the check box next to State is selected so that your rule is listed as Enabled.
10. Choose Update rule.
Use Human Review Output

After you receive human review results, you can analyze the results and compare them to machine learning predictions. The JSON that is stored in the Amazon S3 bucket contains both the machine learning predictions and the human review results.

More Information

Automating Amazon SageMaker with Amazon EventBridge (p. 3681)

Use APIs in Amazon Augmented AI

You can create a human review workflow or a worker task template programmatically. The APIs you use depend on whether you are creating a Amazon Rekognition, Amazon Textract, or custom task type. This topic provides links to API reference documentation for each task type and programming task.

The following APIs can be used with Augmented AI:

Amazon Augmented AI

Use the Augmented AI API to start, stop, and delete human review loops. You can also list all human review loops and return information about human review loops in your account.

Learn more about human review loop APIs in the Amazon Augmented AI Runtime API Reference.

Amazon Rekognition

Use the `HumanLoopConfig` parameter of the `DetectModerationLabels` API to initiate a human review workflow using Amazon Rekognition.

Amazon SageMaker

Use the Amazon SageMaker API to create a `FlowDefinition`, also known as a human review workflow. You can also create a `HumanTaskUi` or worker task template.

For more information, see the `CreateFlowDefinition` or the `CreateHumanTaskUi` API documentation.

Amazon Textract

Use the `HumanLoopConfig` parameter of the `AnalyzeDocument` API to initiate a human review workflow using Amazon Textract.

Programmatic Tutorials

The following tutorials provide example code and step-by-step instructions for creating human review workflows and worker task templates programmatically.

- Tutorial: Get Started Using the Amazon A2I API (p. 3401)
- Create a Human Review Workflow (API) (p. 3422)
- Create and Start a Human Loop (p. 3438)
- Using Amazon Augmented AI with Amazon Rekognition in the Amazon Rekognition Developer Guide
- Using Amazon Augmented AI with Amazon Textract AnalyzeDocument in the Amazon Textract Developer Guide
Buy and Sell Amazon SageMaker Algorithms and Models in AWS Marketplace

Amazon SageMaker integrates with AWS Marketplace, enabling developers to charge other SageMaker users for the use of their algorithms and model packages. AWS Marketplace is a curated digital catalog that makes it easy for customers to find, buy, deploy, and manage third-party software and services that customers need to build solutions and run their businesses. AWS Marketplace includes thousands of software listings in popular categories, such as security, networking, storage, machine learning, business intelligence, database, and DevOps. It simplifies software licensing and procurement with flexible pricing options and multiple deployment methods.

For information, see AWS Marketplace Documentation.

Topics

- SageMaker Algorithms (p. 3475)
- SageMaker Model Packages (p. 3475)
- Sell Amazon SageMaker Algorithms and Model Packages (p. 3489)
- Find and Subscribe to Algorithms and Model Packages on AWS Marketplace (p. 3492)
- Use Algorithm and Model Package Resources (p. 3482)

SageMaker Algorithms

An algorithm enables you to perform end-to-end machine learning. It has two logical components: training and inference. Buyers can use the training component to create training jobs in SageMaker and build a machine learning model. SageMaker saves the model artifacts generated by the algorithm during training to an Amazon S3 bucket. For more information, see Train a Model with Amazon SageMaker (p. 9).

Buyers use the inference component with the model artifacts generated during a training job to create a deployable model in their SageMaker account. They can use the deployable model for real-time inference by using SageMaker hosting services. Or, they can get inferences for an entire dataset by running batch transform jobs. For more information, see Deploy a Model in Amazon SageMaker (p. 11).

SageMaker Model Packages

Buyers use a model package to build a deployable model in SageMaker. They can use the deployable model for real-time inference by using SageMaker hosting services. Or, they can get inferences for an entire dataset by running batch transform jobs. For more information, see Deploy a Model in Amazon SageMaker (p. 11). As a seller, you can build your model artifacts by training in SageMaker, or you can use your own model artifacts from a model that you trained outside of SageMaker. You can charge buyers for inference.
Use your own algorithms and models with the AWS Marketplace

The following sections show how to create algorithm and model package resources that you can use locally and publish to the AWS Marketplace.

Topics
- Create Algorithm and Model Package Resources (p. 3476)
- Use Algorithm and Model Package Resources (p. 3482)

Create Algorithm and Model Package Resources

After your training and/or inference code is packaged in Docker containers, create algorithm and model package resources that you can use in your Amazon SageMaker account and, optionally, publish on AWS Marketplace.

Topics
- Create an Algorithm Resource (p. 3476)
- Create a Model Package Resource (p. 3479)

Create an Algorithm Resource

To create an algorithm resource that you can use to run training jobs in Amazon SageMaker and publish on AWS Marketplace specify the following information:

- The Docker containers that contains the training and, optionally, inference code.
- The configuration of the input data that your algorithm expects for training.
- The hyperparameters that your algorithm supports.
- Metrics that your algorithm sends to Amazon CloudWatch during training jobs.
- The instance types that your algorithm supports for training and inference, and whether it supports distributed training across multiple instances.
- Validation profiles, which are training jobs that SageMaker uses to test your algorithm's training code and batch transform jobs that SageMaker runs to test your algorithm's inference code.

To ensure that buyers and sellers can be confident that products work in SageMaker, we require that you validate your algorithms before listing them on AWS Marketplace. You can list products in the AWS Marketplace only if validation succeeds. To validate your algorithms, SageMaker uses your validation profile and sample data to run the following validations tasks:

1. Create a training job in your account to verify that your training image works with SageMaker.
2. If you included inference code in your algorithm, create a model in your account using the algorithm's inference image and the model artifacts produced by the training job.
3. If you included inference code in your algorithm, create a transform job in your account using the model to verify that your inference image works with SageMaker.

When you list your product on AWS Marketplace, the inputs and outputs of this validation process persist as part of your product and are made available to your buyers. This helps buyers understand and evaluate the product before they buy it. For example, buyers can inspect the input data that you used, the outputs generated, and the logs and metrics emitted by your code. The more comprehensive your validation specification, the easier it is for customers to evaluate your product.
Note
In your validation profile, provide only data that you want to expose publicly.

Validation can take up to a few hours. To see the status of the jobs in your account, in the SageMaker console, see the Training jobs and Transform jobs pages. If validation fails, you can access the scan and validation reports from the SageMaker console. If any issues are found, you will have to create the algorithm again.

Note
To publish your algorithm on AWS Marketplace, at least one validation profile is required.

You can create an algorithm by using either the SageMaker console or the SageMaker API.

Topics
• Create an Algorithm Resource (Console) (p. 3477)
• Create an Algorithm Resource (API) (p. 3479)

Create an Algorithm Resource (Console)

To create an algorithm resource (console)
2. From the left menu, choose Training.
3. From the dropdown menu, choose Algorithms, then choose Create algorithm.
4. On the Training specifications page, provide the following information:
   a. For Algorithm name, type a name for your algorithm. The algorithm name must be unique in your account and in the AWS region. The name must have 1 to 64 characters. Valid characters are a-z, A-Z, 0-9, and - (hyphen).
   b. Type a description for your algorithm. This description appears in the SageMaker console and in the AWS Marketplace.
   c. For Training image, type the path in Amazon ECR where your training container is stored.
   d. For Support distributed training, Choose Yes if your algorithm supports training on multiple instances. Otherwise, choose No.
   e. For Support instance types for training, choose the instance types that your algorithm supports.
   f. For Channel specification, specify up to 8 channels of input data for your algorithm. For example, you might specify 3 input channels named train, validation, and test. For each channel, specify the following information:
      i. For Channel name, type a name for the channel. The name must have 1 to 64 characters. Valid characters are a-z, A-Z, 0-9, and - (hyphen).
      ii. To require the channel for your algorithm, choose Channel required.
      iii. Type a description for the channel.
      iv. For Supported input modes, choose Pipe mode if your algorithm supports streaming the input data, and File mode if your algorithm supports downloading the input data as a file. You can choose both.
      v. For Supported content types, type the MIME type that your algorithm expects for input data.
      vi. For Supported compression type, choose Gzip if your algorithm supports Gzip compression. Otherwise, choose None.
vii. Choose Add channel to add another data input channel, or choose Next if you are done adding channels.

5. On the Tuning specifications page, provide the following information:

a. For Hyperparameter specification, specify the hyperparameters that your algorithm supports by editing the JSON object. For each hyperparameter that your algorithm supports, construct a JSON block similar to the following:

```json
{
    "DefaultValue": "5",
    "Description": "The first hyperparameter",
    "IsRequired": true,
    "IsTunable": false,
    "Name": "intRange",
    "Range": {
        "IntegerParameterRangeSpecification": {
            "MaxValue": "10",
            "MinValue": "1"
        },
        "Type": "Integer"
    }
}
```

In the JSON, supply the following:

i. For DefaultValue, specify a default value for the hyperparameter, if there is one.

ii. For Description, specify a description for the hyperparameter.

iii. For IsRequired, specify whether the hyperparameter is required.

iv. For IsTunable, specify true if this hyperparameter can be tuned when a user runs a hyperparameter tuning job that uses this algorithm. For information, see Perform Automatic Model Tuning with SageMaker (p. 2436).

v. For Name, specify a name for the hyperparameter.

vi. For Range, specify one of the following:

- IntegerParameterRangeSpecification - the values of the hyperparameter are integers. Specify minimum and maximum values for the hyperparameter.
- ContinuousParameterRangeSpecification - the values of the hyperparameter are floating-point values. Specify minimum and maximum values for the hyperparameter.
- CategoricalParameterRangeSpecification - the values of the hyperparameter are categorical values. Specify a list of all of the possible values.

vii. For Type, specify Integer, Continuous, or Categorical. The value must correspond to the type of Range that you specified.

b. For Metric definitions, specify any training metrics that you want your algorithm to emit. SageMaker uses the regular expression that you specify to find the metrics by parsing the logs from your training container during training. Users can view these metrics when they run training jobs with your algorithm, and they can monitor and plot the metrics in Amazon CloudWatch. For information, see Monitor and Analyze Training Jobs Using Amazon CloudWatch Metrics (p. 2704). For each metric, provide the following information:

i. For Metric name, type a name for the metric.

ii. For Regex, type the regular expression that SageMaker uses to parse training logs so that it can find the metric value.

iii. For Objective metric support choose Yes if this metric can be used as the objective metric for a hyperparameter tuning job. For information, see Perform Automatic Model Tuning with SageMaker (p. 2436).
iv. Choose **Add metric** to add another metric, or choose **Next** if you are done adding metrics.

6. On the **Inference specifications** page, provide the following information if your algorithm supports inference:
   
a. For **Location of inference image**, type the path in Amazon ECR where your inference container is stored.
   
b. For **Container DNS host name**, type the name of a DNS host for your image.
   
c. For **Supported instance types for real-time inference**, choose the instance types that your algorithm supports for models deployed as hosted endpoints in SageMaker. For information, see *Deploy Models for Inference* (p. 2711).
   
d. For **Supported instance types for batch transform jobs**, choose the instance types that your algorithm supports for batch transform jobs. For information, see *Use Batch Transform* (p. 2955).
   
e. For **Supported content types**, type the type of input data that your algorithm expects for inference requests.
   
f. For **Supported response MIME types**, type the MIME types that your algorithm supports for inference responses.
   
g. Choose **Next**.

7. On the **Validation specifications** page, provide the following information:
   
a. For **Publish this algorithm on AWS Marketplace**, choose **Yes** to publish the algorithm on AWS Marketplace.
   
b. For **Validate this resource**, choose **Yes** if you want SageMaker to run training jobs and/or batch transform jobs that you specify to test the training and/or inference code of your algorithm.

   **Note**
   To publish your algorithm on AWS Marketplace, your algorithm must be validated.
   
c. For **IAM role**, choose an IAM role that has the required permissions to run training jobs and batch transform jobs in SageMaker, or choose **Create a new role** to allow SageMaker to create a role that has the AmazonSageMakerFullAccess managed policy attached. For information, see *SageMaker Roles* (p. 3536).
   
d. For **Validation profile**, specify the following:
      
      • A name for the validation profile.
      
      • A **Training job definition**. This is a JSON block that describes a training job. This is in the same format as the *TrainingJobDefinition* input parameter of the *CreateAlgorithm* API.
      
      • A **Transform job definition**. This is a JSON block that describes a batch transform job. This is in the same format as the *TransformJobDefinition* input parameter of the *CreateAlgorithm* API.
      
   e. Choose **Create algorithm**.

**Create an Algorithm Resource (API)**

To create an algorithm resource by using the SageMaker API, call the *CreateAlgorithm* API.

**Create a Model Package Resource**

To create a model package resource that you can use to create deployable models in Amazon SageMaker and publish on AWS Marketplace specify the following information:

• The Docker container that contains the inference code, or the algorithm resource that was used to train the model.
• The location of the model artifacts. Model artifacts can either be packaged in the same Docker container as the inference code or stored in Amazon S3.

• The instance types that your model package supports for both real-time inference and batch transform jobs.

• Validation profiles, which are batch transform jobs that SageMaker runs to test your model package's inference code.

Before listing model packages on AWS Marketplace, you must validate them. This ensures that buyers and sellers can be confident that products work in Amazon SageMaker. You can list products on AWS Marketplace only if validation succeeds.

The validation procedure uses your validation profile and sample data to run the following validations tasks:

1. Create a model in your account using the model package's inference image and the optional model artifacts that are stored in Amazon S3.

   Note
   A model package is specific to the region in which you create it. The S3 bucket where the model artifacts are stored must be in the same region where your created the model package.

2. Create a transform job in your account using the model to verify that your inference image works with SageMaker.

3. Create a validation profile.

   Note
   In your validation profile, provide only data that you want to expose publicly.

Validation can take up to a few hours. To see the status of the jobs in your account, in the SageMaker console, see the Transform jobs pages. If validation fails, you can access the scan and validation reports from the SageMaker console. After fixing issues, recreate the algorithm. When the status of the algorithm is COMPLETED, find it in the SageMaker console and start the listing process.

   Note
   To publish your model package on AWS Marketplace, at least one validation profile is required.

You can create an model package either by using the SageMaker console or by using the SageMaker API.

Topics

• Create a Model Package Resource (Console)  (p. 3480)
• Create a Model Package Resource (API)  (p. 3482)

Create a Model Package Resource (Console)

To create a model package in the SageMaker console:

2. From the left menu, choose Inference.
3. Choose Marketplace model packages, then choose Create marketplace model package.
4. On the Inference specifications page, provide the following information:

   a. For Model package name, type a name for your model package. The model package name must be unique in your account and in the AWS region. The name must have 1 to 64 characters. Valid characters are a-z, A-Z, 0-9, and - (hyphen).
b. Type a description for your model package. This description appears in the SageMaker console and in the AWS Marketplace.

c. For **Inference specification options**, choose **Provide the location of the inference image and model artifacts** to create a model package by using an inference container and model artifacts. Choose **Provide the algorithm used for training and its model artifacts** to create a model package from an algorithm resource that you created or subscribe to from AWS Marketplace.

d. If you chose **Provide the location of the inference image and model artifacts** for **Inference specification options**, provide the following information for **Container definition** and **Supported resources**:
   
i. For **Location of inference image**, type the path to the image that contains your inference code. The image must be stored as a Docker container in Amazon ECR.
   
   ii. For **Location of model data artifacts**, type the location in S3 where your model artifacts are stored.
   
   iii. For **Container DNS host name**, type the name of the DNS host to use for your container.
   
   iv. For **Supported instance types for real-time inference**, choose the instance types that your model package supports for real-time inference from SageMaker hosted endpoints.
   
   v. For **Supported instance types for batch transform jobs**, choose the instance types that your model package supports for batch transform jobs.
   
   vi. **Supported content types**, type the content types that your model package expects for inference requests.
   
   vii. For **Supported response MIME types**, type the MIME types that your model package uses to provide inferences.

e. If you chose **Provide the algorithm used for training and its model artifacts** for **Inference specification options**, provide the following information:
   
i. For **Algorithm ARN**, type the Amazon Resource Name (ARN) of the algorithm resource to use to create the model package.
   
   ii. For **Location of model data artifacts**, type the location in S3 where your model artifacts are stored.

f. Choose **Next**.

5. On the **Validation and scanning** page, provide the following information:
   
a. For **Publish this model package on AWS Marketplace**, choose **Yes** to publish the model package on AWS Marketplace.
   
b. For **Validate this resource**, choose **Yes** if you want SageMaker to run batch transform jobs that you specify to test the inference code of your model package.

   **Note**
   To publish your model package on AWS Marketplace, your model package must be validated.

   c. For **IAM role**, choose an IAM role that has the required permissions to run batch transform jobs in SageMaker, or choose **Create a new role** to allow SageMaker to create a role that has the AmazonSageMakerFullAccess managed policy attached. For information, see [SageMaker Roles](p. 3536).

   d. For **Validation profile**, specify the following:

   • A name for the validation profile.

   • **A Transform job definition**. This is a JSON block that describes a batch transform job. This is in the same format as the `TransformJobDefinition` input parameter of the `CreateAlgorithm` API.

6. Choose **Create marketplace model package**.
Create a Model Package Resource (API)

To create a model package by using the SageMaker API, call the `CreateModelPackage` API.

Use Algorithm and Model Package Resources

You can create algorithms and model packages as resources in your Amazon SageMaker account, and you can find and subscribe to algorithms and model packages on AWS Marketplace.

Use algorithms to:

- Run training jobs. For information, see Use an Algorithm to Run a Training Job (p. 3483).
- Run hyperparameter tuning jobs. For information, see Use an Algorithm to Run a Hyperparameter Tuning Job (p. 3485).
- Create model packages. After you use an algorithm resource to run a training job or a hyperparameter tuning job, you can use the model artifacts that these jobs output along with the algorithm to create a model package. For information, see Create a Model Package Resource (p. 3479).

**Note**
If you subscribe to an algorithm on AWS Marketplace, you must create a model package before you can use it to get inferences by creating hosted endpoint or running a batch transform job.
• Create models that you can use to get real-time inference or run batch transform jobs. For information, see Use a Model Package to Create a Model (p. 3488).
• Create hosted endpoints to get real-time inference. For information, see Deploy the Model to SageMaker Hosting Services (p. 85).
• Create batch transform jobs. For information, see (Optional) Make Prediction with Batch Transform (p. 86).

Topics
• Use an Algorithm to Run a Training Job (p. 3483)
• Use an Algorithm to Run a Hyperparameter Tuning Job (p. 3485)
• Use a Model Package to Create a Model (p. 3488)

Use an Algorithm to Run a Training Job

You can create an algorithm resource to create a training job by using the Amazon SageMaker console, the low-level Amazon SageMaker API, or the Amazon SageMaker Python SDK.

Topics
• Use an Algorithm to Run a Training Job (Console) (p. 3483)
• Use an Algorithm to Run a Training Job (API) (p. 3484)
• Use an Algorithm to Run a Training Job (Amazon SageMaker Python SDK) (p. 3484)

Use an Algorithm to Run a Training Job (Console)

To use an algorithm to run a training job (console)
2. Choose Algorithms.
3. Choose an algorithm that you created from the list on the My algorithms tab or choose an algorithm that you subscribed to on the AWS Marketplace subscriptions tab.
4. Choose Create training job.
   The algorithm you chose will automatically be selected.
5. On the Create training job page, provide the following information:
   a. For Job name, type a name for the training job.
   b. For IAM role, choose an IAM role that has the required permissions to run training jobs in SageMaker, or choose Create a new role to allow SageMaker to create a role that has the AmazonSageMakerFullAccess managed policy attached. For information, see SageMaker Roles (p. 3536).
   c. For Resource configuration, provide the following information:
      i. For Instance type, choose the instance type to use for training.
      ii. For Instance count, type the number of ML instances to use for the training job.
      iii. For Additional volume per instance (GB), type the size of the ML storage volume that you want to provision. ML storage volumes store model artifacts and incremental states.
      iv. For Encryption key, if you want Amazon SageMaker to use an AWS Key Management Service key to encrypt data in the ML storage volume attached to the training instance, specify the key.
      v. For Stopping condition, specify the maximum amount of time in seconds, minutes, hours, or days, that you want the training job to run.
d. For VPC, choose a Amazon VPC that you want to allow your training container to access. For more information, see Give SageMaker Training Jobs Access to Resources in Your Amazon VPC (p. 3648).

e. For Hyperparameters, specify the values of the hyperparameters to use for the training job.

f. For Input data configuration, specify the following values for each channel of input data to use for the training job. You can see what channels the algorithm you're using for training support, and the content type, supported compression type, and supported input modes for each channel, under Channel specification section of the Algorithm summary page for the algorithm.

i. For Channel name, type the name of the input channel.

ii. For Content type, type the content type of the data that the algorithm expects for the channel.

iii. For Compression type, choose the data compression type to use, if any.

iv. For Record wrapper, choose RecordIO if the algorithm expects data in the RecordIO format.

v. For S3 data type, S3 data distribution type, and S3 location, specify the appropriate values. For information about what these values mean, see S3DataSource.

vi. For Input mode, choose File to download the data from to the provisioned ML storage volume, and mount the directory to a Docker volume. Choose PipeTo stream data directly from Amazon S3 to the container.

vii. To add another input channel, choose Add channel. If you are finished adding input channels, choose Done.

g. For Output location, specify the following values:

i. For S3 output path, choose the S3 location where the training job stores output, such as model artifacts.

   Note
   You use the model artifacts stored at this location to create a model or model package from this training job.

ii. For Encryption key, if you want SageMaker to use a AWS KMS key to encrypt output data at rest in the S3 location.

h. For Tags, specify one or more tags to manage the training job. Each tag consists of a key and an optional value. Tag keys must be unique per resource.

i. Choose Create training job to run the training job.

Use an Algorithm to Run a Training Job (API)

To use an algorithm to run a training job by using the SageMaker API, specify either the name or the Amazon Resource Name (ARN) as the AlgorithmName field of the AlgorithmSpecification object that you pass to CreateTrainingJob. For information about training models in SageMaker, see Train a Model with Amazon SageMaker (p. 9).

Use an Algorithm to Run a Training Job (Amazon SageMaker Python SDK)

Use an algorithm that you created or subscribed to on AWS Marketplace to create a training job, create an AlgorithmEstimator object and specify either the Amazon Resource Name (ARN) or the name of the algorithm as the value of the algorithm_arn argument. Then call the fit method of the estimator. For example:

```python
from sagemaker import AlgorithmEstimator
data_path = os.path.join(DATA_DIR, 'marketplace', 'training')
```
Use an Algorithm to Run a Hyperparameter Tuning Job

A hyperparameter tuning job finds the best version of a model by running many training jobs on your dataset using the algorithm and ranges of hyperparameters that you specify. It then chooses the hyperparameter values that result in a model that performs the best, as measured by a metric that you choose. For more information, see Perform Automatic Model Tuning with SageMaker (p. 2436).

You can create use an algorithm resource to create a hyperparameter tuning job by using the Amazon SageMaker console, the low-level Amazon SageMaker API, or the Amazon SageMaker Python SDK.

Topics
- Use an Algorithm to Run a Hyperparameter Tuning Job (Console) (p. 3485)
- Use an Algorithm to Run a Hyperparameter Tuning Job (API) (p. 3487)
- Use an Algorithm to Run a Hyperparameter Tuning Job (Amazon SageMaker Python SDK) (p. 3487)

Use an Algorithm to Run a Hyperparameter Tuning Job (Console)

To use an algorithm to run a hyperparameter tuning job (console)

2. Choose Algorithms.
3. Choose an algorithm that you created from the list on the My algorithms tab or choose an algorithm that you subscribed to on the AWS Marketplace subscriptions tab.
4. Choose Create hyperparameter tuning job.

The algorithm you chose will automatically be selected.
5. On the Create hyperparameter tuning job page, provide the following information:
   a. For Warm start, choose Enable warm start to use the information from previous hyperparameter tuning jobs as a starting point for this hyperparameter tuning job. For more information, see Run a Warm Start Hyperparameter Tuning Job (p. 2459).
      i. Choose Identical data and algorithm if your input data is the same as the input data for the parent jobs of this hyperparameter tuning job, or choose Transfer learning to use additional or different input data for this hyperparameter tuning job.
      ii. For Parent hyperparameter tuning job(s), choose up to 5 hyperparameter tuning jobs to use as parents to this hyperparameter tuning job.
   b. For Hyperparameter tuning job name, type a name for the tuning job.
   c. For IAM role, choose an IAM role that has the required permissions to run hyperparameter tuning jobs in SageMaker, or choose Create a new role to allow SageMaker to create a role that has the AmazonSageMakerFullAccess managed policy attached. For information, see SageMaker Roles (p. 3536).
For VPC, choose a Amazon VPC that you want to allow the training jobs that the tuning job launches to access. For more information, see Give SageMaker Training Jobs Access to Resources in Your Amazon VPC (p. 3648).

e. Choose Next.

f. For Objective metric, choose the metric that the hyperparameter tuning job uses to determine the best combination of hyperparameters, and choose whether to minimize or maximize this metric. For more information, see View the Best Training Job (p. 2457).

g. For Hyperparameter configuration, choose ranges for the tunable hyperparameters that you want the tuning job to search, and set static values for hyperparameters that you want to remain constant in all training jobs that the hyperparameter tuning job launches. For more information, see Define Hyperparameter Ranges (p. 2440).

h. Choose Next.

i. For Input data configuration, specify the following values for each channel of input data to use for the hyperparameter tuning job. You can see what channels the algorithm you're using for hyperparameter tuning supports, and the content type, supported compression type, and supported input modes for each channel, under Channel specification section of the Algorithm summary page for the algorithm.

   i. For Channel name, type the name of the input channel.

   ii. For Content type, type the content type of the data that the algorithm expects for the channel.

   iii. For Compression type, choose the data compression type to use, if any.

   iv. For Record wrapper, choose RecordIO if the algorithm expects data in the RecordIO format.

   v. For S3 data type, S3 data distribution type, and S3 location, specify the appropriate values. For information about what these values mean, see S3DataSource.

   vi. For Input mode, choose File to download the data from to the provisioned ML storage volume, and mount the directory to a Docker volume. Choose PipeTo stream data directly from Amazon S3 to the container.

   vii. To add another input channel, choose Add channel. If you are finished adding input channels, choose Done.

j. For Output location, specify the following values:

   i. For S3 output path, choose the S3 location where the training jobs that this hyperparameter tuning job launches store output, such as model artifacts.

      **Note**
      
      You use the model artifacts stored at this location to create a model or model package from this hyperparameter tuning job.

   ii. For Encryption key, if you want SageMaker to use a AWS KMS key to encrypt output data at rest in the S3 location.

k. For Resource configuration, provide the following information:

   i. For Instance type, choose the instance type to use for each training job that the hyperparameter tuning job launches.

   ii. For Instance count, type the number of ML instances to use for each training job that the hyperparameter tuning job launches.

   iii. For Additional volume per instance (GB), type the size of the ML storage volume that you want to provision each training job that the hyperparameter tuning job launches. ML storage volumes store model artifacts and incremental states.

   iv. For Encryption key, if you want Amazon SageMaker to use an AWS Key Management Service key to encrypt data in the ML storage volume attached to the training instances, specify the key.
Use Algorithm and Model Package Resources

For **Resource limits**, provide the following information:

i. **For Maximum training jobs**, specify the maximum number of training jobs that you want the hyperparameter tuning job to launch. A hyperparameter tuning job can launch a maximum of 500 training jobs.

ii. **For Maximum parallel training jobs**, specify the maximum number of concurrent training jobs that the hyperparameter tuning job can launch. A hyperparameter tuning job can launch a maximum of 10 concurrent training jobs.

iii. **For Stopping condition**, specify the maximum amount of time in seconds, minutes, hours, or days, that you want each training job that the hyperparameter tuning job launches to run.

m. **For Tags**, specify one or more tags to manage the hyperparameter tuning job. Each tag consists of a key and an optional value. Tag keys must be unique per resource.

n. Choose **Create jobs** to run the hyperparameter tuning job.

### Use an Algorithm to Run a Hyperparameter Tuning Job (API)

To use an algorithm to run a hyperparameter tuning job by using the SageMaker API, specify either the name or the Amazon Resource Name (ARN) of the algorithm as the **AlgorithmName** field of the **AlgorithmSpecification** object that you pass to **CreateHyperParameterTuningJob**. For information about hyperparameter tuning in SageMaker, see [Perform Automatic Model Tuning with SageMaker](p. 2436).

### Use an Algorithm to Run a Hyperparameter Tuning Job (Amazon SageMaker Python SDK)

Use an algorithm that you created or subscribed to on AWS Marketplace to create a hyperparameter tuning job, create an **AlgorithmEstimator** object and specify either the Amazon Resource Name (ARN) or the name of the algorithm as the value of the **algorithm_arn** argument. Then initialize a **HyperparameterTuner** object with the **AlgorithmEstimator** you created as the value of the **estimator** argument. Finally, call the **fit** method of the **AlgorithmEstimator**. For example:

```python
from sagemaker import AlgorithmEstimator
from sagemaker.tuner import HyperparameterTuner

data_path = os.path.join(DATA_DIR, 'marketplace', 'training')
algo = AlgorithmEstimator(
    role='SageMakerRole',
    instance_count=1,
    instance_type='ml.c4.xlarge',
    sagemaker_session=sagemaker_session,
    base_job_name='test-marketplace')

train_input = algo.sagemaker_session.upload_data(
    path=data_path, key_prefix='integ-test-data/marketplace/train')

algo.set_hyperparameters(max_leaf_nodes=10)
tuner = HyperparameterTuner(estimator=algo, base_tuning_job_name='some-name',
                           objective_metric_name='validation:accuracy',
                           hyperparameter_ranges=hyperparameter_ranges,
                           max_jobs=2, max_parallel_jobs=2)

tuner.fit({'training': train_input}, include_cls_metadata=False)
tuner.wait()
```
Use a Model Package to Create a Model

Use a model package to create a deployable model that you can use to get real-time inferences by creating a hosted endpoint or to run batch transform jobs. You can create a deployable model from a model package by using the Amazon SageMaker console, the low-level SageMaker API, or the Amazon SageMaker Python SDK.

Topics

• Use a Model Package to Create a Model (Console) (p. 3488)
• Use a Model Package to Create a Model (API) (p. 3488)
• Use a Model Package to Create a Model (Amazon SageMaker Python SDK) (p. 3489)

Use a Model Package to Create a Model (Console)

To create a deployable model from a model package (console)

2. Choose Model packages.
3. Choose a model package that you created from the list on the My model packages tab or choose a model package that you subscribed to on the AWS Marketplace subscriptions tab.
4. Choose Create model.
5. For Model name, type a name for the model.
6. For IAM role, choose an IAM role that has the required permissions to call other services on your behalf, or choose Create a new role to allow SageMaker to create a role that has the AmazonSageMakerFullAccess managed policy attached. For information, see SageMaker Roles (p. 3536).
7. For VPC, choose a Amazon VPC that you want to allow the model to access. For more information, see Give SageMaker Hosted Endpoints Access to Resources in Your Amazon VPC (p. 3650).
8. Leave the default values for Container input options and Choose model package.
9. For environment variables, provide the names and values of environment variables you want to pass to the model container.
10. For Tags, specify one or more tags to manage the model. Each tag consists of a key and an optional value. Tag keys must be unique per resource.
11. Choose Create model.

After you create a deployable model, you can use it to set up an endpoint for real-time inference or create a batch transform job to get inferences on entire datasets. For information about hosting endpoints in SageMaker, see Deploy Models for Inference.

Use a Model Package to Create a Model (API)

To use a model package to create a deployable model by using the SageMaker API, specify the name or the Amazon Resource Name (ARN) of the model package as the ModelPackageName field of the ContainerDefinition object that you pass to the CreateModel API.

After you create a deployable model, you can use it to set up an endpoint for real-time inference or create a batch transform job to get inferences on entire datasets. For information about hosted endpoints in SageMaker, see Deploy Models for Inference.
Use a Model Package to Create a Model (Amazon SageMaker Python SDK)

To use a model package to create a deployable model by using the SageMaker Python SDK, initialize a ModelPackage object, and pass the Amazon Resource Name (ARN) of the model package as the model_package_arn argument. For example:

```python
from sagemaker import ModelPackage
data = ModelPackage(role='SageMakerRole',
                     model_package_arn='training-job-scikit-decision-trees-1542660466-6f92',
                     sagemaker_session=sagemaker_session)
```

After you create a deployable model, you can use it to set up an endpoint for real-time inference or create a batch transform job to get inferences on entire datasets. For information about hosting endpoints in SageMaker, see Deploy Models for Inference.

Sell Amazon SageMaker Algorithms and Model Packages

Selling Amazon SageMaker algorithms and model packages is a three-step process:

1. Develop your algorithm or model, and package it in a Docker container. For information, see Develop Algorithms and Models in Amazon SageMaker (p. 3490).
2. Create an algorithm or model package resource in SageMaker. For information, see Create Algorithm and Model Package Resources (p. 3476).
3. Register as a seller on AWS Marketplace and list your algorithm or model package on AWS Marketplace. For information about registering as a seller, see Getting Started as a Seller in the User Guide for AWS Marketplace Providers. For information about listing and monetizing your algorithms and model packages, see Listing Algorithms and Model Packages in AWS Marketplace for Machine Learning in the User Guide for AWS Marketplace Providers.
Develop Algorithms and Models in Amazon SageMaker

Before you can create algorithm and model package resources to use in Amazon SageMaker or list on AWS Marketplace, you have to develop them and package them in Docker containers.

Note
When algorithms and model packages are created for listing on AWS Marketplace, SageMaker scans the containers for security vulnerabilities on supported operating systems. Only the following operating system versions are supported:

- Debian: 6.0, 7, 8, 9, 10
- CentOS: 5, 6, 7
- Oracle Linux: 5, 6, 7
- Alpine: 3.3, 3.4, 3.5
- Amazon Linux

Develop Algorithms in SageMaker

An algorithm should be packaged as a docker container and stored in Amazon ECR to use it in SageMaker. The Docker container contains the training code used to run training jobs and, optionally, the inference code used to get inferences from models trained by using the algorithm.

For information about developing algorithms in SageMaker and packaging them as containers, see Using Docker containers with SageMaker (p. 3149). For a complete example of how to create an algorithm container, see the sample notebook at https://sagemaker-examples.readthedocs.io/en/latest/advanced_functionality/scikitbring_your_own/scikitbring_your_own.html. You can also find the sample notebook in a SageMaker notebook instance. The notebook is in the Advanced Functionality section, and is named scikitbring_your_own.ipynb. For information about using the sample notebooks in a notebook instance, see Example Notebooks (p. 306).

Always thoroughly test your algorithms before you create algorithm resources to publish on AWS Marketplace.

Note
When a buyer subscribes to your containerized product, the Docker containers run in an isolated (internet-free) environment. When you create your containers, do not rely on making outgoing calls over the internet. Calls to AWS services are also not allowed.
Develop Models in SageMaker

A deployable model in SageMaker consists of inference code, model artifacts, an IAM role that is used to access resources, and other information required to deploy the model in SageMaker. Model artifacts are the results of training a model by using a machine learning algorithm. The inference code must be packaged in a Docker container and stored in Amazon ECR. You can either package the model artifacts in the same container as the inference code, or store them in Amazon S3.

You create a model by running a training job in SageMaker, or by training a machine learning algorithm outside of SageMaker. If you run a training job in SageMaker, the resulting model artifacts are available in the ModelArtifacts field in the response to a call to the DescribeTrainingJob operation. For information about how to develop a SageMaker model container, see Use Your Own Inference Code (p. 3191). For a complete example of how to create a model container from a model trained outside of SageMaker, see the sample notebook at https://sagemaker-examples.readthedocs.io/en/latest/advanced_functionality/xgboostbring_your_own_model/xgboostbring_your_own_model.html. You can also find the sample notebook in a SageMaker notebook instance. The notebook is in the Advanced Functionality section, and is named xgboostbring_your_own_model.ipynb. For information about using the sample notebooks in a notebook instance, see Example Notebooks (p. 306).

Always thoroughly test your models before you create model packages to publish on AWS Marketplace.

Note
When a buyer subscribes to your containerized product, the Docker containers run in an isolated (internet-free) environment. When you create your containers, do not rely on making outgoing calls over the internet. Calls to AWS services are also not allowed.

List Your Algorithm or Model Package on AWS Marketplace

After creating and validating your algorithm or model in Amazon SageMaker, list your product on AWS Marketplace. The listing process makes your products available in the AWS Marketplace and the SageMaker console.

To list products on AWS Marketplace, you must be a registered seller. To register, use the self-registration process from the AWS Marketplace Management Portal (AMMP). For information, see Getting Started as a Seller in the User Guide for AWS Marketplace Providers. When you start the product listing process from the Amazon SageMaker console, we check your seller registration status. If you have not registered, we direct you to do so.

To start the listing process, do one of the following:

- From the SageMaker console, choose the product, choose Actions, and choose Publish new ML Marketplace listing. This carries over your product reference, the Amazon Resource Name (ARN), and directs you to the AMMP to create the listing.
- Go to ML listing process, manually enter the Amazon Resource Name (ARN), and start your product listing. This process carries over the product metadata that you entered when creating the product in SageMaker. For an algorithm listing, the information includes the supported instance types and hyperparameters. In addition, you can enter a product description, promotional information, and support information as you would with other AWS Marketplace products.
Find and Subscribe to Algorithms and Model Packages on AWS Marketplace

With AWS Marketplace, you can browse and search for hundreds of machine learning algorithms and models in a broad range of categories, such as computer vision, natural language processing, speech recognition, text, data, voice, image, video analysis, fraud detection, predictive analysis, and more.

To find algorithms on AWS Marketplace

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. Choose Algorithms, then choose Find algorithms.

This takes you to the AWS Marketplace algorithms page. For information about finding and subscribing to algorithms on AWS Marketplace, see Machine Learning Products in the AWS Marketplace User Guide for AWS Consumers.

To find model packages on AWS Marketplace

2. Choose Model packages, then choose Find model packages.

This takes you to the AWS Marketplace model packages page. For information about finding and subscribing to model packages on AWS Marketplace, see Machine Learning Products in the AWS Marketplace User Guide for AWS Consumers.

Use Algorithms and Model Packages

For information about using algorithms and model packages that you subscribe to in SageMaker, see Use Algorithm and Model Package Resources (p. 3482).

Note
When you create a training job, inference endpoint, and batch transform job from an algorithm or model package that you subscribe to on AWS Marketplace, the training and inference containers do not have access to the internet. Because the containers do not have access to the internet, the seller of the algorithm or model package does not have access to your data.
Security in Amazon SageMaker

Cloud security at AWS is the highest priority. As an AWS customer, you benefit from a data center and network architecture that is built to meet the requirements of the most security-sensitive organizations.

Security is a shared responsibility between AWS and you. The shared responsibility model describes this as security of the cloud and security in the cloud:

- **Security of the cloud** – AWS is responsible for protecting the infrastructure that runs AWS services in the AWS Cloud. AWS also provides you with services that you can use securely. Third-party auditors regularly test and verify the effectiveness of our security as part of the AWS compliance programs. To learn about the compliance programs that apply to Amazon SageMaker, see AWS Services in Scope by Compliance Program.

- **Security in the cloud** – Your responsibility is determined by the AWS service that you use. You are also responsible for other factors including the sensitivity of your data, your company’s requirements, and applicable laws and regulations.

This documentation helps you understand how to apply the shared responsibility model when using SageMaker. The following topics show you how to configure SageMaker to meet your security and compliance objectives. You also learn how to use other AWS services that help you to monitor and secure your SageMaker resources.

**Topics**
- Access Control (p. 3493)
- Data Protection in Amazon SageMaker (p. 3495)
- Identity and Access Management for Amazon SageMaker (p. 3500)
- Logging and Monitoring (p. 3628)
- Compliance Validation for Amazon SageMaker (p. 3629)
- Resilience in Amazon SageMaker (p. 3629)
- Infrastructure Security in Amazon SageMaker (p. 3630)

Access Control

Amazon SageMaker Studio notebooks and SageMaker notebook instances differ in their runtime environments. The following topics describe how to control root access to these notebooks.

**Topics**
- Access control and SageMaker Studio notebooks (p. 3493)
- Control root access to a SageMaker notebook instance (p. 3495)

Access control and SageMaker Studio notebooks

Amazon SageMaker Studio uses filesystem and container permissions for access control and isolation of Studio users and notebooks. This is one of the major differences between Studio notebooks and SageMaker notebook instances. This topic describes how permissions are set up to avoid security threats, what SageMaker does by default, and how the customer can customize the permissions. For more information about Studio notebooks and their runtime environment, see Use Amazon SageMaker Studio Notebooks (p. 129).

**SageMaker app permissions**
A run-as user is a POSIX user/group which is used to run the JupyterServer app and KernelGateway apps inside the container.

The run-as user for the JupyterServer app is sagemaker-user (1000) by default. This user has sudo permissions to enable the installation of dependencies such as yum packages.

The run-as user for the KernelGateway apps is root (0) by default. This user is able to install dependencies using pip/apt-get/conda.

Due to user remapping, neither user is able to access resources or make changes to the host instance.

User remapping

SageMaker performs user-remapping to map a user inside the container to a user on the host instance outside the container. The range of user IDs (0 - 65535) in the container are mapped to non-privileged user IDs above 65535 on the instance. For example, sagemaker-user (1000) inside the container might map to user (200001) on the instance, where the number in parentheses is the user ID. If the customer creates a new user/group inside the container, it won't be privileged on the host instance regardless of the user/group ID. The root user of the container is also mapped to a non-privileged user on the instance. For more information, see Isolate containers with a user namespace.

Custom image permissions

Customers can bring their own custom SageMaker images. These images can specify a different run-as user/group to launch the KernelGateway app. The customer can implement fine grained permission control inside the image, for example, to disable root access or perform other actions. The same user remapping applies here. For more information, see Bring your own SageMaker image (p. 152).

Container isolation

Docker keeps a list of default capabilities that the container can use. SageMaker doesn't add additional capabilities. SageMaker adds specific route rules to block requests to Amazon EFS and the instance metadata service (IMDS) from the container. Customers can't change these route rules from the container. For more information, see Runtime privilege and Linux capabilities.

App metadata access

Metadata used by running apps are mounted to the container with read-only permission. Customers aren't able to modify this metadata from the container. For the available metadata, see Get Notebook and App Metadata (p. 139).

User isolation on EFS

When you onboard to Studio, SageMaker creates an Amazon Elastic File System (EFS) volume for your domain that is shared by all Studio users in the domain. Each user gets their own private home directory on the EFS volume. This home directory is used to store the user's notebooks, Git repositories, and other data. To prevent other users in the domain from accessing the user's data, SageMaker creates a globally unique user ID for the user's profile and applies it as a POSIX user/group ID for the user's home directory.

EBS access

An Amazon Elastic Block Store (Amazon EBS) volume is attached to the host instance and shared across all images. It's used for the root volume of the notebooks and stores temporary data that's generated inside the container. The storage isn't persisted when the instance running the notebooks is deleted. The root user inside the container can't access the EBS volume.

IMDS access

Due to security concerns, access to the Amazon Elastic Compute Cloud (Amazon EC2) Instance Metadata Service (IMDS) is unavailable in SageMaker Studio. For more information on IMDS, see Instance metadata and user data.
Control root access to a SageMaker notebook instance

By default, when you create a notebook instance, users that log into that notebook instance have root access. Data science is an iterative process that might require the data scientist to test and use different software tools and packages, so many notebook instance users need to have root access to be able to install these tools and packages. Because users with root access have administrator privileges, users can access and edit all files on a notebook instance with root access enabled.

If you don't want users to have root access to a notebook instance, when you call CreateNotebookInstance or UpdateNotebookInstance operations, set the RootAccess field to Disabled. You can also disable root access for users when you create or update a notebook instance in the Amazon SageMaker console. For information, see Step 1: Create an Amazon SageMaker Notebook Instance (p. 74).

Note
Lifecycle configurations need root access to be able to set up a notebook instance. Because of this, lifecycle configurations associated with a notebook instance always run with root access even if you disable root access for users.

Note
For security reasons, Rootless Docker is installed on root-disabled notebook instances instead of regular Docker. For more information, see Run the Docker daemon as a non-root user (Rootless mode)

Data Protection in Amazon SageMaker

The AWS shared responsibility model applies to data protection in Amazon SageMaker. As described in this model, AWS is responsible for protecting the global infrastructure that runs all of the AWS Cloud. You are responsible for maintaining control over your content that is hosted on this infrastructure. This content includes the security configuration and management tasks for the AWS services that you use. For more information about data privacy, see the Data Privacy FAQ. For information about data protection in Europe, see the AWS Shared Responsibility Model and GDPR blog post on the AWS Security Blog.

For data protection purposes, we recommend that you protect AWS account credentials and set up individual user accounts with AWS Identity and Access Management (IAM). That way each user is given only the permissions necessary to fulfill their job duties. We also recommend that you secure your data in the following ways:

- Use multi-factor authentication (MFA) with each account.
- Use SSL/TLS to communicate with AWS resources. We recommend TLS 1.2 or later.
- Set up API and user activity logging with AWS CloudTrail.
- Use AWS encryption solutions, along with all default security controls within AWS services.
- Use advanced managed security services such as Amazon Macie, which assists in discovering and securing personal data that is stored in Amazon S3.
- If you require FIPS 140-2 validated cryptographic modules when accessing AWS through a command line interface or an API, use a FIPS endpoint. For more information about the available FIPS endpoints, see Federal Information Processing Standard (FIPS) 140-2.

We strongly recommend that you never put confidential or sensitive information, such as your customers' email addresses, into tags or free-form fields such as a Name field. This includes when you work with Amazon SageMaker or other AWS services using the console, API, AWS CLI, or AWS SDKs. Any data that you enter into tags or free-form fields used for names may be used for billing or
diagnostic logs. If you provide a URL to an external server, we strongly recommend that you do not include credentials information in the URL to validate your request to that server.

Topics
- Protect Data at Rest Using Encryption (p. 3496)
- Protecting Data in Transit with Encryption (p. 3497)
- Key Management (p. 3500)
- Internetwork Traffic Privacy (p. 3500)

Protect Data at Rest Using Encryption

To protect your Amazon SageMaker Studio notebooks and SageMaker notebook instances, along with your model-building data and model artifacts, SageMaker encrypts the notebooks, as well as output from Training and Batch Transform jobs. SageMaker encrypts these by default using the AWS Managed Key for Amazon S3. This AWS Managed Key for Amazon S3 cannot be shared for cross-account access. For cross-account access, specify your customer managed key while creating SageMaker resources so that it can be shared for cross-account access. For more information on AWS KMS, see What is AWS Key Management Service?

Topics
- Studio notebooks (p. 3496)
- Notebook instances, SageMaker jobs, and Endpoints (p. 3496)

Studio notebooks

In Amazon SageMaker Studio, your SageMaker Studio notebooks and data can be stored in the following locations:

- An S3 bucket – When you onboard to Studio and enable shareable notebook resources, SageMaker shares notebook snapshots and metadata in an Amazon Simple Storage Service (Amazon S3) bucket.
- An EFS volume – When you onboard to Studio, SageMaker attaches an Amazon Elastic File System (Amazon EFS) volume to your domain for storing your Studio notebooks and data files. The EFS volume persists after the domain is deleted.
- An EBS volume – When you open a notebook in Studio, an Amazon Elastic Block Store (Amazon EBS) is attached to the instance that the notebook runs on. The EBS volume persists for the duration of the instance.

SageMaker uses the AWS Key Management Service (AWS KMS) to encrypt the S3 bucket and both volumes. By default, it uses an AWS managed key. For more control, you can specify your own customer managed key when you onboard to Studio or through the SageMaker API. For more information, see Onboard to Amazon SageMaker Domain (p. 35) and CreateDomain.

In the CreateDomain API, you use the S3KmsKeyId parameter to specify the customer managed key for shareable notebooks. You use the KmsKeyId parameter to specify the customer managed key for the EFS and EBS volumes. The same customer managed key is used for both volumes. The customer managed key for shareable notebooks can be the same customer managed key as used for the volumes or a different customer managed key.

Notebook instances, SageMaker jobs, and Endpoints

To encrypt the machine learning (ML) storage volume that is attached to notebooks, processing jobs, training jobs, hyperparameter tuning jobs, batch transform jobs, and endpoints, you can pass a AWS KMS
key to SageMaker. If you don't specify a KMS key, SageMaker encrypts storage volumes with a transient key and discards it immediately after encrypting the storage volume. For notebook instances, if you don't specify a KMS key, SageMaker encrypts both OS volumes and ML data volumes with a system-managed KMS key.

You can use an AWS managed AWS KMS key to encrypt all instance OS volumes. You can encrypt all ML data volumes for all SageMaker instances with a AWS KMS key that you specify. ML storage volumes are mounted as follows:

- Notebooks - `/home/ec2-user/SageMaker`
- Processing - `/opt/ml/processing` and `/tmp/`
- Training - `/opt/ml/` and `/tmp/`
- Batch - `/opt/ml/` and `/tmp/`
- Endpoints - `/opt/ml/` and `/tmp/`

Processing, batch transform, and training job containers and their storage are ephemeral in nature. When the job completes, output is uploaded to Amazon S3 using AWS KMS encryption with an optional AWS KMS key that you specify and the instance is torn down. If a AWS KMS Key is not provided in the job request, the output is encrypted by default using your AWS Managed Key for Amazon S3.

**Note**
The key policy for an AWS Managed Key for Amazon S3 cannot be edited, so cross-account permissions cannot be granted for these key policies. If the output Amazon S3 bucket for the request is from another account, specify your own AWS KMS Customer Key in the job request and ensure that the job's execution role has permissions to encrypt data with it.

**Important**
Sensitive data that needs to be encrypted with a KMS key for compliance reasons should be stored in the ML storage volume or in Amazon S3, both of which can be encrypted using a KMS key you specify.

When you open a notebook instance, SageMaker saves it and any files associated with it in the SageMaker folder in the ML storage volume by default. When you stop a notebook instance, SageMaker creates a snapshot of the ML storage volume. Any customizations to the operating system of the stopped instance, such as installed custom libraries or operating system level settings, are lost. Consider using a lifecycle configuration to automate customizations of the default notebook instance. When you terminate an instance, the snapshot and the ML storage volume are deleted. Any data that you need to persist beyond the lifespan of the notebook instance should be transferred to an Amazon S3 bucket.

**Note**
Certain Nitro-based SageMaker instances include local storage, depending on the instance type. Local storage volumes are encrypted using a hardware module on the instance. You can't use a KMS key on an instance type with local storage. For a list of instance types that support local instance storage, see [Instance Store Volumes](#). For more information about storage volumes on Nitro-based instances, see [Amazon EBS and NVMe on Linux Instances](#). For more information about local instance storage encryption, see [SSD Instance Store Volumes](#).

## Protecting Data in Transit with Encryption

All internetwork data in transit supports TLS 1.2 encryption.

With Amazon SageMaker, machine learning (ML) model artifacts and other system artifacts are encrypted in transit and at rest. Requests to the SageMaker API and console are made over a secure (SSL) connection. You pass AWS Identity and Access Management roles to SageMaker to provide permissions to access resources on your behalf for training and deployment. Use encrypted Amazon S3 buckets for model artifacts and data, and to pass an AWS KMS key to SageMaker instances to encrypt the attached ML storage volumes.
Some intranetwork data in transit (inside the service platform) is unencrypted. This includes:

- Command and control communications between the service control plane and training job instances (not customer data).
- Communications between nodes in distributed processing jobs (intranetwork).
- Communications between nodes in distributed training jobs (intranetwork).

There are no inter-node communications for batch processing.

You can choose to encrypt communication between nodes in a training cluster.

**Note**
For use cases in the healthcare sector, the best practice for security is to encrypt communication between the nodes.

For information about how to encrypt communication, see the next topic at Protect Communications Between ML Compute Instances in a Distributed Training Job (p. 3498).

**Note**
Encrypting inter-container traffic can increase training time, especially if you use distributed deep learning algorithms. For affected algorithms, this additional level of security also increases cost. The training time for most SageMaker built-in algorithms, such as XGBoost, DeepAR, and linear learner, typically aren't affected.

FIPS validated endpoints are available for the SageMaker API and request router for hosted models (runtime). For information about FIPS compliant endpoints, see Federal Information Processing Standard (FIPS) 140-2.

**Protect Communications with RStudio on Amazon SageMaker**

RStudio on Amazon SageMaker provides encryption for all communications that involve SageMaker components. However, the previous version did not support encryption between the RStudioServerPro and RSession apps.

RStudio released version 2022.02.2-485.pro2 in April 2022. This version supports encryption between RStudioServerPro and RSession apps to enable end-to-end encryption. The version upgrade, however, is not completely backward compatible. As a result, you must update all of your RStudioServerPro and RSession apps. For information about how to update your apps, see Upgrade the RStudio Version (p. 184).

**Protect Communications Between ML Compute Instances in a Distributed Training Job**

By default, Amazon SageMaker runs training jobs in an Amazon Virtual Private Cloud (Amazon VPC) to help keep your data secure. You can add another level of security to protect your training containers and data by configuring a private VPC. Distributed ML frameworks and algorithms usually transmit information that is directly related to the model, such as weights, not the training dataset. When performing distributed training, you can further protect data that is transmitted between instances. This can help you to comply with regulatory requirements. To do this, use inter-container traffic encryption.

**Note**
For use cases in the healthcare sector, the best practice for security is to encrypt communication between the nodes.

Enabling inter-container traffic encryption can increase training time, especially if you are using distributed deep learning algorithms. Enabling inter-container traffic encryption doesn't affect training jobs with a single compute instance. However, for training jobs with several compute instances, the effect
on training time depends on the amount of communication between compute instances. For affected algorithms, adding this additional level of security also increases cost. The training time for most SageMaker built-in algorithms, such as XGBoost, DeepAR, and linear learner, typically aren't affected.

You can enable inter-container traffic encryption for training jobs or hyperparameter tuning jobs. You can use SageMaker APIs or console to enable inter-container traffic encryption.

For information about running training jobs in a private VPC, see Give SageMaker Training Jobs Access to Resources in Your Amazon VPC (p. 3648).

Enable Inter-container Traffic Encryption (API)

Before enabling inter-container traffic encryption on training or hyperparameter tuning jobs with APIs, add inbound and outbound rules to your private VPC's security group.

To enable inter-container traffic encryption (API)

1. Add the following inbound and outbound rules in the security group for your private VPC:

<table>
<thead>
<tr>
<th>Protocol</th>
<th>Port Range</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>UDP</td>
<td>500</td>
<td>Self Security Group ID</td>
</tr>
<tr>
<td>ESP 50</td>
<td>N/A</td>
<td>Self Security Group ID</td>
</tr>
</tbody>
</table>

2. When you send a request to the CreateTrainingJob or CreateHyperParameterTuningJob API, specify True for the EnableInterContainerTrafficEncryption parameter.

Note
For the ESP 50 protocol, the AWS Security Group Console might display the port range as "All". However, Amazon EC2 ignores the specified port range because it is not applicable for the ESP 50 IP protocol.

Enable Inter-container Traffic Encryption (Console)

Enable Inter-container Traffic Encryption in a Training Job

To enable inter-container traffic encryption in a training job

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the navigation pane, choose Training, then choose Training jobs.
3. Choose Create training job.
4. Under Network, choose a VPC. You can use the default VPC or one that you have created.
5. Choose Enable inter-container traffic encryption.

After you enable inter-container traffic encryption, finish creating the training job. For more information, see Step 4: Train a Model (p. 81).

Enable Inter-container Traffic Encryption in a Hyperparameter Tuning Job

To enable inter-container traffic encryption in a hyperparameter tuning job

1. Open the Amazon SageMaker console at https://console.aws.amazon.com/sagemaker/.
2. In the navigation pane, choose Training, then choose Hyperparameter tuning jobs.
3. Choose Create hyperparameter tuning job.
4. Under **Network**, choose a **VPC**. You can use the default VPC or one that you created.
5. Choose **Enable inter-container traffic encryption**.

After enabling inter-container traffic encryption, finish creating the hyperparameter tuning job. For more information, see **Configure and Launch a Hyperparameter Tuning Job** (p. 2450).

## Key Management

Customers can specify AWS KMS keys, including bring your own keys (BYOK), to use for envelope encryption with Amazon S3 input/output buckets and machine learning (ML) Amazon EBS volumes. ML volumes for notebook instances and for processing, training, and hosted model Docker containers can be optionally encrypted by using AWS KMS customer-owned keys. All instance OS volumes are encrypted with an AWS-managed AWS KMS key.

**Note**

Certain Nitro-based instances include local storage, dependent on the instance type. Local storage volumes are encrypted using a hardware module on the instance. You can't request a **VolumeKmsKeyId** when using an instance type with local storage. For a list of instance types that support local instance storage, see [Instance Store Volumes](#). For more information about local instance storage encryption, see [SSD Instance Store Volumes](#). For more information about storage volumes on nitro-based instances, see [Amazon EBS and NVMe on Linux Instances](#).

For information about AWS KMS keys see [What is AWS Key Management Service?](#) in the [AWS Key Management Service Developer Guide](#).

## Internetwork Traffic Privacy

This topic describes how Amazon SageMaker secures connections from the service to other locations.

Internetwork communications support TLS 1.2 encryption between all components and clients.

Instances can be connected to Customer VPC, providing access to S3 VPC endpoints or customer repositories. Internet egress can be managed through this interface by the customer if service platform internet egress is disabled for notebooks. For training and hosting, egress through the service platform is not available when connected to the customer’s VPC.

By default, API calls made to published endpoints traverse the public network to the request router. SageMaker supports Amazon Virtual Private Cloud interface endpoints powered by AWS PrivateLink for private connectivity between the customer’s VPC and the request router to access hosted model endpoints. For information about Amazon VPC, see [Connect to SageMaker Through a VPC Interface Endpoint](#).

## Identity and Access Management for Amazon SageMaker

AWS Identity and Access Management (IAM) is an AWS service that helps an administrator securely control access to AWS resources. IAM administrators control who can be **authenticated** (signed in) and **authorized** (have permissions) to use SageMaker resources. IAM is an AWS service that you can use with no additional charge.

**Topics**

- Audience (p. 3501)
Audience

How you use AWS Identity and Access Management (IAM) differs, depending on the work that you do in SageMaker.

Service user – If you use the SageMaker service to do your job, then your administrator provides you with the credentials and permissions that you need. As you use more SageMaker features to do your work, you might need additional permissions. Understanding how access is managed can help you request the right permissions from your administrator. If you cannot access a feature in SageMaker, see Troubleshooting Amazon SageMaker Identity and Access (p. 3626).

Service administrator – If you're in charge of SageMaker resources at your company, you probably have full access to SageMaker. It's your job to determine which SageMaker features and resources your service users should access. You must then submit requests to your IAM administrator to change the permissions of your service users. Review the information on this page to understand the basic concepts of IAM. To learn more about how your company can use IAM with SageMaker, see How Amazon SageMaker Works with IAM (p. 3505).

IAM administrator – If you're an IAM administrator, you might want to learn details about how you can write policies to manage access to SageMaker. To view example SageMaker identity-based policies that you can use in IAM, see Amazon SageMaker Identity-Based Policy Examples (p. 3507).

Authenticating with Identities

Authentication is how you sign in to AWS using your identity credentials. You must be authenticated (signed in to AWS) as the AWS account root user, as an IAM user, or by assuming an IAM role.

You can sign in to AWS as a federated identity by using credentials provided through an identity source. AWS IAM Identity Center (successor to AWS Single Sign-On) (IAM Identity Center) users, your company's single sign-on authentication, and your Google or Facebook credentials are examples of federated identities. When you sign in as a federated identity, your administrator previously set up identity federation using IAM roles. When you access AWS by using federation, you are indirectly assuming a role.

Depending on the type of user you are, you can sign in to the AWS Management Console or the AWS access portal. For more information about signing in to AWS, see How to sign in to your AWS account in the AWS Sign-In User Guide.

If you access AWS programmatically, AWS provides a software development kit (SDK) and a command line interface (CLI) to cryptographically sign your requests using your credentials. If you don't use AWS tools, you must sign requests yourself. For more information about using the recommended method to sign requests yourself, see Signature Version 4 signing process in the AWS General Reference.

Regardless of the authentication method that you use, you might be required to provide additional security information. For example, AWS recommends that you use multi-factor authentication (MFA)
to increase the security of your account. To learn more, see Multi-factor authentication in the AWS IAM Identity Center (successor to AWS Single Sign-On) User Guide and Using multi-factor authentication (MFA) in AWS in the IAM User Guide.

AWS account root user

When you create an AWS account, you begin with one sign-in identity that has complete access to all AWS services and resources in the account. This identity is called the AWS account root user and is accessed by signing in with the email address and password that you used to create the account. We strongly recommend that you do not use the root user for your everyday tasks. Safeguard your root user credentials and use them to perform the tasks that only the root user can perform. For the complete list of tasks that require you to sign in as the root user, see Tasks that require root user credentials in the AWS General Reference.

IAM Users and Groups

An IAM user is an identity within your AWS account that has specific permissions for a single person or application. Where possible, we recommend relying on temporary credentials instead of creating IAM users who have long-term credentials such as passwords and access keys. However, if you have specific use cases that require long-term credentials with IAM users, we recommend that you rotate access keys. For more information, see Rotate access keys regularly for use cases that require long-term credentials in the IAM User Guide.

An IAM group is an identity that specifies a collection of IAM users. You can't sign in as a group. You can use groups to specify permissions for multiple users at a time. Groups make permissions easier to manage for large sets of users. For example, you could have a group named IAMAdmins and give that group permissions to administer IAM resources.

Users are different from roles. A user is uniquely associated with one person or application, but a role is intended to be assumable by anyone who needs it. Users have permanent long-term credentials, but roles provide temporary credentials. To learn more, see When to create an IAM user (instead of a role) in the IAM User Guide.

IAM Roles

An IAM role is an identity within your AWS account that has specific permissions. It is similar to an IAM user, but is not associated with a specific person. You can temporarily assume an IAM role in the AWS Management Console by switching roles. You can assume a role by calling an AWS CLI or AWS API operation or by using a custom URL. For more information about methods for using roles, see Using IAM roles in the IAM User Guide.

IAM roles with temporary credentials are useful in the following situations:

- **Federated user access** – To assign permissions to a federated identity, you create a role and define permissions for the role. When a federated identity authenticates, the identity is associated with the role and is granted the permissions that are defined by the role. For information about roles for federation, see Creating a role for a third-party Identity Provider in the IAM User Guide. If you use IAM Identity Center, you configure a permission set. To control what your identities can access after they authenticate, IAM Identity Center correlates the permission set to a role in IAM. For information about permissions sets, see Permission sets in the AWS IAM Identity Center (successor to AWS Single Sign-On) User Guide.

- **Temporary IAM user permissions** – An IAM user or role can assume an IAM role to temporarily take on different permissions for a specific task.

- **Cross-account access** – You can use an IAM role to allow someone (a trusted principal) in a different account to access resources in your account. Roles are the primary way to grant cross-account access. However, with some AWS services, you can attach a policy directly to a resource (instead of using a role
as a proxy). To learn the difference between roles and resource-based policies for cross-account access, see How IAM roles differ from resource-based policies in the IAM User Guide.

- **Cross-service access** – Some AWS services use features in other AWS services. For example, when you make a call in a service, it’s common for that service to run applications in Amazon EC2 or store objects in Amazon S3. A service might do this using the calling principal’s permissions, using a service role, or using a service-linked role.

- **Principal permissions** – When you use an IAM user or role to perform actions in AWS, you are considered a principal. Policies grant permissions to a principal. When you use some services, you might perform an action that then triggers another action in a different service. In this case, you must have permissions to perform both actions. To see whether an action requires additional dependent actions in a policy, see Actions, Resources, and Condition Keys for Amazon SageMaker in the Service Authorization Reference.

- **Service role** – A service role is an IAM role that a service assumes to perform actions on your behalf. An IAM administrator can create, modify, and delete a service role from within IAM. For more information, see Creating a role to delegate permissions to an AWS service in the IAM User Guide.

- **Service-linked role** – A service-linked role is a type of service role that is linked to an AWS service. The service can assume the role to perform an action on your behalf. Service-linked roles appear in your IAM account and are owned by the service. An IAM administrator can view, but not edit the permissions for service-linked roles.

- **Applications running on Amazon EC2** – You can use an IAM role to manage temporary credentials for applications that are running on an EC2 instance and making AWS CLI or AWS API requests. This is preferable to storing access keys within the EC2 instance. To assign an AWS role to an EC2 instance and make it available to all of its applications, you create an instance profile that is attached to the instance. An instance profile contains the role and enables programs that are running on the EC2 instance to get temporary credentials. For more information, see Using an IAM role to grant permissions to applications running on Amazon EC2 instances in the IAM User Guide.

To learn whether to use IAM roles or IAM users, see When to create an IAM role (instead of a user) in the IAM User Guide.

## Managing Access Using Policies

You control access in AWS by creating policies and attaching them to AWS identities or resources. A policy is an object in AWS that, when associated with an identity or resource, defines their permissions. AWS evaluates these policies when a principal (user, root user, or role session) makes a request. Permissions in the policies determine whether the request is allowed or denied. Most policies are stored in AWS as JSON documents. For more information about the structure and contents of JSON policy documents, see Overview of JSON policies in the IAM User Guide.

Administrators can use AWS JSON policies to specify who has access to what. That is, which principal can perform actions on what resources, and under what conditions.

Every IAM entity (user or role) starts with no permissions. By default, users can do nothing, not even change their own password. To give a user permission to do something, an administrator must attach a permissions policy to a user. Or the administrator can add the user to a group that has the intended permissions. When an administrator gives permissions to a group, all users in that group are granted those permissions.

IAM policies define permissions for an action regardless of the method that you use to perform the operation. For example, suppose that you have a policy that allows the iam:GetRole action. A user with that policy can get role information from the AWS Management Console, the AWS CLI, or the AWS API.

### Identity-Based Policies

Identity-based policies are JSON permissions policy documents that you can attach to an identity, such as an IAM user, group of users, or role. These policies control what actions users and roles can perform,
Identity-based policies can be further categorized as inline policies or managed policies. Inline policies are embedded directly into a single user, group, or role. Managed policies are standalone policies that you can attach to multiple users, groups, and roles in your AWS account. Managed policies include AWS managed policies and customer managed policies. To learn how to choose between a managed policy or an inline policy, see Choosing between managed policies and inline policies in the IAM User Guide.

Resource-Based Policies

Resource-based policies are JSON policy documents that you attach to a resource. Examples of resource-based policies are IAM role trust policies and Amazon S3 bucket policies. In services that support resource-based policies, service administrators can use them to control access to a specific resource. For the resource where the policy is attached, the policy defines what actions a specified principal can perform on that resource and under what conditions. You must specify a principal in a resource-based policy. Principals can include accounts, users, roles, federated users, or AWS services.

Resource-based policies are inline policies that are located in that service. You can't use AWS managed policies from IAM in a resource-based policy.

Access Control Lists (ACLs)

Access control lists (ACLs) control which principals (account members, users, or roles) have permissions to access a resource. ACLs are similar to resource-based policies, although they do not use the JSON policy document format.

Amazon S3, AWS WAF, and Amazon VPC are examples of services that support ACLs. To learn more about ACLs, see Access control list (ACL) overview in the Amazon Simple Storage Service Developer Guide.

Other Policy Types

AWS supports additional, less-common policy types. These policy types can set the maximum permissions granted to you by the more common policy types.

- **Permissions boundaries** – A permissions boundary is an advanced feature in which you set the maximum permissions that an identity-based policy can grant to an IAM entity (IAM user or role). You can set a permissions boundary for an entity. The resulting permissions are the intersection of entity's identity-based policies and its permissions boundaries. Resource-based policies that specify the user or role in the Principal field are not limited by the permissions boundary. An explicit deny in any of these policies overrides the allow. For more information about permissions boundaries, see Permissions boundaries for IAM entities in the IAM User Guide.

- **Service control policies (SCPs)** – SCPs are JSON policies that specify the maximum permissions for an organization or organizational unit (OU) in AWS Organizations. AWS Organizations is a service for grouping and centrally managing multiple AWS accounts that your business owns. If you enable all features in an organization, then you can apply service control policies (SCPs) to any or all of your accounts. The SCP limits permissions for entities in member accounts, including each AWS account root user. For more information about Organizations and SCPs, see How SCPs work in the AWS Organizations User Guide.

- **Session policies** – Session policies are advanced policies that you pass as a parameter when you programmatically create a temporary session for a role or federated user. The resulting session's permissions are the intersection of the user or role's identity-based policies and the session policies. Permissions can also come from a resource-based policy. An explicit deny in any of these policies overrides the allow. For more information, see Session policies in the IAM User Guide.
Multiple Policy Types

When multiple types of policies apply to a request, the resulting permissions are more complicated to understand. To learn how AWS determines whether to allow a request when multiple policy types are involved, see Policy evaluation logic in the IAM User Guide.

How Amazon SageMaker Works with IAM

Before you use IAM to manage access to SageMaker, you should understand what IAM features are available to use with SageMaker. To get a high-level view of how SageMaker and other AWS services work with IAM, see AWS Services That Work with IAM in the IAM User Guide.

Topics

- SageMaker Identity-Based Policies (p. 3505)

SageMaker Identity-Based Policies

With IAM identity-based policies, you can specify allowed or denied actions and resources as well as the conditions under which actions are allowed or denied. SageMaker supports specific actions, resources, and condition keys. To learn about all of the elements that you use in a JSON policy, see IAM JSON Policy Elements Reference in the IAM User Guide.

Actions

Administrators can use AWS JSON policies to specify who has access to what. That is, which principal can perform actions on what resources, and under what conditions.

The Action element of a JSON policy describes the actions that you can use to allow or deny access in a policy. Policy actions usually have the same name as the associated AWS API operation. There are some exceptions, such as permission-only actions that don't have a matching API operation. There are also some operations that require multiple actions in a policy. These additional actions are called dependent actions.

Include actions in a policy to grant permissions to perform the associated operation.

Policy actions in SageMaker use the following prefix before the action: sagemaker:. For example, to grant someone permission to run a SageMaker training job with the SageMaker CreateTrainingJob API operation, you include the sagemaker:CreateTrainingJob action in their policy. Policy statements must include either an Action or NotAction element. SageMaker defines its own set of actions that describe tasks that you can perform with this service.

To specify multiple actions in a single statement, separate them with commas as follows:

```
"Action": [
    "sagemaker:action1",
    "sagemaker:action2"
]
```

You can specify multiple actions using wildcards (*). For example, to specify all actions that begin with the word Describe, include the following action:

```
"Action": "sagemaker:Describe*"
```

To see a list of SageMaker actions, see Actions, resources, and condition keys for Amazon SageMaker in the Service Authorization Reference.
Resources

SageMaker does not support specifying resource ARNs in a policy.

Condition Keys

Administrators can use AWS JSON policies to specify who has access to what. That is, which principal can perform actions on what resources, and under what conditions.

The Condition element (or Condition block) lets you specify conditions in which a statement is in effect. The Condition element is optional. You can create conditional expressions that use condition operators, such as equals or less than, to match the condition in the policy with values in the request.

If you specify multiple Condition elements in a statement, or multiple keys in a single Condition element, AWS evaluates them using a logical AND operation. If you specify multiple values for a single condition key, AWS evaluates the condition using a logical OR operation. All of the conditions must be met before the statement's permissions are granted.

You can also use placeholder variables when you specify conditions. For example, you can grant an IAM user permission to access a resource only if it is tagged with their IAM user name. For more information, see IAM policy elements: variables and tags in the IAM User Guide.

AWS supports global condition keys and service-specific condition keys. To see all AWS global condition keys, see AWS global condition context keys in the IAM User Guide.

SageMaker defines its own set of condition keys and also supports using some global condition keys. To see all AWS global condition keys, see AWS Global Condition Context Keys in the IAM User Guide.

SageMaker supports a number of service-specific condition keys that you can use for fine-grained access control for the following operations:

- CreateProcessingJob
- CreateTrainingJob
- CreateModel
- CreateEndpointConfig
- CreateTransformJob
- CreateHyperParameterTuningJob
- CreateLabelingJob
- CreateNotebookInstance
- UpdateNotebookInstance

To see a list of SageMaker condition keys, see Condition keys for Amazon SageMaker in the IAM User Guide. To learn with which actions and resources you can use a condition key, see Actions defined by Amazon SageMaker.

For examples of using SageMaker condition keys, see the following: Control Creation of SageMaker Resources with Condition Keys (p. 3518).

Examples

To view examples of SageMaker identity-based policies, see Amazon SageMaker Identity-Based Policy Examples (p. 3507).
Amazon SageMaker Developer Guide
Identity-Based Policy Examples

SageMaker Resource-Based Policies

SageMaker does not support resource-based policies.

Authorization Based on SageMaker Tags

You can attach tags to SageMaker resources or pass tags in a request to SageMaker. To control access based on tags, you provide tag information in the condition element of a policy using the sagemaker:ResourceTag/key-name, aws:RequestTag/key-name, or aws:TagKeys condition keys. For more information about tagging SageMaker resources, see Control Access to SageMaker Resources by Using Tags (p. 3527).

To view an example identity-based policy for limiting access to a resource based on the tags on that resource, see Control Access to SageMaker Resources by Using Tags (p. 3527).

SageMaker IAM Roles

An IAM role is an entity within your AWS account that has specific permissions.

Using Temporary Credentials with SageMaker

You can use temporary credentials to sign in with federation, assume an IAM role, or to assume a cross-account role. You obtain temporary security credentials by calling AWS STS API operations such as AssumeRole or GetFederationToken.

SageMaker supports using temporary credentials.

Service-Linked Roles

SageMaker partially supports service-linked roles. Service-linked roles are currently available for SageMaker Studio and SageMaker training jobs.

Service Roles

This feature allows a service to assume a service role on your behalf. This role allows the service to access resources in other services to complete an action on your behalf. Service roles appear in your IAM account and are owned by the account. This means that an IAM administrator can change the permissions for this role. However, doing so might break the functionality of the service.

SageMaker supports service roles.

Choosing an IAM Role in SageMaker

When you create a notebook instance, processing job, training job, hosted endpoint, or batch transform job resource in SageMaker, you must choose a role to allow SageMaker to access SageMaker on your behalf. If you have previously created a service role or service-linked role, then SageMaker provides you with a list of roles to choose from. It’s important to choose a role that allows access to the AWS operations and resources you need. For more information, see SageMaker Roles (p. 3536).

Amazon SageMaker Identity-Based Policy Examples

By default, IAM users and roles don’t have permission to create or modify SageMaker resources. They also can’t perform tasks using the AWS Management Console, AWS CLI, or AWS API. An IAM administrator must create IAM policies that grant users and roles permission to perform specific API operations on the specified resources they need. The administrator must then attach those policies to the IAM users or groups that require those permissions. To learn how to attach policies to an IAM user or group, see Adding and Removing IAM Identity Permissions in the IAM User Guide.

To learn how to create an IAM identity-based policy using these example JSON policy documents, see Creating Policies on the JSON Tab in the IAM User Guide.

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Policy Best Practices

Identity-based policies determine whether someone can create, access, or delete SageMaker resources in your account. These actions can incur costs for your AWS account. When you create or edit identity-based policies, follow these guidelines and recommendations:

- **Get started with AWS managed policies and move toward least-privilege permissions** – To get started granting permissions to your users and workloads, use the AWS managed policies that grant permissions for many common use cases. They are available in your AWS account. We recommend that you reduce permissions further by defining AWS customer managed policies that are specific to your use cases. For more information, see AWS managed policies or AWS managed policies for job functions in the IAM User Guide.

- **Apply least-privilege permissions** – When you set permissions with IAM policies, grant only the permissions required to perform a task. You do this by defining the actions that can be taken on specific resources under specific conditions, also known as least-privilege permissions. For more information about using IAM to apply permissions, see Policies and permissions in IAM in the IAM User Guide.

- **Use conditions in IAM policies to further restrict access** – You can add a condition to your policies to limit access to actions and resources. For example, you can write a policy condition to specify that all requests must be sent using SSL. You can also use conditions to grant access to service actions if they are used through a specific AWS service, such as AWS CloudFormation. For more information, see IAM JSON policy elements: Condition in the IAM User Guide.

- **Use IAM Access Analyzer to validate your IAM policies to ensure secure and functional permissions** – IAM Access Analyzer validates new and existing policies so that the policies adhere to the IAM policy language (JSON) and IAM best practices. IAM Access Analyzer provides more than 100 policy checks and actionable recommendations to help you author secure and functional policies. For more information, see IAM Access Analyzer policy validation in the IAM User Guide.

- **Require multi-factor authentication (MFA)** – If you have a scenario that requires IAM users or root users in your account, turn on MFA for additional security. To require MFA when API operations are called, add MFA conditions to your policies. For more information, see Configuring MFA-protected API access in the IAM User Guide.

For more information about best practices in IAM, see Security best practices in IAM in the IAM User Guide.

Using the SageMaker Console

To access the Amazon SageMaker console, you must have a minimum set of permissions. These permissions must allow you to list and view details about the SageMaker resources in your AWS account. If you create an identity-based policy that is more restrictive than the minimum required permissions, the console won’t function as intended for entities (IAM users or roles) with that policy.
To ensure that those entities can still use the SageMaker console, also attach the following AWS managed policy to the entities. For more information, see Adding Permissions to a User in the IAM User Guide:

You don't need to allow minimum console permissions for users that are making calls only to the AWS CLI or the AWS API. Instead, allow access to only the actions that match the API operation that you're trying to perform.

Topics

- Permissions Required to Use the Amazon SageMaker Console (p. 3509)
- Permissions Required to Use the Amazon SageMaker Ground Truth Console (p. 3510)
- Permissions Required to Use the Amazon Augmented AI (Preview) Console (p. 3511)

Permissions Required to Use the Amazon SageMaker Console

The permissions reference table lists the Amazon SageMaker API operations and shows the required permissions for each operation. For more information about Amazon SageMaker API operations, see Amazon SageMaker API Permissions: Actions, Permissions, and Resources Reference (p. 3553).

To use the Amazon SageMaker console, you need to grant permissions for additional actions. Specifically, the console needs permissions that allow the ec2 actions to display subnets, VPCs, and security groups. Optionally, the console needs permission to create execution roles for tasks such as CreateNotebook, CreateTrainingJob, and CreateModel. Grant these permissions with the following permissions policy:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "SageMakerApis",
            "Effect": "Allow",
            "Action": ["sagemaker:*"],
            "Resource": "*"
        },
        {
            "Sid": "VpcConfigurationForCreateForms",
            "Effect": "Allow",
            "Action": ["ec2:DescribeVpcs", "ec2:DescribeSubnets", "ec2:DescribeSecurityGroups"],
            "Resource": "*"
        },
        {
            "Sid": "KmsKeysForCreateForms",
            "Effect": "Allow",
            "Action": ["kms:DescribeKey", "kms:ListAliases"],
            "Resource": "*"
        },
        {
            "Sid": "AccessAwsMarketplaceSubscriptions",
            "Effect": "Allow",
            "Action": ["aws-marketplace:ViewSubscriptions"
```
Permissions Required to Use the Amazon SageMaker Ground Truth Console

To use the Amazon SageMaker Ground Truth console, you need to grant permissions for additional resources. Specifically, the console needs permissions for the AWS Marketplace to view subscriptions, Amazon Cognito operations to manage your private workforce, Amazon S3 actions for access to your input and output files, and AWS Lambda actions to list and invoke functions. Grant these permissions with the following permissions policy:

```json
{
  "Version": "2012-10-17",
  "Statement": [  
    {
      "Effect": "Allow",
      "Action": [
        "codecommit:BatchGetRepositories",
        "codecommit:CreateRepository",
        "codecommit:GetRepository",
        "codecommit:ListRepositories",
        "codecommit:ListBranches",
        "secretsmanager:CreateSecret",
        "secretsmanager:DescribeSecret",
        "secretsmanager:ListSecrets"
      ],
      "Resource": "*"
    },
    {
      "Sid": "ListAndCreateExecutionRoles",
      "Effect": "Allow",
      "Action": [
        "iam:ListRoles",
        "iam:CreateRole",
        "iam:CreatePolicy",
        "iam:AttachRolePolicy"
      ],
      "Resource": "*"
    },
    {
      "Sid": "DescribeECRMetaData",
      "Effect": "Allow",
      "Action": [  
        "ecr:Describe*"
      ],
      "Resource": "*"
    },
    {
      "Sid": "PassRoleForExecutionRoles",
      "Effect": "Allow",
      "Action": [
        "iam:PassRole"
      ],
      "Resource": "*",
      "Condition": {
        "StringEquals": {
          "iam:PassedToService": "sagemaker.amazonaws.com"
        }
      }
    }
  ]
}
```
Identity-Based Policy Examples

```
{
  "Sid": "GroundTruthConsole",
  "Effect": "Allow",
  "Action": [
    "aws-marketplace:DescribeListings",
    "aws-marketplace:ViewSubscriptions",
    "cognito-idp:AdminAddUserToGroup",
    "cognito-idp:AdminCreateUser",
    "cognito-idp:AdminDeleteUser",
    "cognito-idp:AdminDisableUser",
    "cognito-idp:AdminEnableUser",
    "cognito-idp:AdminRemoveUserFromGroup",
    "cognito-idp:CreateGroup",
    "cognito-idp:CreateUserPool",
    "cognito-idp:CreateUserPoolClient",
    "cognito-idp:CreateUserPoolDomain",
    "cognito-idp:DescribeUserPool",
    "cognito-idp:DescribeUserPoolClient",
    "cognito-idp:ListGroups",
    "cognito-idp:ListIdentityProviders",
    "cognito-idp:ListUsers",
    "cognito-idp:ListUsersInGroup",
    "cognito-idp:ListUserPools",
    "cognito-idp:ListUserPoolClients",
    "cognito-idp:ListUserPoolClients",
    "groundtruthlabeling:DescribeConsoleJob",
    "groundtruthlabeling:ListDatasetObjects",
    "groundtruthlabeling:RunFilterOrSampleManifestJob",
    "groundtruthlabeling:RunGenerateManifestByCrawlingJob",
    "lambda:InvokeFunction",
    "lambda:ListFunctions",
    "s3:GetObject",
    "s3:PutObject",
    "s3:SelectObjectContent"
  ],
  "Resource": "*"
}
```

Permissions Required to Use the Amazon Augmented AI (Preview) Console

To use the Augmented AI console, you need to grant permissions for additional resources. Grant these permissions with the following permissions policy:

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "sagemaker:*Algorithm",
        "sagemaker:*Algorithms",
        "sagemaker:*App",
        "sagemaker:*Apps",
        "sagemaker:*AutoMLJob",
        "sagemaker:*AutoMLJobs",
        "sagemaker:*CodeRepositories",
        "sagemaker:*CodeRepository"
      ],
      "Resource": "*"
    }
  ]
}
```
"sagemaker:*CompilationJob",
"sagemaker:*CompilationJobs",
"sagemaker:*Endpoint",
"sagemaker:*EndpointConfig",
"sagemaker:*EndpointConfigs",
"sagemaker:*EndpointWeightsAndCapacities",
"sagemaker:*Endpoints",
"sagemaker:*Environment",
"sagemaker:*EnvironmentVersion",
"sagemaker:*EnvironmentVersions",
"sagemaker:*Environments",
"sagemaker:*Experiment",
"sagemaker:*Experiments",
"sagemaker:*FlowDefinitions",
"sagemaker:*HumanLoop",
"sagemaker:*HumanLoops",
"sagemaker:*HumanTaskUi",
"sagemaker:*HumanTaskUis",
"sagemaker:*HyperParameterTuningJob",
"sagemaker:*HyperParameterTuningJobs",
"sagemaker:*LabelingJob",
"sagemaker:*LabelingJobs",
"sagemaker:*Metrics",
"sagemaker:*Model",
"sagemaker:*ModelPackage",
"sagemaker:*ModelPackages",
"sagemaker:*Models",
"sagemaker:*MonitoringExecutions",
"sagemaker:*MonitoringSchedule",
"sagemaker:*MonitoringSchedules",
"sagemaker:*NotebookInstance",
"sagemaker:*NotebookInstanceLifecycleConfig",
"sagemaker:*NotebookInstanceLifecycleConfigs",
"sagemaker:*NotebookInstanceUrl",
"sagemaker:*NotebookInstances",
"sagemaker:*ProcessingJob",
"sagemaker:*ProcessingJobs",
"sagemaker:*RenderUiTemplate",
"sagemaker:*Search",
"sagemaker:*SearchSuggestions",
"sagemaker:*Tags",
"sagemaker:*TrainingJob",
"sagemaker:*TrainingJobs",
"sagemaker:*TransformJob",
"sagemaker:*TransformJobs",
"sagemaker:*Trial",
"sagemaker:*TrialComponent",
"sagemaker:*TrialComponents",
"sagemaker:*Trials",
"sagemaker:*Workteam",
"sagemaker:*Workteams"
],
"Resource": "*
",
{
  "Effect": "Allow",
  "Action": [
    "sagemaker:*FlowDefinition"
  ],
  "Resource": "*
",
  "Condition": {
    "StringEqualsIfExists": {
      "sagemaker:WorkteamType": [
        "private-crowd",
        "vendor-crowd"
      ]
    }
  }
}
"Effect": "Allow",
"Action": [  "application-autoscaling:DeleteScalingPolicy",
"application-autoscaling:DeleteScheduledAction",
"application-autoscaling:DeregisterScalableTarget",
"application-autoscaling:DescribeScalableTargets",
"application-autoscaling:DescribeScalingActivities",
"application-autoscaling:DescribeScalingPolicies",
"application-autoscaling:DescribeScheduledActions",
"application-autoscaling:PutScalingPolicy",
"application-autoscaling:PutScheduledAction",
"application-autoscaling:RegisterScalableTarget",
"aws-marketplace:ViewSubscriptions",
"cloudbformation:CreateStack",
"cloudbformation:DeleteStack",
"cloudbformation:DescribeStacks",
"cloudbformation:UpdateStack",
"cloudbreak:ListDatabases",
"cloudbreak:ListGroups",
"cloudbreak:ListInstances",
"cloudbreak:ListRewardSchemes",
"cloudbreak:ListTables",
"cloudbreak:ListUsers",
"cloudbreak:PutDatabases",
"cloudbreak:PutGroups",
"cloudbreak:PutInstances",
"cloudbreak:PutRewardSchemes",
"cloudbreak:PutTables",
"cloudbreak:PutUsers",
"cloudformation:CreateChangeSet",
"cloudformation:DeleteChangeSet",
"cloudformation:DescribeChangeSets",
"cloudformation:ExecuteChangeSet",
"cloudformation:MarshallChangeSet",
"cloudfront:CreateDistribution",
"cloudfront:DeleteDistribution",
"cloudfront:GetDistribution",
"cloudfront:GetKeyNames",
"cloudfront:ListDistributions",
"cloudfront:ListKeyNames",
"cloudfront:ListTagsForResource",
"cloudfront:MarshallDistribution",
"cloudfront:PutKeyNames",
"cloudfront:TagResource",
"cloudfront:UnmarshallDistribution",
"cloudfront:GetPriceList",
"cloudfront:ListPriceLists",
"cloudfront:ListTagsForResource",
"cloudtrail:createTrail",
"cloudtrail:deleteTrail",
"cloudtrail:getTrail",
"cloudtrail:listTrails",
"cloudtrail:updateTrail",
"cloudwatch:CreateAlarm",
"cloudwatch:DeleteAlarm",
"cloudwatch:GetAlarm",
"cloudwatch:GetMetricAlarm",
"cloudwatch:GetMetricData",
"cloudwatch:GetMetricStatistics",
"cloudwatch:ListMetrics",
"cloudwatch:PutAlarm",
"cloudwatch:PutMetricAlarm",
"cloudwatch:PutMetricData",
"cloudwatch:PutMetricUnits",
"cloudwatch:PutMetricWarning",
"codedeploy:DescribeAppVersion",
"codedeploy:DescribeDeployment",
"codedeploy:DescribeEnvironment",
"codedeploy:DescribeDeploymentGroup",
"codedeploy:DescribeDeploymentTarget",
"codedeploy:DescribeApplication",
"codedeploy:DescribeInstancesInDeployment",
"codedeploy:DescribeDeploymentConfig",
"codedeploy:DescribeEnvironmentDefaultRevision",
"codedeploy:DescribeLifecycleConfiguration",
"codedeploy:DescribeLogEntries",
"codedeploy:DescribePipeline",
"codedeploy:DescribeRelease",
"codedeploy:DescribeRevision",
"codedeploy:DescribeReviewerGroups",
"codedeploy:DescribeRollouts",
"codedeploy:DescribeTrigger",
"codedeploy:ListAppVersions",
"codedeploy:ListDeploymentGroups",
"codedeploy:ListDeploymentStatuses",
"codedeploy:ListDeployments",
"codedeploy:ListEnvironments",
"codedeploy:ListInstancesInDeployment",
"codedeploy:ListPipelineStages",
"codedeploy:ListPipelines",
"codedeploy:ListRevisions",
"codedeploy:ListReviewersForApproval",
"codedeploy:ListRollouts",
"codedeploy:ListTagsForResource",
"codedeploy:TagResource",
"codedeploy:UntagResource",
"codedeploy:UpdateDeploymentConfig",
"codedeploy:UpdateEnvironment",
"codedeploy:UpdateEnvironmentVariables",
"codedeploy:UpdateDeploymentGroup",
"codedeploy:UpdateDeploymentTarget",
"codedeploy:UpdatePipeline",
"codedeploy:UpdateRelease",
"codedeploy:UpdateRevision",
"codedeploy:UpdateReviewerGroups",
"codedeploy:UpdateRolloutGroup",
"codedeploy:UpdateTrigger",
"codebuild:BatchGetProjects",
"codebuild:CreateProject",
"codebuild:DeleteProject",
"codebuild:DescribeProject",
"codebuild:GetProjectEnvironmentVariables",
"codebuild:GetProjectPhaseExecution",
"codebuild:GetProjectReport",
"codebuild:ListProjects",
"codebuild:ListProjectArtifacts",
"codebuild:ListProjectSourceEntries",
"codebuild:ListProjectSourceControlConnections",
"codebuild:ListProjectSourceConnections",
"codebuild:ListProjectSourceRepositories",
"codebuild:ListProjectTargets",
"codebuild:ListProjectVariables",
"codebuild:StartBuild",
"codebuild:StartBuildBatch",
"codebuild:StartBuildRun",
"codebuild:StopBuild",
"codebuild:StopBuildBatch",
"codebuild:StopBuildRun",
"codebuild:UpdateProject",
"codecommit:BatchGetRepositories",
"codecommit:CreateRepository",
"codecommit:GetRepository",
"codecommit:GetBranch",
"codecommit:GetCommit",
"codecommit:GetCommitFileChangeSet",
"codecommit:GetCommitSignature",
"codecommit:GetDeregisteredUserFromGroup",
"codecommit:GetDeregisteredUsersFromGroup",
"codecommit:GetDefaultBranch",
"codecommit:GetRepositoryIdentity",
"codecommit:GetRepositoryPushRules",
"codecommit:GetRepositoryStatus",
"codecommit:GetTag",
"codecommit:GetTagsForRepository",
"codecommit:GetUserFromGroup",
"codecommit:GetUserFromRepository",
"codecommit:GetUserGroupsForRepository",
"codecommit:GetUserRepositories",
"codecommit:GetUserSigninToken",
"codecommit:GetUserToGroup",
"codecommit:SynchronizeRepository",
"codecommit:BatchDeleteRepositories",
"codecommit:BatchGetRepositoryStatuses",
"codecommit:BatchSetPushRules",
"codecommit:CreateBranch",
"codecommit:CreateCommitFileChangeSet",
"codecommit:CreateCommitSignature",
"codecommit:CreateDeregisteredUserFromGroup",
"codecommit:CreateDeregisteredUsersFromGroup",
"codecommit:CreateDefaultBranch",
"codecommit:CreateRepositoryIdentity",
"codecommit:CreateRepositoryPushRules",
"codecommit:CreateRepositoryStatus",
"codecommit:CreateTag",
"codecommit:CreateTagsForRepository",
"codecommit:CreateUserFromGroup",
"codecommit:CreateUserFromRepository",
"codecommit:CreateUserGroupsForRepository",
"codecommit:DeleteBranch",
"codecommit:DeleteCommitFileChangeSet",
"codecommit:DeleteCommitSignature",
"codecommit:DeleteDeregisteredUserFromGroup",
"codecommit:DeleteDeregisteredUsersFromGroup",
"codecommit:DeleteDefaultBranch",
"codecommit:DeleteRepositoryIdentity",
"codecommit:DeleteRepositoryPushRules",
"codecommit:DeleteRepositoryStatus",
"codecommit:DeleteTag",
"codecommit:DeleteTagsForRepository",
"codecommit:DeleteUserFromGroup",
"codecommit:DeleteUserFromRepository",
"codecommit:DeleteUserGroupsForRepository",
"codecommit:GetSigninToken",
"codecommit:GetUserFromGroup",
"codecommit:GetUserFromRepository",
"codecommit:GetUserGroupsForRepository",
"codecommit:GetUserRepositories",
"codecommit:PutSigninToken",
"codecommit:PutUserFromGroup",
"codecommit:PutUserFromRepository",
"codecommit:PutUserGroupsForRepository",
"codecommit:RegisterUserWithRepository",
"codecommit:ResyncRepository",
"codecommit:TagResource",
"codecommit:UntagResource"
]
"ecr:GetDownloadUrlForLayer",
"elastic-inference:Connect",
"elasticfilesystem:DescribeFileSystems",
"elasticfilesystem:DescribeMountTargets",
"fsx:DescribeFileSystems",
"glue:CreateJob",
"glue:DeleteJob",
"glue:GetJob",
"glue:GetJobRun",
"glue:GetJobRuns",
"glue:GetJobs",
"glue:ResetJobBookmark",
"glue:StartJobRun",
"glue:UpdateJob",
"groundtruthlabeling:*",
"iam:ListRoles",
"kms:DescribeKey",
"kms:ListAliases",
"lambda:ListFunctions",
"logs:CreateLogGroup",
"logs:CreateLogStream",
"logs:DescribeLogGroups",
"logs:DescribeLogStreams",
"logs:GetLogEvents",
"logs:PutLogEvents",
"sns:ListTopics"
],
"Resource": "*"
},

{  
"Effect": "Allow",
"Action": [
"logs:CreateLogDelivery",
"logs:DeleteLogDelivery",
"logs:DescribeResourcePolicies",
"logs:GetLogDelivery",
"logs:ListLogDeliveries",
"logs:GetResourcePolicy",
"logs:UpdateLogDelivery"
],
"Resource": "*"
},

{  
"Effect": "Allow",
"Action": [
"codecommit:GitPull",
"codecommit:GitPush"
],
"Resource": [
"arn:aws:codecommit:*:*:*sagemaker*",
"arn:aws:codecommit:*:*:*SageMaker*",
"arn:aws:codecommit:*:*:*Sagemaker*"
]
{ "Effect": "Allow", "Action": [ "secretsmanager:ListSecrets" ], "Resource": "*" },
"arn:aws:s3:::*SageMaker*",
"arn:aws:s3:::*Sagemaker*",
"arn:aws:s3:::*sagemaker*",
"arn:aws:s3:::*aws-glue*"
],
{
"Effect": "Allow",
"Action": [
"s3:CreateBucket",
"s3:GetBucketLocation",
"s3:ListBucket",
"s3:ListAllMyBuckets"
],
"Resource": "*"
},
{
"Effect": "Allow",
"Action": [
"s3:GetObject"
],
"Resource": "*",
"Condition": {
"StringEqualsIgnoreCase": {
"s3:ExistingObjectTag/SageMaker": "true"
}
}
},
{
"Effect": "Allow",
"Action": [
"lambda:InvokeFunction"
],
"Resource": [
"arn:aws:lambda::*:*:function:*SageMaker*",
"arn:aws:lambda::*:*:function:*sagemaker*",
"arn:aws:lambda::*:*:function:*Sagemaker*",
"arn:aws:lambda::*:*:function:*LabelingFunction*"
]
},
{
"Action": "iam:CreateServiceLinkedRole",
"Effect": "Allow",
"Resource": "arn:aws:iam::*:*role/aws-service-role/sagemaker.application-autoscaling.amazonaws.com/AWSServiceRoleForApplicationAutoScaling_SageMakerEndpoint",
"Condition": {
"StringLike": {
"iam:AWSServiceName": "sagemaker.application-autoscaling.amazonaws.com"
}
}
},
{
"Effect": "Allow",
"Action": "iam:CreateServiceLinkedRole",
"Resource": "*",
"Condition": {
"StringEquals": {
"iam:AWSServiceName": "robomaker.amazonaws.com"
}
}
},
{
"Effect": "Allow",
"Action": "sns:Subscribe",
"sns:CreateTopic"
Allow Users to View Their Own Permissions

This example shows how you might create a policy that allows IAM users to view the inline and managed policies that are attached to their user identity. This policy includes permissions to complete this action on the console or programmatically using the AWS CLI or AWS API.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Sid": "ViewOwnUserInfo",
         "Effect": "Allow",
         "Action": [
            "iam:GetUserPolicy",
            "iam:ListGroupsForUser",
            "iam:ListAttachedUserPolicies",
            "iam:GetUserPolicy",
            "iam:GetUser"
         ],
         "Resource": ["arn:aws:iam::*:user/${aws:username}"],
      },
      {
         "Sid": "NavigateInConsole",
         "Effect": "Allow",
         "Action": [
            "iam:GetGroupPolicy",
            "iam:GetPolicyVersion",
            "iam:GetPolicy",
            "iam:ListAttachedGroupPolicies",
            "iam:ListGroupPolicies",
            "iam:ListPolicyVersions",
            "iam:ListPolicies",
            "iam:ListUsers"
         ],
         "Resource": "*
      }
   ]
}
```
Control Creation of SageMaker Resources with Condition Keys

Control fine-grained access to allow the creation of SageMaker resources by using SageMaker-specific condition keys. For information about using condition keys in IAM policies, see IAM JSON Policy Elements: Condition in the IAM User Guide.

The condition keys, along with related API actions, and links to relevant documentation are listed in Condition Keys for SageMaker in the IAM User Guide.

The following examples show how to use the SageMaker condition keys to control access.

Topics
• Control Access to SageMaker Resources by Using File System Condition Keys (p. 3518)
• Restrict Training to a Specific VPC (p. 3520)
• Restrict Access to Workforce Types for Ground Truth Labeling Jobs and Amazon A2I Human Review Workflows (p. 3520)
• Enforce Encryption of Input Data (p. 3522)
• Enforce Encryption of Notebook Instance Storage Volume (p. 3522)
• Enforce Network Isolation for Training Jobs (p. 3523)
• Enforce a Specific Instance Type for Training Jobs (p. 3523)
• Enforce a Specific EI Accelerator for Training Jobs (p. 3523)
• Enforce Disabling Internet Access and Root Access for Creating Notebook Instances (p. 3524)

Control Access to SageMaker Resources by Using File System Condition Keys

SageMaker training provides a secure infrastructure for the training algorithm to run in, but for some cases you may want increased defense in depth. For example, you minimize the risk of running untrusted code in your algorithm, or you have specific security mandates in your organization. For these scenarios, you can use the service-specific condition keys in the Condition element of an IAM policy to scope down the user to specific file systems, directories, access modes (read-write, read-only) and security groups.

Topics
• Restrict an IAM User to Specific Directories and Access Modes (p. 3518)
• Restrict an IAM User to a Specific File System (p. 3519)

Restrict an IAM User to Specific Directories and Access Modes

The policy below restricts an IAM user to the /sagemaker/xgboost-dm/train and /sagemaker/xgboost-dm/validation directories of an EFS file system to ro (read-only) AccessMode:

Note
When a directory is allowed, all of its subdirectories are also accessible by the training algorithm. POSIX permissions are ignored.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "AccessToElasticFileSystem",
            "Effect": "Allow",
            "Action": ["sagemaker:CreateTrainingJob",
```

3518
Restrict an IAM User to a Specific File System

To prevent a malicious algorithm using a user space client from accessing any file system directly in your account, you can restrict networking traffic by allowing ingress from a specific security group. In the following example, the IAM user can only use the specified security group to access the file system:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "AccessToLustreFileSystem",
            "Effect": "Allow",
            "Action": [
                "sagemaker:CreateTrainingJob",
                "sagemaker:CreateHyperParameterTuningJob"
            ],
            "Resource": "*",
            "Condition": {
                "StringEquals": {
                    "sagemaker:FileSystemId": "fs-12345678",
                    "sagemaker:FileSystemAccessMode": "ro",
                    "sagemaker:FileSystemType": "FSxLustre",
                    "sagemaker:FileSystemDirectoryPath": "/fsx/sagemaker/xgboost/train"
                },
                "ForAllValues:StringEquals": {
                    "sagemaker:VpcSecurityGroupIds": [
                        "sg-12345678"
                    ]
                }
            }
        }
    ]
}
```
Although the above example can restrict an algorithm to a specific file system, it does not prevent an algorithm from accessing any directory within that file system using the user space client. To mitigate this, you can:

- Ensure that the file system only contains data that you trust your IAM users to access
- Create an IAM role that restricts your IAM users to launching training jobs with algorithms from approved ECR repositories

For more information on how to use roles with SageMaker, see SageMaker Roles.

**Restrict Training to a Specific VPC**

Restrict an AWS user to creating training jobs from within a Amazon VPC. When a training job is created within a VPC, you can use VPC flow logs to monitor all traffic to and from the training cluster. For information about using VPC flow logs, see VPC Flow Logs in the Amazon Virtual Private Cloud User Guide.

The following policy enforces that a training job is created by an IAM user calling CreateTrainingJob from within a VPC:

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Sid": "AllowFromVpc",
         "Effect": "Allow",
         "Action": [
            "sagemaker:CreateTrainingJob",
            "sagemaker:CreateHyperParameterTuningJob"
         ],
         "Resource": "*",
         "Condition": {
            "ForAllValues:StringEquals": {
               "sagemaker:VpcSubnets": ["subnet-a1234"],
               "sagemaker:VpcSecurityGroupIds": ["sg12345", "sg-67890"]
            },
            "Null": {
               "sagemaker:VpcSubnets": "false",
               "sagemaker:VpcSecurityGroupIds": "false"
            }
         }
      }
   ]
}
```

**Restrict Access to Workforce Types for Ground Truth Labeling Jobs and Amazon A2I Human Review Workflows**

Amazon SageMaker Ground Truth and Amazon Augmented AI work teams fall into one of three workforce types: public (with Amazon Mechanical Turk), private, and vendor. To restrict IAM user access to a specific work team using one of these types or the work team ARN, use the `sagemaker:WorkteamType` and/or the `sagemaker:WorkteamArn` condition keys.

For the `sagemaker:WorkteamType` condition key, use string condition operators. For the `sagemaker:WorkteamArn` condition key, use Amazon Resource Name (ARN) condition operators. If the user attempts to create a labeling job with a restricted work team, SageMaker returns an access denied error.
The policies below demonstrate different ways to use the `sagemaker:WorkteamType` and `sagemaker:WorkteamArn` condition keys with appropriate condition operators and valid condition values.

The following example uses the `sagemaker:WorkteamType` condition key with the `StringEquals` condition operator to restrict access to a public work team. It accepts condition values in the following format: `workforcetype-crowd`, where `workforcetype` can equal public, private, or vendor.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "RestrictWorkteamType",
            "Effect": "Deny",
            "Action": "sagemaker:CreateLabelingJob",
            "Resource": "*",
            "Condition": {
                "StringEquals": {
                    "sagemaker:WorkteamType": "public-crowd"
                }
            }
        }
    ]
}
```

The following policies show how to restrict access to a public work team using the `sagemaker:WorkteamArn` condition key. The first shows how to use it with a valid IAM regex-variant of the work team ARN and the `ArnLike` condition operator. The second shows how to use it with the `ArnEquals` condition operator and the work team ARN.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "RestrictWorkteamType",
            "Effect": "Deny",
            "Action": "sagemaker:CreateLabelingJob",
            "Resource": "*",
            "Condition": {
                "ArnLike": {
                    "sagemaker:WorkteamArn": "arn:aws:sagemaker:*::*:workteam/public-crowd/*"
                }
            }
        }
    ]
}
```

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "RestrictWorkteamType",
            "Effect": "Deny",
            "Action": "sagemaker:CreateLabelingJob",
            "Resource": "*",
            "Condition": {
                "ArnEquals": {
                }
            }
        }
    ]
}
```
Enforce Encryption of Input Data

The following policy restricts an IAM user to specify an AWS KMS key to encrypt input data when creating training, hyperparameter tuning, and labeling jobs by using the `sagemaker:VolumeKmsKey` condition key:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "EnforceEncryption",
            "Effect": "Allow",
            "Action": [
                "sagemaker:CreateTrainingJob",
                "sagemaker:CreateHyperParameterTuningJob",
                "sagemaker:CreateLabelingJob",
                "sagemaker:CreateFlowDefinition"
            ],
            "Resource": "*",
            "Condition": {
                "ArnEquals": {
                    "sagemaker:VolumeKmsKey": "arn:aws:kms:us-west-2:111122223333:key/1234abcd-12ab-34cd-56ef-1234567890ab"
                }
            }
        }
    ]
}
```

Enforce Encryption of Notebook Instance Storage Volume

The following policy restricts an IAM user to specify an AWS KMS key to encrypt the attached storage volume when creating or updating a notebook instance by using the `sagemaker:VolumeKmsKey` condition key:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "EnforceEncryption",
            "Effect": "Allow",
            "Action": [
                "sagemaker:CreateNotebookInstance"
            ],
            "Resource": "*",
            "Condition": {
                "ArnLike": {
                    "sagemaker:VolumeKmsKey": "*key/volume-kms-key-12345"
                }
            }
        }
    ]
}
```
Enforce Network Isolation for Training Jobs

The following policy restricts an IAM user to enable network isolation when creating training jobs by using the sagemaker:NetworkIsolation condition key:

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "EnforceIsolation",
      "Effect": "Allow",
      "Action": [
        "sagemaker:CreateTrainingJob",
        "sagemaker:CreateHyperParameterTuningJob"
      ],
      "Resource": "*",
      "Condition": {
        "Bool": {
          "sagemaker:NetworkIsolation": "true"
        }
      }
    }
  ]
}
```

Enforce a Specific Instance Type for Training Jobs

The following policy restricts an IAM user to use a specific instance type when creating training jobs by using the sagemaker:InstanceTypes condition key:

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "EnforceInstanceType",
      "Effect": "Allow",
      "Action": [
        "sagemaker:CreateTrainingJob",
        "sagemaker:CreateHyperParameterTuningJob"
      ],
      "Resource": "*",
      "Condition": {
        "ForAllValues:StringLike": {
          "sagemaker:InstanceTypes": ["ml.c5.*"]
        }
      }
    }
  ]
}
```

Enforce a Specific EI Accelerator for Training Jobs

The following policy restricts an IAM user to use a specific elastic inference (EI) accelerator, if an accelerator is provided, when creating or updating notebook instances and when creating endpoint configurations by using the sagemaker:AcceleratorTypes condition key:

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
    }
  ]
}
```
Enforce Disabling Internet Access and Root Access for Creating Notebook Instances

You can disable both internet access and root access to notebook instances to help make them more secure. For information about controlling root access to a notebook instance, see Control root access to a SageMaker notebook instance (p. 3495). For information about disabling internet access for a notebook instance, see Connect a Notebook Instance in a VPC to External Resources (p. 3633).

The following policy requires an IAM user to disable network access when creating instance, and disable root access when creating or updating a notebook instance.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "LockDownCreateNotebookInstance",
      "Effect": "Allow",
      "Action": [
        "sagemaker:CreateNotebookInstance"
      ],
      "Resource": "*",
      "Condition": {
        "StringEquals": {
          "sagemaker:DirectInternetAccess": "Disabled",
          "sagemaker:RootAccess": "Disabled"
        },
        "Null": {
          "sagemaker:VpcSubnets": "false",
          "sagemaker:VpcSecurityGroupIds": "false"
        }
      }
    }
  
    {
      "Sid": "LockDownUpdateNotebookInstance",
      "Effect": "Allow",
      "Action": [
        "sagemaker:UpdateNotebookInstance"
      ],
      "Resource": "*",
      "Condition": {
        "StringEquals": {
          "sagemaker:RootAccess": "Disabled"
        }
      }
    }
  
  }
}
```
Control Access to the SageMaker API by Using Identity-based Policies

To control access to SageMaker API calls and calls to SageMaker hosted endpoints, use identity-based IAM policies.

Topics

- Restrict Access to SageMaker API and Runtime to Calls from Within Your VPC (p. 3525)

Restrict Access to SageMaker API and Runtime to Calls from Within Your VPC

If you set up an interface endpoint in your VPC, individuals outside the VPC can still connect to the SageMaker API and runtime over the internet unless you attach an IAM policy that restricts access to calls coming from within the VPC to all users and groups that have access to your SageMaker resources. For information about creating a VPC interface endpoint for the SageMaker API and runtime, see Connect to SageMaker Through a VPC Interface Endpoint (p. 3635).

Important

If you apply an IAM policy similar to one of the following, users can't access the specified SageMaker APIs through the console.

To restrict access to only connections made from within your VPC, create an AWS Identity and Access Management policy that restricts access to only calls that come from within your VPC. Then add that policy to every AWS Identity and Access Management user, group, or role used to access the SageMaker API or runtime.

Note

This policy allows connections only to callers within a subnet where you created an interface endpoint.

```json
{
  "Id": "api-example-1",
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "EnableAPIAccess",
      "Effect": "Allow",
      "Action": [
        "sagemaker:*"
      ],
      "Resource": "*",
      "Condition": {
        "StringEquals": {
          "aws:SourceVpc": "vpc-11bbaaa"
        }
      }
    }
  ]
}
```

If you want to restrict access to the API to only calls made using the interface endpoint, use the `aws:SourceVpce` condition key instead of `aws:SourceVpc`:

```json
{
  "Id": "api-example-1",
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "EnableAPIAccess",
      "Effect": "Allow",
      "Action": [
        "sagemaker:*"
      ],
      "Resource": "*",
      "Condition": {
        "StringEquals": {
          "aws:SourceVpce": "vpc-11bbaaa"
        }
      }
    }
  ]
}
```
Identity-Based Policy Examples

Limit Access to SageMaker API and Runtime Calls by IP Address

To allow access to SageMaker API calls and runtime invocations only from IP addresses in a list that you specify, attach an IAM policy that denies access to the API unless the call comes from an IP address in the list to every AWS Identity and Access Management user, group, or role used to access the API or runtime. For information about creating IAM policies, see Creating IAM Policies in the AWS Identity and Access Management User Guide. To specify the list of IP addresses that you want to have access to the API call, use the IpAddress condition operator and the aws:SourceIp condition context key. For information about IAM condition operators, see IAM JSON Policy Elements: Condition Operators in the AWS Identity and Access Management User Guide. For information about IAM condition context keys, see AWS Global Condition Context Keys.

For example, the following policy allows access to the CreateTrainingJob only from IP addresses in the ranges 192.0.2.0-192.0.2.255 and 203.0.113.0-203.0.113.255:

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": "sagemaker:CreateTrainingJob",
         "Resource": "*",
         "Condition": {
            "IpAddress": {
               "aws:SourceIp": [
                  "192.0.2.0/24",
                  "203.0.113.0/24"
               ]
            }
         }
      }
   ]
}
```

Limit Access to a Notebook Instance by IP Address

To allow access to a notebook instance only from IP addresses in a list that you specify, attach an IAM policy that denies access to CreatePresignedNotebookInstanceUrl unless the call comes from an
IP address in the list to every AWS Identity and Access Management user, group, or role used to access the notebook instance. For information about creating IAM policies, see Creating IAM Policies in the AWS Identity and Access Management User Guide. To specify the list of IP addresses that you want to have access to the notebook instance, use the IpAddress condition operator and the aws:SourceIP condition context key. For information about IAM condition operators, see IAM JSON Policy Elements: Condition Operators in the AWS Identity and Access Management User Guide. For information about IAM condition context keys, see AWS Global Condition Context Keys.

For example, the following policy allows access to a notebook instance only from IP addresses in the ranges `192.0.2.0-192.0.2.255` and `203.0.113.0-203.0.113.255`:

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": "sagemaker:CreatePresignedNotebookInstanceUrl",
         "Resource": "*",
         "Condition": {
            "IpAddress": {
               "aws:SourceIp": [
                  "192.0.2.0/24",
                  "192.0.2.0/24",
                  "203.0.113.0/24"
               ]
            }
         }
      }
   ]
}
```

The policy restricts access to both the call to CreatePresignedNotebookInstanceUrl and to the URL that the call returns. The policy also restricts access to opening a notebook instance in the console and is enforced for every HTTP request and WebSocket frame that attempts to connect to the notebook instance.

**Note**

Using this method to filter by IP address is incompatible when connecting to SageMaker through a VPC interface endpoint. For information about restricting access to a notebook instance when connecting through a VPC interface endpoint, see Connect to a Notebook Instance Through a VPC Interface Endpoint (p. 3641).

### Control Access to SageMaker Resources by Using Tags

Control access to groups of SageMaker resources by attaching tags to the resources and specifying ResourceTag conditions in IAM policies.

**Note**

Tag-based policies don't work to restrict the following API calls:

- DeleteImageVersion
- DescribeImageVersion
- ListAlgorithms
- ListCodeRepositories
- ListCompilationJobs
- ListEndpointConfigs
- ListEndpoints
- ListFlowDefinitions
For example, suppose you've defined two different IAM groups, named DevTeam1 and DevTeam2, in your AWS account. Suppose also that you've created 10 notebook instances, 5 of which are used for one project, and 5 of which are used for a second project. You want to allow members of DevTeam1 to make API calls on notebook instances used for the first project, and members of DevTeam2 to make API calls on notebook instances used for the second project.

To control access to API calls (example)

1. Add a tag with the key Project and value A to the notebook instances used for the first project. For information about adding tags to SageMaker resources, see AddTags.
2. Add a tag with the key Project and value B to the notebook instances used for the second project.
3. Create an IAM policy with a ResourceTag condition that denies access to the notebook instances used for the second project, and attach that policy to DevTeam1. The following is an example of a policy that denies all API calls on any notebook instance that has a tag with a key of Project and a value of B:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": "sagemaker:*",
            "Resource": "*"
        },
        {
            "Effect": "Deny",
            "Action": "sagemaker:*",
            "Resource": "*",
            "Condition": {
                "StringEquals": {
                    "sagemaker:ResourceTag/Project": "B"
                }
            }
        },
        {
            "Effect": "Deny",
            "Action": [ "sagemaker:AddTags",
```
4. Create an IAM policy with a `ResourceTag` condition that denies access to the notebook instances used for the first project, and attach that policy to DevTeam2. The following is an example of a policy that denies all API calls on any notebook instance that has a tag with a key of `Project` and a value of `A`:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": "sagemaker:*",
            "Resource": "*"
        },
        {
            "Effect": "Deny",
            "Action": "sagemaker:*",
            "Resource": "*",
            "Condition": {
                "StringEquals": {
                    "sagemaker:ResourceTag/Project": "A"
                }
            }
        },
        {
            "Effect": "Deny",
            "Action": [
                "sagemaker:AddTags",
                "sagemaker:DeleteTags"
            ],
            "Resource": "*"
        }
    ]
}
```

**Require the Presence or Absence of Tags for API Calls**

Require the presence or absence of specific tags or specific tag values by using `RequestTag` condition keys in an IAM policy. For example, if you want to require that every endpoint created by any member of an IAM group to be created with a tag with the key `environment` and value `dev`, create a policy as follows:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": "sagemaker:CreateEndpoint",
            "Resource": "arn:aws:sagemaker:*:*:endpoint/**",
            "Condition": {
                "StringEquals": {
                    "aws:RequestTag/environment": "dev"
                }
            }
        }
    ]
}
```
Cross-Service Confused Deputy Prevention

The confused deputy problem is a security issue where an entity that doesn't have permission to perform an action can coerce a more-privileged entity to perform the action. In AWS, cross-service impersonation can result in the confused deputy problem. Cross-service impersonation can occur when one service (the calling service) calls another service (the called service). The calling service can be manipulated to use its permissions to act on another customer's resources in a way it should not otherwise have permission to access. To prevent this, AWS provides tools that help you protect your data for all services with service principals that have been given access to resources in your account.

Read on for general guidance or navigate to an example for a specific SageMaker feature:

Topics
- Limit Permissions With Global Condition Keys (p. 3530)
- SageMaker Edge Manager (p. 3531)
- SageMaker Images (p. 3531)
- SageMaker Inference (p. 3532)
- SageMaker Batch Transform Jobs (p. 3532)
- SageMaker Marketplace (p. 3533)
- SageMaker Neo (p. 3533)
- SageMaker Pipelines (p. 3534)
- SageMaker Processing Jobs (p. 3534)
- SageMaker Studio (p. 3535)
- SageMaker Training Jobs (p. 3535)

Limit Permissions With Global Condition Keys

We recommend using the `aws:SourceArn` and `aws:SourceAccount` global condition keys in resource policies to limit the permissions to the resource that Amazon SageMaker gives another service. If you use both global condition keys and the `aws:SourceArn` value contains the account ID, the `aws:SourceAccount` value and the account in the `aws:SourceArn` value must use the same account ID when used in the same policy statement. Use `aws:SourceArn` if you want only one resource to be associated with the cross-service access. Use `aws:SourceAccount` if you want to allow any resource in that account to be associated with the cross-service use.

The most effective way to protect against the confused deputy problem is to use the `aws:SourceArn` global condition key with the full ARN of the resource. If you don't know the full ARN of the resource or if you are specifying multiple resources, use the `aws:SourceArn` global condition key with wildcards (*) for the unknown portions of the ARN. For example, `arn:aws:sagemaker:*:123456789012:*`.

The following example shows how you can use the `aws:SourceArn` and `aws:SourceAccount` global condition keys in SageMaker to prevent the confused deputy problem.

```json
{
    "Version": "2012-10-17",
    "Statement": {
        "Sid": "ConfusedDeputyPreventionExamplePolicy",
        "Effect": "Allow",
```
The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker Edge Manager created by account number `123456789012` in the `us-west-2` Region.

```json
{
  "Version": "2012-10-17",
  "Statement": {
    "Effect": "Allow",
    "Principal": { "Service": "sagemaker.amazonaws.com" },
    "Action": "sts:AssumeRole",
    "Condition": {
      "ArnLike": {
        "aws:SourceArn": "arn:partition:sagemaker:region:123456789012:*"
      }
    }
  }
}
```

You can replace the `aws:SourceArn` in this template with the full ARN of one specific packaging job to further limit permissions.

### SageMaker Images

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker Images. Use this template with either `Image` or `ImageVersion`. This example uses an `ImageVersion` record ARN with the account number `123456789012`. Note that because the account number is part of the `aws:SourceArn` value, you do not need to specify an `aws:SourceAccount` value.

```json
{
  "Version": "2012-10-17",
  "Statement": {
    "Effect": "Allow",
    "Principal": { "Service": "sagemaker.amazonaws.com" },
    "Action": "sts:AssumeRole",
    "Condition": {
      "ArnLike": {
      }
    }
  }
}
```
Do not replace the `aws:SourceArn` in this template with the full ARN of a specific image or image version. The ARN must be in the format provided above and specify either image or image-version. The partition placeholder should designate either an AWS commercial partition (`aws`) or an AWS in China partition (`aws-cn`), depending on where the image or image version is running. Similarly, the region placeholder in the ARN can be any valid Region where SageMaker images are available.

**SageMaker Inference**

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker real-time, serverless, and asynchronous inference. Note that because the account number is part of the `aws:SourceArn` value, you do not need to specify an `aws:SourceAccount` value.

```json
{
  "Version": "2012-10-17",
  "Statement": {
    "Effect": "Allow",
    "Principal": { "Service": "sagemaker.amazonaws.com" },
    "Action": "sts:AssumeRole",
    "Condition": {
      "ArnLike": {
      }
    }
  }
}
```

Do not replace the `aws:SourceArn` in this template with the full ARN of a specific model or endpoint. The ARN must be in the format provided above. The asterisk in the ARN template does not stand for wildcard and should not be changed.

**SageMaker Batch Transform Jobs**

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker batch transform jobs created by account number `123456789012` in the `us-west-2` Region. Note that because the account number is in the ARN, you do not need to specify an `aws:SourceAccount` value.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Principal": { "Service": "sagemaker.amazonaws.com" },
      "Action": "sts:AssumeRole",
      "Condition": {
        "ArnLike": {
        }
      }
    }
  ]
}
```
You can replace the `aws:SourceArn` in this template with the full ARN of one specific batch transform job to further limit permissions.

### SageMaker Marketplace

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker Marketplace resources created by account number 123456789012 in the us-west-2 Region. Note that because the account number is in the ARN, you do not need to specify an `aws:SourceAccount` value.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            },
            "Action": "sts:AssumeRole",
            "Condition": {
                "ArnLike": {
                    "aws:SourceArn": "arn:aws:sagemaker:us-west-2:123456789012:*"
                }
            }
        }
    ]
}
```

Do not replace the `aws:SourceArn` in this template with the full ARN of a specific algorithm or model package. The ARN must be in the format provided above. The asterisk in the ARN template does stand for wildcard and covers all training jobs, models, and batch transform jobs from validation steps, as well as algorithm and model packages published to SageMaker Marketplace.

### SageMaker Neo

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker Neo compilation jobs created by account number 123456789012 in the us-west-2 Region. Note that because the account number is in the ARN, you do not need to specify an `aws:SourceAccount` value.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            },
            "Action": "sts:AssumeRole",
            "Condition": {
                "ArnLike": {
                }
            }
        }
    ]
}
```

You can replace the `aws:SourceArn` in this template with the full ARN of one specific compilation job to further limit permissions.
SageMaker Pipelines

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker Pipelines using pipeline execution records from one or more pipelines. Note that because the account number is in the ARN, you do not need to specify an `aws:SourceAccount` value.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            },
            "Action": "sts:AssumeRole",
            "Condition": {
                "ArnLike": {
                    "aws:SourceArn": "arn:aws:sagemaker:region:123456789012:pipeline/mypipeline/*"
                }
            }
        }
    ]
}
```

Do not replace the `aws:SourceArn` in this template with the full ARN of a specific pipeline execution. The ARN must be in the format provided above. The `partition` placeholder should designate either an AWS commercial partition (aws) or an AWS in China partition (aws-cn), depending on where the pipeline is running. Similarly, the `region` placeholder in the ARN can be any valid Region where SageMaker Pipelines is available.

The asterisk in the ARN template does stand for wildcard and covers all pipeline executions of a pipeline named `mypipeline`. If you want to allow the `AssumeRole` permissions for all pipelines in account `123456789012` rather than one specific pipeline, then the `aws:SourceArn` would be `arn:aws:sagemaker:*:123456789012:pipeline/*`.

SageMaker Processing Jobs

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker processing jobs created by account number `123456789012` in the `us-west-2` Region. Note that because the account number is in the ARN, you do not need to specify an `aws:SourceAccount` value.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            },
            "Action": "sts:AssumeRole",
            "Condition": {
                " ArnLike": {
                }
            }
        }
    ]
}
```
You can replace the `aws:SourceArn` in this template with the full ARN of one specific processing job to further limit permissions.

**SageMaker Studio**

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker Studio created by account number 123456789012 in the `us-west-2` Region. Note that because the account number is part of the `aws:SourceArn` value, you do not need to specify an `aws:SourceAccount` value.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            },
            "Action": "sts:AssumeRole",
            "Condition": {
                "ArnLike": {
                    "aws:SourceArn": "arn:aws:sagemaker:us-west-2:123456789012:*"
                }
            }
        }
    ]
}
```

Do not replace the `aws:SourceArn` in this template with the full ARN of a specific Studio application, user profile, or domain. The ARN must be in the format provided in the previous example. The asterisk in the ARN template does not stand for wildcard and should not be changed.

**SageMaker Training Jobs**

The following example shows how you can use the `aws:SourceArn` global condition key to prevent the cross-service confused deputy problem for SageMaker training jobs created by account number 123456789012 in the `us-west-2` Region. Note that because the account number is in the ARN, you do not need to specify an `aws:SourceAccount` value.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            },
            "Action": "sts:AssumeRole",
            "Condition": {
                "ArnLike": {
                }
            }
        }
    ]
}
```
You can replace the `aws:SourceArn` in this template with the full ARN of one specific training job to further limit permissions.

Next Up

For more information on managing execution roles, see SageMaker Roles.

**SageMaker Roles**

As a managed service, Amazon SageMaker performs operations on your behalf on the AWS hardware that is managed by SageMaker. SageMaker can perform only operations that the user permits.

A SageMaker user can grant these permissions with an IAM role (referred to as an execution role).

To create and use a locally available execution role, you can use the following procedures.

**Get execution role**

You can find the IAM execution role in the following ways:

**From the notebook**

When you run a notebook within SageMaker (from the SageMaker console or SageMaker Studio) you can access the execution role with the following code:

```python
sagemaker_session = sagemaker.Session()
role = sagemaker.get_execution_role()
```

**Note**

The execution role is available only when running a notebook within SageMaker. If you run `get_execution_role` in a notebook not on SageMaker, expect a "region" error.

**From the SageMaker console**

Under Notebook > Notebook instances, select the notebook. The ARN is given in the Permissions and encryption section.

**Create execution role**

Use the following procedure to create an execution role with the IAM managed policy, `AmazonSageMakerFullAccess`, attached. If your use case requires more granular permissions, use other sections on this page to create an execution role that meets your business needs.

**Important**

The IAM managed policy, `AmazonSageMakerFullAccess`, used in the following procedure only grants the execution role permission to perform certain Amazon S3 actions on buckets or objects with SageMaker, Sagemaker, sagemaker, or aws-glue in the name. To learn how to add an additional policy to an execution role to grant it access to other Amazon S3 buckets and objects, see Add Additional Amazon S3 Permissions to a SageMaker Execution Role (p. 3537).

**To create a new role**

1. Open the IAM console at https://console.aws.amazon.com/iam/.
2. Select Roles and then select Create role.
4. Select Next: Permissions.
5. The IAM managed policy, `AmazonSageMakerFullAccess` is automatically attached to this role. To see the permissions included in this policy, select the sideways arrow next to the policy name. Select Next: Tags.
6. (Optional) Add tags and select **Next: Review**.
7. Give the role a name in the text field under **Role name** and select **Create role**.
8. On the **Roles** section of the IAM console, select the role you just created. If needed, use the text box to search for the role using the role name you entered in step 7.
9. On the role summary page, make note of the ARN.

With a known ARN for your role, you can programmatically check the role when running the notebook locally or on SageMaker. Replace `RoleName` with your known ARN:

```python
try:
    role = sagemaker.get_execution_role()
except ValueError:
    iam = boto3.client('iam')
    role = iam.get_role(RoleName='AmazonSageMaker-ExecutionRole-20201200T100000')['Role']['Arn']
```

### Add Additional Amazon S3 Permissions to a SageMaker Execution Role

When you use a SageMaker feature with resources in Amazon S3, such as input data, the execution role you specify in your request (for example `CreateTrainingJob`) is used to access these resources.

If you attach the IAM managed policy, `AmazonSageMakerFullAccess`, to an execution role, that role has permission to perform certain Amazon S3 actions on buckets or objects with `SageMaker`, `Sagemaker`, `sagemaker`, or `aws-glue` in the name. It also has permission to perform the following actions on any Amazon S3 resource:

- `s3:CreateBucket`
- `s3:GetBucketLocation`
- `s3:ListBucket`
- `s3:ListAllMyBuckets`
- `s3:GetBucketCors`
- `s3:PutBucketCors`

To give an execution role permissions to access one or more specific buckets in Amazon S3, you can attach a policy similar to the following to the role. This policy grants an IAM role permission to perform all actions that `AmazonSageMakerFullAccess` allows but restricts this access to the buckets `DOC-EXAMPLE-BUCKET1` and `DOC-EXAMPLE-BUCKET2`. Refer to the security documentation for the specific SageMaker feature you are using to learn more about the Amazon S3 permissions required for that feature.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [
                "s3:GetObject",
                "s3:PutObject",
                "s3:DeleteObject",
                "s3:AbortMultipartUpload"
            ],
            "Resource": [
                "arn:aws:s3:::DOC-EXAMPLE-BUCKET1/*",
                "arn:aws:s3:::DOC-EXAMPLE-BUCKET2/*"
            ]
        },
        {
            "Effect": "Allow",
            "Action": [
```
Passing Roles

Actions like passing a role between services are a common function within SageMaker. You can find more details on Actions, Resources, and Condition Keys for SageMaker in the IAM User Guide.

You pass the role (iam:PassRole) when making these API calls: CreateAutoMLJob, CreateCompilationJob, CreateDomain, CreateFlowDefinition, CreateHyperParameterTuningJob, CreateImage, CreateLabelingJob, CreateModel, CreateMonitoringSchedule, CreateNotebookInstance, CreateProcessingJob, CreateTrainingJob, CreateUserProfile, RenderUiTemplate, and UpdateImage.

You attach the following trust policy to the IAM role which grants SageMaker principal permissions to assume the role, and is the same for all of the execution roles:

```
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Principal": {
                "Service": "sagemaker.amazonaws.com"
            },
            "Action": "sts:AssumeRole"
        }
    ]
}
```

The permissions that you need to grant to the role vary depending on the API that you call. The following sections explain these permissions.

**Note**

Instead of managing permissions by crafting a permission policy, you can use the AWS-managed AmazonSageMakerFullAccess permission policy. The permissions in this policy are fairly broad, to allow for any actions you might want to perform in SageMaker. For a listing of the policy including information about the reasons for adding many of the permissions, see AWS managed policy: AmazonSageMakerFullAccess (p. 3572). If you prefer to create custom policies and manage permissions to scope the permissions only to the actions you need to perform with the execution role, see the following topics.
Important
If you’re running into issues, see Troubleshooting Amazon SageMaker Identity and Access (p. 3626).

For more information about IAM roles, see IAM Roles in the IAM User Guide.

Topics
- CreateAutoMLJob API: Execution Role Permissions (p. 3539)
- CreateDomain API: Execution Role Permissions (p. 3540)
- CreateImage and UpdateImage APIs: Execution Role Permissions (p. 3541)
- CreateNotebookInstance API: Execution Role Permissions (p. 3542)
- CreateHyperParameterTuningJob API: Execution Role Permissions (p. 3545)
- CreateProcessingJob API: Execution Role Permissions (p. 3547)
- CreateTrainingJob API: Execution Role Permissions (p. 3549)
- CreateModel API: Execution Role Permissions (p. 3552)

CreateAutoMLJob API: Execution Role Permissions

For an execution role that you can pass in a CreateAutoMLJob API request, you can attach the following minimum permission policy to the role:

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "iam:PassRole",
        "sagemaker:DescribeEndpointConfig",
        "sagemaker:DescribeModel",
        "sagemaker:InvokeEndpoint",
        "sagemaker:ListTags",
        "sagemaker:DescribeEndpoint",
        "sagemaker:CreateModel",
        "sagemaker:CreateEndpointConfig",
        "sagemaker:CreateEndpoint",
        "sagemaker:DeleteModel",
        "sagemaker:DeleteEndpointConfig",
        "sagemaker:DeleteEndpoint",
        "cloudwatch:PutMetricData",
        "logs:CreateLogStream",
        "logs:PutLogEvents",
        "logs:CreateLogGroup",
        "logs:DescribeLogStreams",
        "s3:GetObject",
        "s3:PutObject",
        "s3:ListBucket",
        "ecr:GetAuthorizationToken",
```
"ecr:BatchCheckLayerAvailability",
"ecr:GetDownloadUrlForLayer",
"ecr:BatchGetImage"
],
"Resource": "*"
}
}

If you specify a private VPC for your AutoML job, add the following permissions:

[
   "Effect": "Allow",
   "Action": [
      "ec2:CreateNetworkInterface",
      "ec2:CreateNetworkInterfacePermission",
      "ec2:DeleteNetworkInterface",
      "ec2:DeleteNetworkInterfacePermission",
      "ec2:DescribeNetworkInterfaces",
      "ec2:DescribeVpcs",
      "ec2:DescribeDhcpOptions",
      "ec2:DescribeSubnets",
      "ec2:DescribeSecurityGroups"
   ]
]

If your input is encrypted using server-side encryption with an AWS KMS–managed key (SSE-KMS), add the following permissions:

[
   "Effect": "Allow",
   "Action": ["kms:Decrypt"
]
]

If you specify a KMS key in the output configuration of your AutoML job, add the following permissions:

[
   "Effect": "Allow",
   "Action": ["kms:Encrypt"
]
]

If you specify a volume KMS key in the resource configuration of your AutoML job, add the following permissions:

[
   "Effect": "Allow",
   "Action": ["kms:CreateGrant"
]
]

CreateDomain API: Execution Role Permissions

The execution role for domains with IAM Identity Center and the user/execution role for IAM domains need the following permissions when you pass an AWS KMS customer managed key as the KmsKeyId in the CreateDomain API request. The permissions are enforced during the CreateApp API call.
For an execution role that you can pass in the CreateDomain API request, you can attach the following permission policy to the role:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [
                "kms:CreateGrant",
                "kms:DescribeKey"
            ],
            "Resource": "arn:aws:kms:region:account-id:key/kms-key-id"
        }
    ]
}
```

Alternatively, if the permissions are specified in a KMS policy, you can attach the following policy to the role:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Sid": "Allow use of the key",
            "Effect": "Allow",
            "Principal": {
                "AWS": [
                    "arn:aws:iam::account-id:role/ExecutionRole"
                ]
            },
            "Action": [
                "kms:CreateGrant",
                "kms:DescribeKey"
            ],
            "Resource": "*"
        }
    ]
}
```

CreateImage and UpdateImage APIs: Execution Role Permissions

For an execution role that you can pass in a CreateImage or UpdateImage API request, you can attach the following permission policy to the role:

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [
                "ecr:BatchGetImage",
                "ecr:GetDownloadUrlForLayer"
            ],
            "Resource": "*"
        },
        {
            "Effect": "Allow",
            "Action": [
                "iam:PassRole"
            ],
            "Resource": "*"
        }
    ]
}
```
CreateNotebookInstance API: Execution Role Permissions

The permissions that you grant to the execution role for calling the CreateNotebookInstance API depend on what you plan to do with the notebook instance. If you plan to use it to invoke SageMaker APIs and pass the same role when calling the CreateTrainingJob and CreateModel APIs, attach the following permissions policy to the role:

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "sagemaker:*",
        "ecr:GetAuthorizationToken",
        "ecr:GetDownloadUrlForLayer",
        "ecr:BatchGetImage",
        "ecr:BatchCheckLayerAvailability",
        "ecr:SetRepositoryPolicy",
        "ecr:CompleteLayerUpload",
        "ecr:BatchDeleteImage",
        "ecr:UploadLayerPart",
        "ecr:DeleteRepositoryPolicy",
        "ecr:InitiateLayerUpload",
        "ecr:DeleteRepository",
        "ecr:PutImage",
        "ecr:CreateRepository",
        "cloudwatch:PutMetricData",
        "cloudwatch:GetMetricData",
        "cloudwatch:GetMetricStatistics",
        "cloudwatch:ListMetrics",
        "logs:CreateLogGroup",
        "logs:CreateLogStream",
        "logs:DescribeLogStreams",
        "logs:PutLogEvents",
        "logs:GetLogEvents",
        "s3:CreateBucket",
        "s3:ListBucket",
        "s3:GetBucketLocation",
        "s3:GetObject",
        "s3:PutObject",
        "s3:DeleteObject",
        "robomaker:CreateSimulationApplication",
        "robomaker:DescribeSimulationApplication",
        "robomaker:DeleteSimulationApplication",
        "robomaker:CreateSimulationJob",
        "robomaker:DescribeSimulationJob",
        "robomaker:CancelSimulationJob",
        "ec2:CreateVpcEndpoint",
        "ec2:DescribeRouteTables",
        "elasticfilesystem:DescribeMountTargets"
      ],
      "Resource": "*"
    }
  ]
}
```
To tighten the permissions, limit them to specific Amazon S3 and Amazon ECR resources, by restricting "Resource": "**", as follows:

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "sagemaker:*",
        "ecr:GetAuthorizationToken",
        "cloudwatch:PutMetricData",
        "logs:CreateLogGroup",
        "logs:CreateLogStream",
        "logs:DescribeLogStreams",
        "logs:PutLogEvents",
        "logs:GetLogEvents"
      ],
      "Resource": "**"
    },
    {
      "Effect": "Allow",
      "Action": [
        "iam:PassRole"
      ],
      "Resource": "**",
      "Condition": {
        "StringEquals": {
          "iam:PassedToService": "sagemaker.amazonaws.com"
        }
      }
    },
    {
      "Effect": "Allow",
      "Action": [
        "s3:ListBucket"
      ],
      "Resource": "**"
    }
  ]
}
```
If you plan to access other resources, such as Amazon DynamoDB or Amazon Relational Database Service, add the relevant permissions to this policy.

In the preceding policy, you scope the policy as follows:

- Scope the `s3:ListBucket` permission to the specific bucket that you specify as `InputDataConfig.DataSource.S3DataSource.S3Uri` in a CreateTrainingJob request.
- Scope `s3:GetObject`, `s3:PutObject`, and `s3:DeleteObject` permissions as follows:
  - Scope to the following values that you specify in a CreateTrainingJob request:
    
    ```
    InputDataConfig.DataSource.S3DataSource.S3Uri
    OutputDataConfig.S3OutputPath
    ```
  - Scope to the following values that you specify in a CreateModel request:
    
    ```
    PrimaryContainer.ModelDataUrl
    SuplementalContainers.ModelDataUrl
    ```
- Scope ecr permissions as follows:
  - Scope to the `AlgorithmSpecification.TrainingImage` value that you specify in a CreateTrainingJob request.
  - Scope to the `PrimaryContainer.Image` value that you specify in a CreateModel request.

The `cloudwatch` and `logs` actions are applicable for `*` resources. For more information, see [CloudWatch Resources and Operations](https://docs.aws.amazon.com/AmazonCloudWatch/latest/monitoring/cloudwatch-events-resource-based-policy.html) in the Amazon CloudWatch User Guide.
CreateHyperParameterTuningJob API: Execution Role Permissions

For an execution role that you can pass in a CreateHyperParameterTuningJob API request, you can attach the following permission policy to the role:

```
{
   "Version": "2012-10-17",
   "Statement": [
       {
           "Effect": "Allow",
           "Action": [
               "cloudwatch:PutMetricData",
               "logs:CreateLogStream",
               "logs:PutLogEvents",
               "logs:CreateLogGroup",
               "logs:DescribeLogStreams",
               "s3:GetObject",
               "s3:PutObject",
               "s3:ListBucket",
               "ecr:GetAuthorizationToken",
               "ecr:BatchCheckLayerAvailability",
               "ecr:GetDownloadUrlForLayer",
               "ecr:BatchGetImage"
           ],
           "Resource": "*"
       }]
}
```

Instead of specifying "Resource": "*", you could scope these permissions to specific Amazon S3 and Amazon ECR resources:

```
{
   "Version": "2012-10-17",
   "Statement": [
       {
           "Effect": "Allow",
           "Action": [
               "cloudwatch:PutMetricData",
               "logs:CreateLogStream",
               "logs:PutLogEvents",
               "logs:CreateLogGroup",
               "logs:DescribeLogStreams",
               "ecr:GetAuthorizationToken"
           ],
           "Resource": "*"
       },
       {
           "Effect": "Allow",
           "Action": [
               "s3:ListBucket"
           ],
           "Resource": [
               "arn:aws:s3:::inputbucket"
           ]
       },
       {
           "Effect": "Allow",
           "Action": [
               "s3:GetObject",
               "s3:PutObject"
           ],
           "Resource": "*"
       }
   ]
}
```
If the training container associated with the hyperparameter tuning job needs to access other data sources, such as DynamoDB or Amazon RDS resources, add relevant permissions to this policy.

In the preceding policy, you scope the policy as follows:

- Scope the `s3:ListBucket` permission to a specific bucket that you specify as the `InputDataConfig.DataSource.S3DataSource.S3Uri` in a `CreateTrainingJob` request.
- Scope the `s3:GetObject` and `s3:PutObject` permissions to the following objects that you specify in the input and output data configuration in a `CreateHyperParameterTuningJob` request:
  - `InputDataConfig.DataSource.S3DataSource.S3Uri`
  - `OutputDataConfig.S3OutputPath`
- Scope Amazon ECR permissions to the registry path (AlgorithmSpecification.TrainingImage) that you specify in a `CreateHyperParameterTuningJob` request.

The `cloudwatch` and `logs` actions are applicable for `*` resources. For more information, see CloudWatch Resources and Operations in the Amazon CloudWatch User Guide.

If you specify a private VPC for your hyperparameter tuning job, add the following permissions:

```json
{
  "Effect": "Allow",
  "Action": [
    "ec2:CreateNetworkInterface",
    "ec2:CreateNetworkInterfacePermission",
    "ec2:DeleteNetworkInterface",
    "ec2:DeleteNetworkInterfacePermission",
    "ec2:DescribeNetworkInterfaces",
    "ec2:DescribeVpcs",
    "ec2:DescribeDhcpOptions",
    "ec2:DescribeSubnets",
    "ec2:DescribeSecurityGroups"
  ]
}
```

If your input is encrypted using server-side encryption with an AWS KMS–managed key (SSE-KMS), add the following permissions:

```json
{
  "Effect": "Allow",
  "Action": [
    "kms:Encrypt",
    "kms:Decrypt",
    "kms:GenerateDataKey",
    "kms:ReEncrypt`
```
If you specify a KMS key in the output configuration of your hyperparameter tuning job, add the following permissions:

```
{
  "Effect": "Allow",
  "Action": [
    "kms:Decrypt"
  ]
}
```

If you specify a volume KMS key in the resource configuration of your hyperparameter tuning job, add the following permissions:

```
{
  "Effect": "Allow",
  "Action": [
    "kms:Encrypt"
  ]
}
```

### CreateProcessingJob API: Execution Role Permissions

For an execution role that you can pass in a CreateProcessingJob API request, you can attach the following permission policy to the role:

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "cloudwatch:PutMetricData",
        "logs:CreateLogStream",
        "logs:PutLogEvents",
        "logs:CreateLogGroup",
        "logs:DescribeLogStreams",
        "s3:GetObject",
        "s3:PutObject",
        "s3:ListBucket",
        "ecr:GetAuthorizationToken",
        "ecr:BatchCheckLayerAvailability",
        "ecr:GetDownloadUrlForLayer",
        "ecr:GetDownloadUrlForLayer",
        "ecr:GetDownloadUrlForLayer"
      ],
      "Resource": "*"
    }
  ]
}
```

Instead of specifying "Resource": "*", you could scope these permissions to specific Amazon S3 and Amazon ECR resources:

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "cloudwatch:PutMetricData",
        "logs:CreateLogStream",
        "logs:PutLogEvents",
        "logs:CreateLogGroup",
        "logs:DescribeLogStreams",
        "s3:GetObject",
        "s3:PutObject",
        "s3:ListBucket",
        "ecr:GetAuthorizationToken",
        "ecr:BatchCheckLayerAvailability",
        "ecr:GetDownloadUrlForLayer",
        "ecr:GetDownloadUrlForLayer"
      ],
      "Resource": "*"
    }
  ]
}
```
"Statement": [

    {
        "Effect": "Allow",
        "Action": [
            "cloudwatch:PutMetricData",
            "logs:CreateLogStream",
            "logs:PutLogEvents",
            "logs:CreateLogGroup",
            "logs:DescribeLogStreams",
            "ecr:GetAuthorizationToken"
        ],
        "Resource": "*"
    },

    {
        "Effect": "Allow",
        "Action": [
            "s3:ListBucket"
        ],
        "Resource": [
            "arn:aws:s3:::inputbucket"
        ]
    },

    {
        "Effect": "Allow",
        "Action": [
            "s3:GetObject",
            "s3:PutObject"
        ],
        "Resource": [
            "arn:aws:s3:::inputbucket/object",
            "arn:aws:s3:::outputbucket/path"
        ]
    },

    {
        "Effect": "Allow",
        "Action": [
            "ecr:BatchCheckLayerAvailability",
            "ecr:GetDownloadUrlForLayer",
            "ecr:BatchGetImage"
        ],
        "Resource": "arn:aws:ecr:region::repository/my-repo"
    }
]

If CreateProcessingJob.AppSpecification.ImageUri needs to access other data sources, such as DynamoDB or Amazon RDS resources, add relevant permissions to this policy.

In the preceding policy, you scope the policy as follows:

- **Scope the s3:ListBucket permission to a specific bucket that you specify as the ProcessingInputs in a CreateProcessingJob request.**
- **Scope the s3:GetObject and s3:PutObject permissions to the objects that will be downloaded or uploaded in the ProcessingInputs and ProcessingOutputConfig in a CreateProcessingJob request.**
- **Scope Amazon ECR permissions to the registry path (AppSpecification.ImageUri) that you specify in a CreateProcessingJob request.**

The cloudwatch and logs actions are applicable for "*" resources. For more information, see CloudWatch Resources and Operations in the Amazon CloudWatch User Guide.

If you specify a private VPC for your processing job, add the following permissions:
If your input is encrypted using server-side encryption with an AWS KMS–managed key (SSE-KMS), add the following permissions:

```
{
  "Effect": "Allow",
  "Action": [
    "kms:Decrypt"
  ]
}
```

If you specify a KMS key in the output configuration of your processing job, add the following permissions:

```
{
  "Effect": "Allow",
  "Action": [
    "kms:Encrypt"
  ]
}
```

If you specify a volume KMS key in the resource configuration of your processing job, add the following permissions:

```
{
  "Effect": "Allow",
  "Action": [
    "kms:CreateGrant"
  ]
}
```

**CreateTrainingJob API: Execution Role Permissions**

For an execution role that you can pass in a CreateTrainingJob API request, you can attach the following permission policy to the role:

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "cloudwatch:PutMetricData",
        "logs:CreateLogStream",
        "logs:PutLogEvents",
```
Instead of specifying "Resource": "*", you could scope these permissions to specific Amazon S3 and Amazon ECR resources:

```json
{  
"Version": "2012-10-17",  
"Statement": [  
{    
"Effect": "Allow",    
"Action": [      
"cloudwatch:PutMetricData",      
"logs:CreateLogStream",      
"logs:PutLogEvents",      
"logs:CreateLogGroup",      
"logs:DescribeLogStreams",      
"ecr:GetAuthorizationToken"    
],    
"Resource": "*"
  },  
{    
"Effect": "Allow",    
"Action": [      
"s3:ListBucket"
],    
"Resource": [      
"arn:aws:s3:::inputbucket"
    ]
  },  
{    
"Effect": "Allow",    
"Action": [      
"s3:GetObject",      
"s3:PutObject"
],    
"Resource": [      
"arn:aws:s3:::inputbucket/object",      
"arn:aws:s3:::outputbucket/path"
    ]
  },  
{    
"Effect": "Allow",    
"Action": [      
"ecr:BatchCheckLayerAvailability",      
"ecr:GetDownloadUrlForLayer",      
"ecr:BatchGetImage"
],    
"Resource": "arn:aws:ecr::region::repository/my-repo"
  }
]}
```
If `CreateTrainingJob.AlgorithmSpecifications.TrainingImage` needs to access other data sources, such as DynamoDB or Amazon RDS resources, add relevant permissions to this policy.

In the preceding policy, you scope the policy as follows:

- Scope the `s3:ListBucket` permission to a specific bucket that you specify as the `InputDataConfig.DataSource.S3DataSource.S3Uri` in a `CreateTrainingJob` request.
- Scope the `s3:GetObject` and `s3:PutObject` permissions to the following objects that you specify in the input and output data configuration in a `CreateTrainingJob` request:
  - `InputDataConfig.DataSource.S3DataSource.S3Uri`
  - `OutputDataConfig.S3OutputPath`
- Scope Amazon ECR permissions to the registry path (`AlgorithmSpecification.TrainingImage`) that you specify in a `CreateTrainingJob` request.

The `cloudwatch` and `logs` actions are applicable for ")" resources. For more information, see CloudWatch Resources and Operations in the Amazon CloudWatch User Guide.

If you specify a private VPC for your training job, add the following permissions:

```
{
  "Effect": "Allow",
  "Action": [
    "ec2:CreateNetworkInterface",
    "ec2:CreateNetworkInterfacePermission",
    "ec2:DeleteNetworkInterface",
    "ec2:DeleteNetworkInterfacePermission",
    "ec2:DescribeNetworkInterfaces",
    "ec2:DescribeVpcs",
    "ec2:DescribeDhcpOptions",
    "ec2:DescribeSubnets",
    "ec2:DescribeSecurityGroups"
  ]
}
```

If your input is encrypted using server-side encryption with an AWS KMS–managed key (SSE-KMS), add the following permissions:

```
{
  "Effect": "Allow",
  "Action": [
    "kms:Decrypt"
  ]
}
```

If you specify a KMS key in the output configuration of your training job, add the following permissions:

```
{
  "Effect": "Allow",
  "Action": [
    "kms:Encrypt"
  ]
}
```

If you specify a volume KMS key in the resource configuration of your training job, add the following permissions:

```
{
}
```
CreateModel API: Execution Role Permissions

For an execution role that you can pass in a CreateModel API request, you can attach the following permission policy to the role:

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["kms:CreateGrant"]
    }
  ]
}
```

Instead of specifying "Resource": "*", you can scope these permissions to specific Amazon S3 and Amazon ECR resources:

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["cloudwatch:PutMetricData",
                  "logs:CreateLogStream",
                  "logs:PutLogEvents",
                  "logs:CreateLogGroup",
                  "logs:DescribeLogStreams",
                  "s3:GetObject",
                  "s3:ListBucket",
                  "ecr:GetAuthorizationToken",
                  "ecr:BatchCheckLayerAvailability",
                  "ecr:GetDownloadUrlForLayer",
                  "ecr:BatchGetImage"
                ],
      "Resource": "*
    }
  ]
}
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["s3:GetObject"
                ],
      "Resource": ["arn:aws:s3:::inputbucket/object"
                ]
    }
  ]
}
```

"Effect": "Allow",
"Action": [
  "kms:CreateGrant"
]
}
If `CreateModel.PrimaryContainer.Image` need to access other data sources, such as Amazon DynamoDB or Amazon RDS resources, add relevant permissions to this policy.

In the preceding policy, you scope the policy as follows:

- **•** Scope S3 permissions to objects that you specify in the `PrimaryContainer.ModelDataUrl` in a `CreateModel` request.
- **•** Scope Amazon ECR permissions to a specific registry path that you specify as the `PrimaryContainer.Image` and `SecondaryContainer.Image` in a `CreateModel` request.

The `cloudwatch` and `logs` actions are applicable for "*" resources. For more information, see [CloudWatch Resources and Operations](https://docs.aws.amazon.com/AmazonCloudWatch/latest/monitoring/cloudwatch-resource-summary.html) in the Amazon CloudWatch User Guide.

If you specify a private VPC for your model, add the following permissions:

```json
{
  "Effect": "Allow",
  "Action": [
    "ec2:CreateNetworkInterface",
    "ec2:CreateNetworkInterfacePermission",
    "ec2:DeleteNetworkInterface",
    "ec2:DeleteNetworkInterfacePermission",
    "ec2:DescribeNetworkInterfaces",
    "ec2:DescribeVpcs",
    "ec2:DescribeDhcpOptions",
    "ec2:DescribeSubnets",
    "ec2:DescribeSecurityGroups"
  ]
}
```

### Amazon SageMaker API Permissions: Actions, Permissions, and Resources Reference

When you are setting up access control and writing a permissions policy that you can attach to an IAM identity (an identity-based policy), use the following as a reference. The each Amazon SageMaker API operation, the corresponding actions for which you can grant permissions to perform the action, and the AWS resource for which you can grant the permissions. You specify the actions in the policy's `Action` field, and you specify the resource value in the policy's `Resource` field.

**Note**

Except for the ListTags API, resource-level restrictions are not available on List- calls. Any user calling a List- API will see all resources of that type in the account.

To express conditions in your Amazon SageMaker policies, you can use AWS-wide condition keys. For a complete list of AWS-wide keys, see [Available Keys](https://docs.aws.amazon.com/IAM/latest/UserGuide/reference_policies_elements_condition-keys.html) in the IAM User Guide.
### Amazon SageMaker API Operations and Required Permissions for Actions

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<tr>
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<tr>
<td></td>
<td>iam:PassRole</td>
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</tr>
<tr>
<td></td>
<td>The following permission is required only if the associated ResourceConfig has a specified VolumeKmsKeyId and the associated role does not have a policy that permits this action:</td>
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<tr>
<td></td>
<td>kms:CreateGrant</td>
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<tr>
<td>CreateDomain</td>
<td>sagemaker:CreateDomain</td>
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<tr>
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<td>Required if a KMS customer managed key is specified for KmsKeyId:</td>
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<td></td>
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<tr>
<td></td>
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<td>kms:Decrypt</td>
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<tr>
<td></td>
<td>kms:DescribeKey</td>
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<td></td>
<td>kms:GenerateDataKeyWithoutPlainText</td>
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<tr>
<td></td>
<td>Required to create a domain that supports RStudio:</td>
<td></td>
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<tr>
<td></td>
<td>sagemaker:CreateApp</td>
<td></td>
</tr>
<tr>
<td>CreateEndpoint</td>
<td>sagemaker:CreateEndpoint</td>
<td>arn:aws:sagemaker:region:account-id:endpoint/end-pointName</td>
</tr>
<tr>
<td></td>
<td>kms:CreateGrant (required only if the associated EndpointConfig has a KmsKeyId specified)</td>
<td>arn:aws:sagemaker:region:account-id:endpoint-endpointConfigName</td>
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<tr>
<td>CreateEndpointConfig</td>
<td>sagemaker:CreateEndpointConfig</td>
<td>arn:aws:sagemaker:region:account-id:endpoint-config/endpointConfigName</td>
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<tr>
<td>CreateFlowDefinition</td>
<td>sagemaker:CreateFlowDefinition</td>
<td>arn:aws:sagemaker:region:account-id:flow-definition/flowDefinitionName</td>
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<tr>
<td>CreateHumanTaskUi</td>
<td>sagemaker:CreateHumanTaskUi</td>
<td>arn:aws:sagemaker:region:account-id:human-task-ui/humanTaskUiName</td>
</tr>
<tr>
<td>CreateHyperParameterTuningJob</td>
<td>sagemaker:CreateHyperParameterTuningJob</td>
<td>arn:aws:sagemaker:region:account-id:hyper-parameter-tuning-job/hyperParameterTuningJobName</td>
</tr>
<tr>
<td>CreateImage</td>
<td>sagemaker:CreateImage</td>
<td>arn:aws:sagemaker:region:account-id:image/*</td>
</tr>
<tr>
<td>CreateModel</td>
<td>sagemaker:CreateModel</td>
<td>arn:aws:sagemaker:region:account-id:model/modelName</td>
</tr>
</tbody>
</table>

The following permissions are required only if you specify an encryption key:
- kms:CreateGrant
- kms:Decrypt
- kms:DescribeKey
- kms:GenerateDataKey

The following permission is required only if any of the associated ResourceConfig have a specified VolumeKmsKeyId and the associated role does not have a policy that permits this action:
- kms:CreateGrant
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<td>sagemaker:CreateNotebookInstance</td>
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<tr>
<td></td>
<td></td>
<td>arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName</td>
</tr>
<tr>
<td>CreatePipeline</td>
<td>sagemaker:CreatePipeline</td>
<td>iam:PassRole</td>
</tr>
<tr>
<td></td>
<td></td>
<td>arn:aws:partition:sagemaker:region:account-id:pipeline/pipeline-name</td>
</tr>
<tr>
<td></td>
<td></td>
<td>arn:aws:partition:iam::account-id:role/role-name</td>
</tr>
</tbody>
</table>

The following permissions are required only if you specify a VPC for your notebook instance:
- ec2:CreateNetworkInterface
- ec2:DescribeSecurityGroups
- ec2:DescribeSubnets
- ec2:DescribeVpcs

The following permission is required only if you specify a VPC and an elastic inference accelerator for your notebook instance:
- ec2:DescribeVpcEndpoints

The following permissions are required only if you specify an encryption key:
- kms:DescribeKey
- kms:CreateGrant

The following permission is required only if you specify an AWS Secrets Manager secret to access a private Git repository:
- secretsmanager:GetSecretValue
<table>
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<tr>
<th>Amazon SageMaker API Operations</th>
<th>Required Permissions (API Actions)</th>
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</thead>
<tbody>
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<td>CreatePresignedDomainUrl</td>
<td>sagemaker:CreatePresignedDomainUrl</td>
<td>arn:aws:sagemaker:region:account-id:app/domain-id/userProfileName/*</td>
</tr>
<tr>
<td>CreatePresignedNotebookInstanceUrl</td>
<td>sagemaker:CreatePresignedNotebookInstanceUrl</td>
<td>arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName</td>
</tr>
<tr>
<td>CreateProcessingJob</td>
<td>sagemaker:CreateProcessingJob iam:PassRole kms:CreateGrant (required only if the associated ProcessingResources has a specified VolumeKmsKeyId and the associated role does not have a policy that permits this action)</td>
<td>arn:aws:sagemaker:region:account-id:processing-job/processingJobName</td>
</tr>
<tr>
<td>CreateTrainingJob</td>
<td>sagemaker:CreateTrainingJob iam:PassRole kms:CreateGrant (required only if the associated ResourceConfig has a specified VolumeKmsKeyId and the associated role does not have a policy that permits this action)</td>
<td>arn:aws:sagemaker:region:account-id:training-job/trainingJobName</td>
</tr>
<tr>
<td>CreateTransformJob</td>
<td>sagemaker:CreateTransformJob kms:CreateGrant (required only if the associated TransformResources has a specified VolumeKmsKeyId and the associated role does not have a policy that permits this action)</td>
<td>arn:aws:sagemaker:region:account-id:transform-job/transformJobName</td>
</tr>
<tr>
<td>CreateUserProfile</td>
<td>sagemaker:CreateUserProfile iam:PassRole</td>
<td>arn:aws:sagemaker:region:account-id:user-profile/domain-id/userProfileName</td>
</tr>
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<td>Amazon SageMaker API Operations</td>
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</tr>
<tr>
<td>CreateWorkforce</td>
<td>sagemaker:CreateWorkforce</td>
<td>arn:aws:sagemaker:region:account-id:workforce/*</td>
</tr>
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<td></td>
<td>cognito-iddp:DescribeUserPoolClient</td>
<td></td>
</tr>
<tr>
<td></td>
<td>cognito-iddp:UpdateUserPool</td>
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</tr>
<tr>
<td></td>
<td>cognito-iddp:DescribeUserPool</td>
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<tr>
<td></td>
<td>cognito-iddp:UpdateUserPoolClient</td>
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</tr>
<tr>
<td>CreateWorkteam</td>
<td>sagemaker:CreateWorkteam</td>
<td>arn:aws:sagemaker:region:account-id:workteam/private-crowd/work team name</td>
</tr>
<tr>
<td></td>
<td>cognito-iddp:DescribeUserPoolClient</td>
<td></td>
</tr>
<tr>
<td></td>
<td>cognito-iddp:UpdateUserPool</td>
<td></td>
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<tr>
<td></td>
<td>cognito-iddp:DescribeUserPool</td>
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<td></td>
<td>cognito-iddp:UpdateUserPoolClient</td>
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<td>DeleteApp</td>
<td>sagemaker:DeleteApp</td>
<td>arn:aws:sagemaker:region:account-id:app/domain-id/user-profile-name/app-type/appName</td>
</tr>
<tr>
<td>DeleteDomain</td>
<td>sagemaker:DeleteDomain</td>
<td>arn:aws:sagemaker:region:account-id:domain/domainId</td>
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<tr>
<td>DeleteEndpoint</td>
<td>sagemaker:DeleteEndpoint</td>
<td>arn:aws:sagemaker:region:account-id:endpoint/endpointName</td>
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<td>sagemaker:DeleteEndpointConfig</td>
<td>arn:aws:sagemaker:region:account-id:endpoint-config/endpointConfigName</td>
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<td>DeleteHumanLoop</td>
<td>sagemaker:DeleteHumanLoop</td>
<td>arn:aws:sagemaker:region:account-id:human-loop/humanLoopName</td>
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<td>DeleteImage</td>
<td>sagemaker:DeleteImage</td>
<td>arn:aws:sagemaker:region:account-id:image/imageName</td>
</tr>
<tr>
<td>Amazon SageMaker API Operations</td>
<td>Required Permissions (API Actions)</td>
<td>Resources</td>
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<tr>
<td>DeleteModel</td>
<td>sagemaker:DeleteModel</td>
<td>arn:aws:sagemaker:region:accountId:model/modelName</td>
</tr>
<tr>
<td>DeleteModelPackage</td>
<td>sagemaker:DeleteModelPackage</td>
<td>arn:aws:sagemaker:region:accountId:model-package/modelPackageName</td>
</tr>
<tr>
<td>DeleteNotebookInstance</td>
<td>sagemaker:DeleteNotebookInstance</td>
<td>arn:aws:sagemaker:region:accountId:notebook-instance/notebookInstanceName</td>
</tr>
<tr>
<td>DeletePipeline</td>
<td>sagemaker:DeletePipeline</td>
<td>arn:partition:sagemaker:region:accountId:pipeline/pipeline-name</td>
</tr>
<tr>
<td>DeleteTags</td>
<td>sagemaker:DeleteTags</td>
<td>arn:aws:sagemaker:region:accountId:*</td>
</tr>
<tr>
<td>DeleteUserProfile</td>
<td>sagemaker:DeleteUserProfile</td>
<td>arn:aws:sagemaker:region:accountId:user-profile/domain-id/userProfileName</td>
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<tr>
<td>DeleteWorkforce</td>
<td>sagemaker:DeleteWorkforce</td>
<td>arn:aws:sagemaker:region:accountId:workforce/*</td>
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<tr>
<td>DeleteWorkteam</td>
<td>sagemaker:DeleteWorkteam</td>
<td>arn:aws:sagemaker:region:accountId:workteam/private-crowd/*</td>
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<td>DescribeApp</td>
<td>sagemaker:DescribeApp</td>
<td>arn:aws:sagemaker:region:accountId:app/domain-id/user-profile-name/app-type/appName</td>
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<tr>
<td>Amazon SageMaker API Operations</td>
<td>Required Permissions (API Actions)</td>
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<td>DescribeDomain</td>
<td>sagemaker:DescribeDomain</td>
<td>arn:aws:sagemaker:region:account-id:domain/domainId</td>
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<tr>
<td>DescribeEndpoint</td>
<td>sagemaker:DescribeEndpoint</td>
<td>arn:aws:sagemaker:region:account-id:endpoint/endpointName</td>
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<td>DescribeEndpointConfig</td>
<td>sagemaker:DescribeEndpointConfig</td>
<td>arn:aws:sagemaker:region:account-id:endpoint-config/endpointConfigName</td>
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<td>Amazon SageMaker API Operations</td>
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<td>DescribePipeline</td>
<td>sagemaker:DescribePipeline</td>
<td>arn:aws-partition:sagemaker:region:account-id:pipeline/pipeline-name</td>
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<td>DescribePipelineDefinitionForExecution</td>
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<td>DescribePipelineExecution</td>
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<td>arn:aws-partition:sagemaker:region:account-id:pipeline/pipeline-name/execution/execution-id</td>
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<td>DescribeUserProfile</td>
<td>sagemaker:DescribeUserProfile</td>
<td>arn:aws:sagemaker:region:account-id:training-job/trainingjobname</td>
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<td>DescribeWorkforce</td>
<td>sagemaker:DescribeWorkforce</td>
<td>arn:aws:sagemaker:region:account-id:workforce/*</td>
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<tr>
<td>InvokeEndpoint</td>
<td>sagemaker:InvokeEndpoint</td>
<td>arn:aws:sagemaker:region:account-id:endpoint/endpointName</td>
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<td>Amazon SageMaker API Operations</td>
<td>Required Permissions (API Actions)</td>
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<tr>
<td>ListEndpointConfigs</td>
<td>sagemaker:ListEndpointConfigs</td>
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<td>ListLabelingJobs</td>
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<td>ListLabelingJobsForWorkteam</td>
<td>sagemaker:ListLabelingJobsForWorkteam</td>
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<td>ListModels</td>
<td>sagemaker:ListModels</td>
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<td>ListNotebookInstances</td>
<td>sagemaker:ListNotebookInstances</td>
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<tr>
<td>ListPipelineExecutions</td>
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<td>arn:aws:sagemaker:region:account-id:pipeline/pipeline-name</td>
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<td>Amazon SageMaker API Operations</td>
<td>Required Permissions (API Actions)</td>
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<tr>
<td>ListSubscribedWorkteams</td>
<td>sagemaker:ListSubscribedWorkteams</td>
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<tr>
<td></td>
<td>aws-marketplace:ViewSubscriptions</td>
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<td>ListTags</td>
<td>sagemaker:ListTags</td>
<td>arn:aws:sagemaker:region:account-id:*</td>
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<td>ListTrainingJobs</td>
<td>sagemaker:ListTrainingJobs</td>
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<td>ListTransformJobs</td>
<td>sagemaker:ListTransformJobs</td>
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<tr>
<td>ListWorkforces</td>
<td>sagemaker:ListWorkforces</td>
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<td>ListWorkteams</td>
<td>sagemaker:ListWorkteams</td>
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<td>SendPipelineExecutionStepFailure</td>
<td>sagemaker:SendPipelineExecutionStepFailure</td>
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<td>SendPipelineExecutionStepSuccess</td>
<td>sagemaker:SendPipelineExecutionStepSuccess</td>
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<td>StartHumanLoop</td>
<td>sagemaker:StartHumanLoop</td>
<td>arn:aws:sagemaker:region:account-id:human-loop/humanLoopName</td>
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<td>Amazon SageMaker API Operations</td>
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<td><code>iam:PassRole</code></td>
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<td><code>ec2:CreateNetworkInterface</code></td>
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<td><code>ec2:DescribeNetworkInterfaces</code></td>
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<td><code>ec2:DescribeSecurityGroups</code></td>
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<td><code>ec2:DescribeSubnets</code></td>
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<td><code>ec2:DescribeVpcs</code></td>
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<td>required only if you specified a</td>
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<td>VPC when you created your</td>
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<td>notebook instance:</td>
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<td></td>
<td><code>ec2:DescribeVpcEndpoints</code></td>
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<td>The following permissions are</td>
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<td>required only if you specified an</td>
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<td>encryption key when you created</td>
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<td>the notebook instance:</td>
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<td></td>
<td><code>kms:DescribeKey</code></td>
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<td></td>
<td><code>kms:CreateGrant</code></td>
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<td>required only if you specified an</td>
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<td>AWS Secrets Manager secret to</td>
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<td></td>
<td>access a private Git repository</td>
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<td></td>
<td>when you created the notebook</td>
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<td>instance:</td>
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<tr>
<td></td>
<td><code>secretsmanager:GetSecretValue</code></td>
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<thead>
<tr>
<th>Amazon SageMaker API Operations</th>
<th>Required Permissions (API Actions)</th>
<th>Resources</th>
</tr>
</thead>
<tbody>
<tr>
<td>StopNotebookInstance</td>
<td>sagemaker:StopNotebookInstance</td>
<td>arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName</td>
</tr>
<tr>
<td>StopPipelineExecution</td>
<td>sagemaker:StopPipelineExecution</td>
<td>arn:aws:partition:sagemaker:region:account-id:pipeline/pipeline-name/execution/execution-id</td>
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<tr>
<td>StopProcessingJob</td>
<td>sagemaker:StopProcessingJob</td>
<td>arn:aws:sagemaker:region:account-id:processing-job/processingJobName</td>
</tr>
<tr>
<td>UpdateDomain</td>
<td>sagemaker:UpdateDomain</td>
<td>arn:aws:sagemaker:region:account-id:domain/domainId</td>
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<tr>
<td>UpdateEndpoint</td>
<td>sagemaker:UpdateEndpoint</td>
<td>arn:aws:sagemaker:region:account-id:endpoint/endpointName</td>
</tr>
<tr>
<td>UpdateEndpointWeightsAndCapacities</td>
<td>sagemaker:UpdateEndpointWeightsAndCapacities</td>
<td>arn:aws:sagemaker:region:account-id:endpoint/endpointName</td>
</tr>
<tr>
<td>Amazon SageMaker API Operations</td>
<td>Required Permissions (API Actions)</td>
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<tr>
<td>UpdatePipeline</td>
<td>sagemaker:UpdatePipeline</td>
<td>arn:aws-partition:sagemaker:region:account-id: pipeline/pipeline-name</td>
</tr>
<tr>
<td></td>
<td>iam:PassRole</td>
<td>arn:aws-partition:iam::account-id:role/role-name</td>
</tr>
<tr>
<td>UpdatePipelineExecution</td>
<td>sagemaker:UpdatePipelineExecution</td>
<td>arn:aws:sagemaker:region:account-id: pipeline/pipeline-name/execution/execution-id</td>
</tr>
<tr>
<td>UpdateUserProfile</td>
<td>sagemaker:UpdateUserProfile</td>
<td>arn:aws:sagemaker:region:account-id:user-profile/domain-id/userProfileName</td>
</tr>
</tbody>
</table>

**Amazon SageMaker API and Required Permissions for Actions**

**API Operation: AddTags**

- Required Permissions (API Action): sagemaker:AddTags
- Resources: *

**API Operation: CreateEndpoint**

- Required Permissions (API Action): sagemaker:CreateEndpoint
- Resources: arn:aws:sagemaker:region:account-id:endpoint/endpointName

**API Operation: CreateEndpointConfig**

- Required Permissions (API Action): sagemaker:CreateEndpointConfig
- Resources: arn:aws:sagemaker:region:account-id:endpoint-config/endpointConfigName

**API Operation: CreateModel**

- Required Permissions (API Action): sagemaker:CreateModel, iam:PassRole
- Resources: arn:aws:sagemaker:region:account-id:model/modelName

**API Operation: CreateLabelingJob**

- Required Permissions (API Action): sagemaker:CreateLabelingJob, iam:PassRole
- Resources: arn:aws:sagemaker:region:account-id:labeling-job/labelingJobName

**API Operation: CreateNotebookInstance**

- Required Permissions (API Action): sagemaker:CreateNotebookInstance, iam:PassRole, ec2:CreateNetworkInterface, ec2:AttachNetworkInterface,
ec2:ModifyNetworkInterfaceAttribute, ec2:DescribeAvailabilityZones,
ec2:DescribeInternetGateways, ec2:DescribeSecurityGroups,
ec2:DescribeSubnets, ec2:DescribeVpcs, kms:CreateGrant

Resources: arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName

API Operation: CreateTrainingJob

Required Permissions (API Action): sagemaker:CreateTrainingJob, iam:PassRole

Resources: arn:aws:sagemaker:region:account-id:training-job/trainingJobName

API Operation: CreateWorkforce


API Operation: CreateWorkteam


API Operation: DeleteEndpoint

Required Permissions (API Action): sagemaker:DeleteEndpoint

Resources: arn:aws:sagemaker:region:account-id:endpoint/endpointName

API Operation: DeleteEndpointConfig

Required Permissions (API Action): sagemaker:DeleteEndpointConfig

Resources: arn:aws:sagemaker:region:account-id:endpoint-config/endpointConfigName

API Operation: DeleteModel

Required Permissions (API Action): sagemaker:DeleteModel

Resources: arn:aws:sagemaker:region:account-id:model/modelName

API Operation: DeleteNotebookInstance


Resources: arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName

API Operation: DeleteTags

Required Permissions (API Action): sagemaker:DeleteTags
Resources: *

API Operation: DeleteWorkteam

Required Permissions (API Action): sagemaker:DeleteWorkforce


API Operation: DeleteWorkteam

Required Permissions (API Action): sagemaker:DeleteWorkteam


API Operation: DescribeEndpoint

Required Permissions (API Action): sagemaker:DescribeEndpoint

Resources: arn:aws:sagemaker:region:account-id:endpoint/endpointName

API Operation: DescribeEndpointConfig

Required Permissions (API Action): sagemaker:DescribeEndpointConfig

Resources: arn:aws:sagemaker:region:account-id:endpoint-config/endpointConfigName

API Operation: DescribeLabelingJob

Required Permissions (API Action): sagemaker:DescribeLabelingJob

Resources: arn:aws:sagemaker:region:account-id:labeling-job/labelingJobName

API Operation: DescribeModel

Required Permissions (API Action): sagemaker:DescribeModel

Resources: arn:aws:sagemaker:region:account-id:model/modelName

API Operation: DescribeNotebookInstance

Required Permissions (API Action): sagemaker:DescribeNotebookInstance

Resources: arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName

API Operation: DescribeSubscribedWorkforce

Required Permissions (API Action): sagemaker:DescribeSubscribedWorkforce, aws-marketplace:ViewSubscriptions


API Operation: DescribeSubscribedWorkteam

Required Permissions (API Action): sagemaker:DescribeSubscribedWorkteam, aws-marketplace:ViewSubscriptions


API Operation: DescribeTrainingJob

Required Permissions (API Action): sagemaker:DescribeTrainingJob
Resources: arn:aws:sagemaker:region:account-id:training-job/trainingJobName

**API Operation:** DescribeWorkteam

Required Permissions (API Action): sagemaker:DescribeWorkteam


**API Operation:** CreatePresignedNotebookInstanceUrl

Required Permissions (API Action): sagemaker:CreatePresignedNotebookInstanceUrl

Resources: arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName

**API Operation:** runtime_InvokeEndpoint

Required Permissions (API Action): sagemaker:InvokeEndpoint

Resources: arn:aws:sagemaker:region:account-id:endpoint/endpointName

**API Operation:** ListEndpointConfigs

Required Permissions (API Action): sagemaker:ListEndpointConfigs

Resources: *

**API Operation:** ListEndpoints

Required Permissions (API Action): sagemaker:ListEndpoints

Resources: *

**API Operation:** ListLabelingJobs

Required Permissions (API Action): sagemaker:ListLabelingJobs

Resources: *

**API Operation:** ListLabelingJobsForWorkteam

Required Permissions (API Action): sagemaker:ListLabelingJobsForWorkteam

Resources: *

**API Operation:** ListModels

Required Permissions (API Action): sagemaker:ListModels

Resources: *

**API Operation:** ListNotebookInstances

Required Permissions (API Action): sagemaker:ListNotebookInstances

Resources: *

**API Operation:** ListSubscribedWorkteams


Resources: *
API Operation: ListTags

Required Permissions (API Action): sagemaker:ListTags

Resources: *

API Operation: ListTrainingJobs

Required Permissions (API Action): sagemaker:ListTrainingJobs

Resources: *

API Operation: ListWorkteams

Required Permissions (API Action): sagemaker:ListWorkforces

Resources: *

API Operation: ListWorkteams

Required Permissions (API Action): sagemaker:ListWorkteams

Resources: *

API Operation: StartNotebookInstance


Resources: arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName

API Operation: StopLabelingJob

Required Permissions (API Action): sagemaker:StopLabelingJob

Resources: arn:aws:sagemaker:region:account-id:labeling-job/labelingJobName

API Operation: StopNotebookInstance

Required Permissions (API Action): sagemaker:StopNotebookInstance

Resources: arn:aws:sagemaker:region:account-id:notebook-instance/notebookInstanceName

API Operation: StopTrainingJob

Required Permissions (API Action): sagemaker:StopTrainingJob

Resources: arn:aws:sagemaker:region:account-id:training-job/trainingJobName

API Operation: UpdateEndpoint

Required Permissions (API Action): sagemaker:UpdateEndpoints

Resources: arn:aws:sagemaker:region:account-id:endpoint/endpointName

API Operation: UpdateNotebookInstance

Required Permissions (API Action): sagemaker:UpdateNotebookInstance, iam:PassRole
AWS Managed Policies for Amazon SageMaker

To add permissions to users, groups, and roles, it is easier to use AWS managed policies than to write policies yourself. It takes time and expertise to create IAM customer managed policies that provide your team with only the permissions they need. To get started quickly, you can use our AWS managed policies. These policies cover common use cases and are available in your AWS account. For more information about AWS managed policies, see AWS managed policies in the IAM User Guide.

AWS services maintain and update AWS managed policies. You can't change the permissions in AWS managed policies. Services occasionally add additional permissions to an AWS managed policy to support new features. This type of update affects all identities (users, groups, and roles) to which the policy is attached. Services are most likely to update an AWS managed policy when a new feature is launched or when new operations become available. Services do not remove permissions from an AWS managed policy, so policy updates won't break your existing permissions.

Additionally, AWS supports managed policies for job functions that span multiple services. For example, the ReadOnlyAccess AWS managed policy provides read-only access to all AWS services and resources. When a service launches a new feature, AWS adds read-only permissions for new operations and resources. For a list and descriptions of job function policies, see AWS managed policies for job functions in the IAM User Guide.

Important
We recommend that you use the most restricted policy that allows you to perform your use case.

The following AWS managed policies, which you can attach to users in your account, are specific to Amazon SageMaker:

- **AmazonSageMakerFullAccess** – Grants full access to Amazon SageMaker resources and the supported operations. This does not provide unrestricted Amazon S3 access, but supports buckets and objects with specific sagemaker tags. This policy allows all IAM roles to be passed to Amazon SageMaker, but only allows IAM roles with “AmazonSageMaker” in them to be passed to the AWS Glue, AWS Step Functions, and AWS RoboMaker services.

- **AmazonSageMakerReadOnly** – Grants read-only access to Amazon SageMaker resources.

The following AWS managed policies can be attached to users in your account but are not recommended:

- **AdministratorAccess** – Grants all actions for all AWS services and for all resources in the account.
- **DataScientist** – Grants a wide range of permissions to cover most of the use cases (primarily for analytics and business intelligence) encountered by data scientists.

You can review these permissions policies by signing in to the IAM console and searching for them.

You can also create your own custom IAM policies to allow permissions for Amazon SageMaker actions and resources as you need them. You can attach these custom policies to the IAM users or groups that require them.

Topics

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• AWS managed policy: AmazonSageMakerFullAccess (p. 3572)
• AWS managed policy: AmazonSageMakerReadOnly (p. 3581)
• AWS managed policies for Amazon SageMaker Canvas (p. 3582)
• AWS Managed Policies for Amazon SageMaker Ground Truth (p. 3586)
• AWS Managed Policies for SageMaker Pipelines (p. 3591)
• AWS Managed Policies for SageMaker projects and JumpStart (p. 3593)
• SageMaker Updates to AWS Managed Policies (p. 3626)

**AWS managed policy: AmazonSageMakerFullAccess**

This policy grants administrative permissions that allow a principal full access to all Amazon SageMaker resources and operations. The policy also provides select access to related services. This policy allows all IAM roles to be passed to Amazon SageMaker, but only allows IAM roles with "AmazonSageMaker" in them to be passed to the AWS Glue, AWS Step Functions, and AWS RoboMaker services. This policy does not include permissions to create an Amazon SageMaker domain. For information on the policy needed to create a domain, see Create an IAM Administrator User and Group (p. 34).

**Permissions details**

This policy includes the following permissions.

- **application-autoscaling** – Allows principals to automatically scale a SageMaker real-time inference endpoint.
- **athena** – Allows principals to query a list of data catalogs, databases, and table metadata from Amazon Athena.
- **aws-marketplace** – Allows principals to view AWS AI Marketplace subscriptions. You need this if you want to access SageMaker software subscribed in AWS Marketplace.
- **cloudformation** – Allows principals to get AWS CloudFormation templates for using SageMaker JumpStart solutions and Pipelines. SageMaker JumpStart creates resources necessary to run end-to-end machine learning solutions that tie SageMaker to other AWS services. SageMaker Pipelines creates new projects that are backed by AWS Service Catalog.
- **cloudwatch** – Allows principals to post CloudWatch metrics, interact with alarms, and upload logs to CloudWatch Logs in your account.
- **codebuild** – Allows principals to store AWS CodeBuild artifacts for SageMaker Pipeline and Projects.
- **codecommit** – Needed for AWS CodeCommit integration with SageMaker notebook instances.
- **cognito-idp** – Needed for Amazon SageMaker Ground Truth to define private workforce and work teams.
- **ec2** – Needed for SageMaker to manage Amazon EC2 resources and network interfaces when you specify an Amazon VPC for your SageMaker jobs, models, endpoints, and notebook instances.
- **ecr** – Needed to pull and store Docker artifacts for Amazon SageMaker Studio (custom images), training, processing, batch inference, and inference endpoints. This is also required to use your own container in SageMaker. Additional permissions for SageMaker JumpStart solutions are required to create and remove custom images on behalf of users.
- **elastic-inference** – Allows principals to connect to Amazon Elastic Inference for using SageMaker notebook instances and endpoints.
- **elasticfilesystem** – Allows principals to access Amazon Elastic File System. This is needed for SageMaker to use data sources in Amazon Elastic File System for training machine learning models.
- **fsx** – Allows principals to access Amazon FSx. This is needed for SageMaker to use data sources in Amazon FSx for training machine learning models.
- **glue** – Needed for inference pipeline pre-processing from within SageMaker notebook instances.
• groundtruthlabeling – Needed for Ground Truth labeling jobs. The groundtruthlabeling endpoint is accessed by the Ground Truth console.
• iam – Needed to give the SageMaker console access to available IAM roles and create service-linked roles.
• kms – Needed to give the SageMaker console access to available AWS KMS keys and retrieve them for any specified AWS KMS aliases in jobs and endpoints.
• lambda – Allows principals to invoke and get a list of AWS Lambda functions.
• logs – Needed to allow SageMaker jobs and endpoints to publish log streams.
• redshift – Allows principals to access Amazon Redshift cluster credentials.
• redshift-data – Allows principals to use data from Amazon Redshift to run, describe, and cancel statements; get statement results; and list schemas and tables.
• robomaker – Allows principals to have full access to create, get descriptions, and delete AWS RoboMaker simulation applications and jobs. This is also needed to run reinforcement learning examples on notebook instances.
• s3 – Allows principals to have full access to Amazon S3 resources pertaining to SageMaker, but not all of Amazon S3.
• sagemaker – Allows principals to list tags on Amazon SageMaker user profiles.
• secretsmanager – Allows principals to have full access to AWS Secrets Manager. The principals can securely encrypt, store, and retrieve credentials for databases and other services. This is also needed for SageMaker notebook instances with SageMaker code repositories that use GitHub.
• servicecatalog – Allows principals to use AWS Service Catalog. The principals can create, get a list of, update, or terminate provisioned products, such as servers, databases, websites, or applications deployed using AWS resources. This is needed for SageMaker JumpStart and Projects to find and read service catalog products and launch AWS resources in user accounts.
• sns – Allows principals to get a list of Amazon SNS topics. This is needed for endpoints with Async Inference enabled for notifying users that their inference has completed.
• states – Needed for SageMaker JumpStart and Pipelines to use a service catalog to create step function resources.
• tag – Needed for SageMaker Pipelines to render in Studio. Studio needs resources tagged with particular sagemaker:project-id tag-key. This requires the tag:GetResources permission.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["sagemaker:*"],
      "NotResource": [
        "arn:aws:sagemaker:*:*:domain/*",
        "arn:aws:sagemaker:*:*:user-profile/*",
        "arn:aws:sagemaker:*:*:app/*",
        "arn:aws:sagemaker:*:*:flow-definition/*"
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "sagemaker:CreatePresignedDomainUrl",
        "sagemaker:DescribeDomain",
        "sagemaker:ListDomains",
        "sagemaker:DescribeUserProfile",
        "sagemaker:ListUserProfiles"
      ]
    }
  ]
}
```
"sagemaker:*App",
"sagemaker:ListApps"
],
"Resource": "**"
},
"Effect": "Allow",
"Action": "sagemaker:*",
"Resource": [
"arn:aws:sagemaker:***:flow-definition/**
],
"Condition": {
"StringEqualsIfExists": {
"sagemaker:WorkteamType": [
"private-crowd",
"vendor-crowd"
]
} }
},
"Effect": "Allow",
"Action": [
"application-autoscaling:DeleteScalingPolicy",
"application-autoscaling:DeleteScheduledAction",
"application-autoscaling:DeregisterScalableTarget",
"application-autoscaling:DescribeScalableTargets",
"application-autoscaling:DescribeScalingActivities",
"application-autoscaling:DescribeScalingPolicies",
"application-autoscaling:DescribeScheduledActions",
"application-autoscaling:PutScalingPolicy",
"application-autoscaling:PutScheduledAction",
"application-autoscaling:RegisterScalableTarget",
"aws-marketplace:ViewSubscriptions",
"cloudformation:GetTemplateSummary",
"cloudwatch:DeleteAlarms",
"cloudwatch:DescribeAlarms",
"cloudwatch:GetMetricData",
"cloudwatch:GetMetricStatistics",
"cloudwatch:ListMetrics",
"cloudwatch:PutMetricAlarm",
"cloudwatch:PutMetricData",
"codecommit:BatchGetRepositories",
"codecommit:CreateRepository",
"codecommit:GetRepository",
"codecommit:List",
"cognito-idp:AdminAddUserToGroup",
"cognito-idp:AdminCreateUser",
"cognito-idp:AdminDeleteUser",
"cognito-idp:AdminDisableUser",
"cognito-idp:AdminEnableUser",
"cognito-idp:AdminRemoveUserFromGroup",
"cognito-idp:CreateGroup",
"cognito-idp:CreateUserPool",
"cognito-idp:CreateUserPoolClient",
"cognito-idp:CreateUserPoolDomain",
"cognito-idp:DescribeUserPool",
"cognito-idp:DescribeUserPoolClient",
"cognito-idp:List",
"cognito-idp:UpdateUserPool",
"cognito-idp:UpdateUserPoolClient",
"ec2:CreateNetworkInterface",
"ec2:CreateNetworkInterfacePermission",
"ec2:CreateVpcEndpoint",
"ec2:DeleteNetworkInterface",
"ec2:DeleteNetworkInterfacePermission",
"ec2:Dispose
}
"ec2:DescribeDhcpOptions",
"ec2:DescribeNetworkInterfaces",
"ec2:DescribeRouteTables",
"ec2:DescribeSecurityGroups",
"ec2:DescribeSubnets",
"ec2:DescribeVpcs",
"ec2:DescribeVpcEndpoints",
"ec2:DescribeVpcs",
"ec2:Describe*",
"elastic-inference:Connect",
"elasticfilesystem:DescribeFileSystems",
"elasticfilesystem:DescribeMountTargets",
"fsx:DescribeFileSystems",
"glue:CreateJob",
"glue:DeleteJob",
"glue:GetJob*",
"glue:GetTable*",
"glue:GetWorkflowRun",
"glue:ResetJobBookmark",
"glue:GetJobRun",
"glue:GetWorkflowRun",
"glue:UpdateJob",
"groundtruthlabeling:*",
"iam:ListRoles",
"kms:DescribeKey",
"kms:ListAllases",
"lambda:ListFunctions",
"logs:CreateLogDelivery",
"logs:CreateLogGroup",
"logs:CreateLogStream",
"logs:DeleteLogDelivery",
"logs:Describe",
"logs:GetLogDelivery",
"logs:GetLogEvents",
"logs:GetLogDeliveries",
"logs:PutLogEvents",
"logs:PutResourcePolicy",
"logs:UpdateLogDelivery",
"robomaker:CreateSimulationApplication",
"robomaker:DescribeSimulationApplication",
"robomaker:DeleteSimulationApplication",
"robomaker:CreateSimulationJob",
"robomaker:DescribeSimulationJob",
"robomaker:CancelSimulationJob",
"secretsmanager:ListSecrets",
"servicecatalog:Describe**",
"servicecatalog:List**",
"servicecatalog:ScanProvisionedProducts",
"servicecatalog:SearchProducts",
"servicecatalog:SearchProvisionedProducts",
"sns:ListTopics",
"tag:GetResources"
],
"Resource": "**",
}
,
{  
"Effect": "Allow",
"Action": [
"ecr:SetRepositoryPolicy",
"ecr:CompleteLayerUpload",
"ecr:BatchDeleteImage",
"ecr:BatchCheckLayerAvailability",
"ecr:BatchGetImage",
"ecr:CreateRepository",
"ecr:Describe**",
"ecr:GetAuthorizationToken",
"ecr:GetDownloadUrlForLayer",
"ecr:StartImageScan",
"elastic-inference:Connect",
"elasticfilesystem:DescribeFileSystems",
"elasticfilesystem:DescribeMountTargets",
"fsx:DescribeFileSystems",
"glue:CreateJob",
"glue:DeleteJob",
"glue:GetJob*",
"glue:GetTable*",
"glue:GetWorkflowRun",
"glue:ResetJobBookmark",
"glue:GetJobRun",
"glue:GetWorkflowRun",
"glue:UpdateJob",
"groundtruthlabeling:*",
"iam:ListRoles",
"kms:DescribeKey",
"kms:ListAllases",
"lambda:ListFunctions",
"logs:CreateLogDelivery",
"logs:CreateLogGroup",
"logs:CreateLogStream",
"logs:DeleteLogDelivery",
"logs:Describe",
"logs:GetLogDelivery",
"logs:GetLogEvents",
"logs:GetLogDeliveries",
"logs:PutLogEvents",
"logs:PutResourcePolicy",
"logs:UpdateLogDelivery",
"robomaker:CreateSimulationApplication",
"robomaker:DescribeSimulationApplication",
"robomaker:DeleteSimulationApplication",
"robomaker:CreateSimulationJob",
"robomaker:DescribeSimulationJob",
"robomaker:CancelSimulationJob",
"secretsmanager:ListSecrets",
"servicecatalog:Describe**",
"servicecatalog:List**",
"servicecatalog:ScanProvisionedProducts",
"servicecatalog:SearchProducts",
"servicecatalog:SearchProvisionedProducts",
"sns:ListTopics",
"tag:GetResources"
],
"Resource": "**",
}
"ecr:UploadLayerPart",
"ecr:DeleteRepositoryPolicy",
"ecr:InitiateLayerUpload",
"ecr:DeleteRepository",
"ecr:PutImage"
],
"Resource": [
  "arn:aws:ecr:*:*:repository/*sagemaker**
]
},
{
  "Effect": "Allow",
  "Action": [
    "codecommit:GitPull",
    "codecommit:GitPush"
  ],
  "Resource": [
    "arn:aws:codecommit:*:*:*sagemaker**",
    "arn:aws:codecommit:*:*:*SageMaker**",
    "arn:aws:codecommit:*:*:*Sagemaker**
  ]
},
{
  "Action": [
    "codebuild:BatchGetBuilds",
    "codebuild:StartBuild"
  ],
  "Resource": [
    "arn:aws:codebuild:*:*:project/sagemaker**",
    "arn:aws:codebuild:*:*:build/*"
  ],
  "Effect": "Allow"
},
{
  "Action": [
    "states:DescribeExecution",
    "states:GetExecutionHistory",
    "states:StartExecution",
    "states:StopExecution",
    "states:UpdateStateMachine"
  ],
  "Resource": [
    "arn:aws:states:*:*:statemachine:*sagemaker**",
    "arn:aws:states:*:*:execution:*sagemaker:*"
  ],
  "Effect": "Allow"
},
{
  "Effect": "Allow",
  "Action": [
    "secretsmanager:DescribeSecret",
    "secretsmanager:GetSecretValue",
    "secretsmanager:CreateSecret"
  ],
  "Resource": [
    "arn:aws:secretsmanager:*:*:secret:AmazonSageMaker-*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "secretsmanager:DescribeSecret",
    "secretsmanager:GetSecretValue"
  ],
  "Resource": "*",
  "Condition": {

"StringEquals": {
  "secretsmanager:ResourceTag/SageMaker": "true"
}
},
{
  "Effect": "Allow",
  "Action": [
    "servicecatalog:ProvisionProduct"
  ],
  "Resource": "*"
},
{
  "Effect": "Allow",
  "Action": [
    "servicecatalog:TerminateProvisionedProduct",
    "servicecatalog:UpdateProvisionedProduct"
  ],
  "Resource": "*",
  "Condition": {
    "StringEquals": {
      "servicecatalog:userLevel": "self"
    }
  }
},
{
  "Effect": "Allow",
  "Action": [
    "s3:GetObject",
    "s3:PutObject",
    "s3:DeleteObject",
    "s3:AbortMultipartUpload"
  ],
  "Resource": [
    "arn:aws:s3:::*SageMaker*",
    "arn:aws:s3:::*Sagemaker*",
    "arn:aws:s3:::*sagemaker*",
    "arn:aws:s3:::*aws-glue*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "s3:GetObject"
  ],
  "Resource": "*",
  "Condition": {
    "StringEqualsIgnoreCase": {
      "s3:ExistingObjectTag/SageMaker": "true"
    }
  }
},
{
  "Effect": "Allow",
  "Action": [
    "s3:GetObject"
  ],
  "Resource": "*",
  "Condition": {
    "StringEquals": {
      "s3:ExistingObjectTag/servicecatalog:provisioning": "true"
    }
  }
},
{
  "Effect": "Allow",
  "Action": [
    "s3:GetObject"
  ],
  "Resource": "*"
}

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[{
  "Effect": "Allow",
  "Action": [
    "iam:PassRole"
  ],
  "Resource": "arn:aws:iam::*:role/*AmazonSageMaker*",
  "Condition": {
    "StringEquals": {
      "iam:PassedToService": [
        "glue.amazonaws.com",
        "robomaker.amazonaws.com",
        "states.amazonaws.com"
      ]
    }
  }
},
{
  "Effect": "Allow",
  "Action": [
    "iam:PassRole"
  ],
  "Resource": "arn:aws:iam::*:role/*",
  "Condition": {
    "StringEquals": {
      "iam:PassedToService": "sagemaker.amazonaws.com"
    }
  }
},
{
  "Effect": "Allow",
  "Action": [
    "athena:ListDataCatalogs",
    "athena:ListDatabases",
    "athena:ListTableMetadata",
    "athena:GetQueryExecution",
    "athena:GetQueryResults",
    "athena:StartQueryExecution",
    "athena:StopQueryExecution"
  ],
  "Resource": [
    "*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "glue:CreateTable"
  ],
  "Resource": [
    "arn:aws:glue:::*:table/*/sagemaker_tmp_*",
    "arn:aws:glue:::*:table/sagemaker_featurestore/**",
    "arn:aws:glue:::*:catalog",
    "arn:aws:glue:::*:database/*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "glue:UpdateTable"
  ],
  "Resource": [
    "arn:aws:glue:::*:table/sagemaker_featurestore/**",
    "arn:aws:glue:::*:catalog",
    "arn:aws:glue:::*:database/sagemaker_featurestore"


```json
]
},
{
  "Effect": "Allow",
  "Action": [
    "glue:DeleteTable"
  ],
  "Resource": [
    "arn:aws:glue:*:*:table/*/sagemaker_tmp_*",
    "arn:aws:glue:*:*:catalog",
    "arn:aws:glue:*:*:database/*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "glue:GetDatabases",
    "glue:GetTable",
    "glue:GetTables"
  ],
  "Resource": [
    "arn:aws:glue:*:*:table/*",
    "arn:aws:glue:*:*:catalog",
    "arn:aws:glue:*:*:database/*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "glue:CreateDatabase",
    "glue:GetDatabase"
  ],
  "Resource": [
    "arn:aws:glue:*:*:catalog",
    "arn:aws:glue:*:*:database/sagemaker_featurestore",
    "arn:aws:glue:*:*:database/sagemaker_processing",
    "arn:aws:glue:*:*:database/default",
    "arn:aws:glue:*:*:database/sagemaker_data_wrangler"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "redshift-data:ExecuteStatement",
    "redshift-data:DescribeStatement",
    "redshift-data:CancelStatement",
    "redshift-data:GetStatementResult",
    "redshift-data:ListSchemas",
    "redshift-data:ListTables"
  ],
  "Resource": [
    "*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "redshift:GetClusterCredentials"
  ],
  "Resource": [
    "arn:aws:redshift:*:*:dbuser/*/sagemaker_access*",
    "arn:aws:redshift:*:*:dbname:*"
  ]
},
{
  "Effect": "Allow",
```
AWS managed policy: AmazonSageMakerReadOnly

This policy grants read-only access to Amazon SageMaker through the AWS Management Console and SDK.

Permissions details

This policy includes the following permissions.

- application-autoscaling – Allows users to browse descriptions of scalable SageMaker real-time inference endpoints.
- aws-marketplace – Allows users to view AWS AI Marketplace subscriptions.
- cloudwatch – Allows users to receive CloudWatch alarms.
- cognito-idp – Needed for Amazon SageMaker Ground Truth to browse descriptions and lists of private workforce and work teams.
- ecr – Needed to read Docker artifacts for training and inference.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": [
            "sagemaker:Describe*",
            "sagemaker:List*",
            "sagemaker:BatchGetMetrics",
            "sagemaker:GetDeviceRegistration",
            "sagemaker:GetDeviceFleetReport",
            "sagemaker:GetSearchSuggestions",
            "sagemaker:BatchGetRecord",
            "sagemaker:GetRecord",
            "sagemaker:Search",
            "sagemaker:QueryLineage",
            "sagemaker:GetLineageGroupPolicy",
            "sagemaker:BatchDescribeModelPackage",
            "sagemaker:GetModelPackageGroupPolicy"
         ],
         "Resource": "*"
      },
      {
         "Effect": "Allow",
         "Action": [
            "application-autoscaling:DescribeScalableTargets",
            "application-autoscaling:DescribeScalingActivities",
            "application-autoscaling:DescribeScalingPolicies",
            "application-autoscaling:DescribeScheduledActions",
            "aws-marketplace:ViewSubscriptions",
            "cloudwatch:DescribeAlarms",
            "cognito-idp:DescribeUserPool",
            "cognito-idp:DescribeUserPoolClient",
            "cognito-idp:ListGroups",
            "cognito-idp:ListIdentityProviders"
         ],
         "Resource": "*
```
AWS managed policies for Amazon SageMaker Canvas

These AWS managed policies add permissions required to use SageMaker Canvas. The policies are available in your AWS account and are used by execution roles created from the SageMaker console.

Topics
- AWS managed policy: AmazonSageMakerCanvasFullAccess (p. 3582)
- AWS managed policy: AmazonSageMakerCanvasForecastAccess (p. 3586)
- Amazon SageMaker updates to Amazon SageMaker Canvas managed policies (p. 3586)

AWS managed policy: AmazonSageMakerCanvasFullAccess

This policy grants permissions that allow full access to Amazon SageMaker Canvas through the AWS Management Console and SDK. The policy also provides select access to related services (for example, Amazon Simple Storage Service (Amazon S3), AWS Identity and Access Management (IAM), Amazon Virtual Private Cloud (Amazon VPC), Amazon Elastic Container Registry (Amazon ECR), Amazon CloudWatch Logs, Amazon Redshift, AWS Secrets Manager, and Amazon Forecast).

Permissions details

This AWS managed policy includes the following permissions.

- **sagemaker** – Allows principals to create and host SageMaker models. These resources are limited to those whose name includes "Canvas", "canvas", or "model-compilation-".
- **ec2** – Allows principals to create Amazon VPC endpoints.
- **ecr** – Allows principals to get information about a container image.
- **iam** – Allows principals to pass an IAM role to Amazon SageMaker and Amazon Forecast.
- **logs** – Allows principals to publish logs from training jobs and endpoints.
- **s3** – Allows principals to add and retrieve objects from Amazon S3 buckets. These objects are limited to those whose name includes "SageMaker", "Sagemaker", or "sagemaker".
- **secretsmanager** – Allows principals to store customer credentials to connect to a Snowflake database using Secrets Manager.
- **redshift-data** – Allows principals to run queries on Amazon Redshift.
- **forecast** – Allows principals to use Amazon Forecast.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": [
            "sagemaker:DescribeDomain",
```
"sagemaker:DescribeUserProfile",
"sagemaker:ListTags"
],
"Resource": "*"},
{ "Effect": "Allow",
"Action": [ "sagemaker:CreateCompilationJob",
"sagemaker:CreateEndpoint",
"sagemaker:CreateEndpointConfig",
"sagemaker:CreateModel",
"sagemaker:CreateProcessingJob",
"sagemaker:CreateAutoMLJob",
"sagemaker:DeleteEndpoint",
"sagemaker:DeleteCompilationJob",
"sagemaker:DeleteEndpoint",
"sagemaker:DeleteEndpointConfig",
"sagemaker:DeleteModel",
"sagemaker:DeleteProcessingJob",
"sagemaker:DeleteAutoMLJob",
"sagemaker:ListCandidatesForAutoMLJob",
"sagemaker:AddTags",
"sagemaker:DeleteApp"
],
"Resource": [ "arn:aws:sagemaker:*:*:*Canvas*",
"arn:aws:sagemaker:*:*:canvas*",
"arn:aws:sagemaker:*:*:model-compilation-*"
]},
{ "Effect": "Allow",
"Action": [ "ec2:CreateVpcEndpoint",
"ec2:DescribeSecurityGroups",
"ec2:DescribeSubnets",
"ec2:DescribeVpcs",
"ec2:DescribeVpcEndpoints",
"ec2:DescribeVpcEndpointServices"
],
"Resource": "*"},
{ "Effect": "Allow",
"Action": [ "ecr:BatchGetImage",
"ecr:GetDownloadUrlForLayer",
"ecr:GetAuthorizationToken"
],
"Resource": "*"},
{ "Effect": "Allow",
"Action": [ "iam:GetRole"
],
"Resource": "arn:aws:iam::*:role/*"},
{ "Effect": "Allow",
"Action": [ "iam:PassRole"
],
"Resource": "arn:aws:iam::*:role/*",
"Condition": {
"StringEquals": {
  "iam:PassedToService": "sagemaker.amazonaws.com"
}
},
{
  "Effect": "Allow",
  "Action": [
    "logs:CreateLogGroup",
    "logs:CreateLogStream",
    "logs:PutLogEvents"
  ],
  "Resource": "arn:aws:logs:*:*:log-group:/aws/sagemaker/*"
},
{
  "Effect": "Allow",
  "Action": [
    "s3:GetObject",
    "s3:PutObject",
    "s3:DeleteObject",
    "s3:CreateBucket",
    "s3:GetBucketCors",
    "s3:GetBucketLocation"
  ],
  "Resource": [
    "arn:aws:s3:::*SageMaker*",
    "arn:aws:s3:::*Sagemaker*",
    "arn:aws:s3:::*sagemaker*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "s3:ListBucket",
    "s3:ListAllMyBuckets"
  ],
  "Resource": "*
},
{
  "Effect": "Allow",
  "Action": [
    "secretsmanager:DescribeSecret",
    "secretsmanager:GetSecretValue",
    "secretsmanager:CreateSecret",
    "secretsmanager:PutResourcePolicy"
  ],
  "Resource": [
    "arn:aws:secretsmanager:*:*:secret:AmazonSageMaker-*"
  ],
  "Condition": {
    "StringEquals": {
      "secretsmanager:ResourceTag/SageMaker": "true"
    }
  }
},
{
  "Effect": "Allow",
  "Action": [
    "secretsmanager:DescribeSecret",
    "secretsmanager:GetSecretValue"
  ],
  "Resource": "*
},

"Effect": "Allow",
"Action": [
  "logs:CreateLogGroup",
  "logs:CreateLogStream",
  "logs:PutLogEvents"
],
"Resource": "arn:aws:logs:*:*:log-group:/aws/sagemaker/*"
"redshift-data:ExecuteStatement",
"redshift-data:DescribeStatement",
"redshift-data:CancelStatement",
"redshift-data:GetStatementResult",
"redshift-data:ListSchemas",
"redshift-data:ListTables",
"redshift-data:DescribeTable"
],
"Resource": "*
",
{
"Effect": "Allow",
"Action": [
"redshift:GetClusterCredentials"
],
"Resource": [
"arn:aws:redshift:*:*:dbuser:*/sagemaker_access*",
"arn:aws:redshift:*:*:dbname:"
]
},
{
"Effect": "Allow",
"Action": [
"forecast:CreateExplainabilityExport",
"forecast:CreateExplainability",
"forecast:CreateForecastEndpoint",
"forecast:CreateAutoPredictor",
"forecast:CreateDatasetImportJob",
"forecast:CreateDatasetGroup",
"forecast:CreateDataset",
"forecast:CreateForecast",
"forecast:CreateForecastExportJob",
"forecast:CreatePredictorBacktestExportJob",
"forecast:CreatePredictor",
"forecast:DescribeExplainabilityExport",
"forecast:DescribeExplainability",
"forecast:DescribeAutoPredictor",
"forecast:DescribeForecastEndpoint",
"forecast:DescribeDatasetImportJob",
"forecast:DescribeDataset",
"forecast:DescribeForecast",
"forecast:DescribeForecastExportJob",
"forecast:DescribePredictorBacktestExportJob",
"forecast:DescribePredictor",
"forecast:GetAccuracyMetrics",
"forecast:InvokeForecastEndpoint",
"forecast:GetRecentForecastContext",
"forecast:DescribePredictor",
"forecast:TagResource"
],
"Resource": [
"arn:aws:forecast:*:*:*Canvas*"
]
},
{
"Effect": "Allow",
"Action": [
"iam:PassRole"
],
"Resource": "arn:aws:iam::*:role/*",
"Condition": {
"StringEquals": {
"iam:PassedToService": "forecast.amazonaws.com"
}
}
}]
}
AWS managed policy: AmazonSageMakerCanvasForecastAccess

This policy grants permissions commonly needed to use SageMaker Canvas with Amazon Forecast.

Permissions details

This AWS managed policy includes the following permissions.

- s3 – Allows principals to add and retrieve objects from Amazon S3 buckets. These objects are limited to those whose case-insensitive name starts with "sagemaker-".

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": [
            "s3:GetObject",
            "s3:PutObject"
         ],
         "Resource": [
            "arn:aws:s3:::sagemaker-*/Canvas",
            "arn:aws:s3:::sagemaker-*/canvas"
         ]
      },
      {
         "Effect": "Allow",
         "Action": ["s3:ListBucket"],
         "Resource": ["arn:aws:s3:::sagemaker-*"]
      }
   ]
}
```

Amazon SageMaker updates to Amazon SageMaker Canvas managed policies

View details about updates to AWS managed policies for SageMaker Canvas since this service began tracking these changes. For automatic alerts about changes to this page, subscribe to the RSS feed on the SageMaker Document history page. (p. 3695)

<table>
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<td>AmazonSageMakerCanvasFullAccess (p. 3582)</td>
<td>Initial policy</td>
<td></td>
<td>September 8, 2022</td>
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<td>AmazonSageMakerCanvasForecastAccess (p. 3586)</td>
<td>Initial policy</td>
<td></td>
<td>August 24, 2022</td>
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AWS Managed Policies for Amazon SageMaker Ground Truth

These AWS managed policies add permissions required to use SageMaker Ground Truth. The policies are available in your AWS account and are used by execution roles created from the SageMaker console.

Topics
• AWS managed policy: AmazonSageMakerGroundTruthExecution (p. 3587)
• AWS managed policy: GroundTruthSyntheticConsoleFullAccess (p. 3589)
• AWS managed policy: GroundTruthSyntheticConsoleReadOnlyAccess (p. 3590)
• Amazon SageMaker updates to SageMaker Ground Truth managed policies (p. 3590)

**AWS managed policy: AmazonSageMakerGroundTruthExecution**

This AWS managed policy grants permissions commonly needed to use SageMaker Ground Truth.

**Permissions details**

This policy includes the following permissions.

- **lambda** – Allows principals to invoke Lambda functions whose name includes "sagemaker" (case-insensitive), "GtRecipe", or "LabelingFunction".
- **s3** – Allows principals to add and retrieve objects from Amazon S3 buckets. These objects are limited to those whose case-insensitive name contains "groundtruth" or "sagemaker", or are tagged with "SageMaker".
- **cloudwatch** – Allows principals to post CloudWatch metrics.
- **logs** – Allows principals to create and access log streams, and post log events.
- **sqs** – Allows principals to create Amazon SQS queues, and send and receive Amazon SQS messages. These permissions are limited to queues whose name includes "GroundTruth".
- **sns** – Allows principals to subscribe to and publish messages to Amazon SNS topics whose case-insensitive name contains "groundtruth" or "sagemaker".
- **ec2** – Allows principals to create, describe, and delete Amazon VPC endpoints whose VPC endpoint service name contains "sagemaker-task-resources" or "labeling".

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "CustomLabelingJobs",
      "Effect": "Allow",
      "Action": [
        "lambda:InvokeFunction"
      ],
      "Resource": [
        "arn:aws:lambda:*:*:function:*GtRecipe*",
        "arn:aws:lambda:*:*:function:*LabelingFunction*",
        "arn:aws:lambda:*:*:function:*SageMaker*",
        "arn:aws:lambda:*:*:function:*sagemaker*",
        "arn:aws:lambda:*:*:function:*Sagemaker*
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "s3:AbortMultipartUpload",
        "s3:GetObject",
        "s3:PutObject"
      ],
      "Resource": [
        "arn:aws:s3:::*GroundTruth*",
        "arn:aws:s3:::*Groundtruth*",
        "arn:aws:s3:::*groundtruth*",
        "arn:aws:s3:::*SageMaker*",
        "arn:aws:s3:::*Sagemaker*"
      ]
    }
  ]
}
```

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"arn:aws:s3:::*sagemaker*"
]
},
{  "Effect": "Allow",
    "Action": [
        "s3:GetObject"
    ],
    "Resource": "*",
    "Condition": {
        "StringEqualsIgnoreCase": {
            "s3:ExistingObjectTag/SageMaker": "true"
        }
    }
},
{  "Effect": "Allow",
    "Action": [
        "s3:GetBucketLocation",
        "s3:ListBucket"
    ],
    "Resource": "*"
},
{  "Sid": "CloudWatch",
    "Effect": "Allow",
    "Action": [
        "cloudwatch:PutMetricData",
        "logs:CreateLogStream",
        "logs:CreateLogGroup",
        "logs:DescribeLogStreams",
        "logs:PutLogEvents"
    ],
    "Resource": "*"
},
{  "Sid": "StreamingQueue",
    "Effect": "Allow",
    "Action": [
        "sqs:CreateQueue",
        "sqs:DeleteMessage",
        "sqs:GetQueueAttributes",
        "sqs:GetQueueUrl",
        "sqs:ReceiveMessage",
        "sqs:SendMessage",
        "sqs:SetQueueAttributes"
    ],
    "Resource": "arn:aws:sqs:*:*:*GroundTruth*"
},
{  "Sid": "StreamingTopicSubscribe",
    "Effect": "Allow",
    "Action": "sns:Subscribe",
    "Resource": [
        "arn:aws:sns:*:*:*GroundTruth*",
        "arn:aws:sns:*:*:*Groundtruth*",
        "arn:aws:sns:*:*:*groundTruth*",
        "arn:aws:sns:*:*:*groundtruth*",
        "arn:aws:sns:*:*:*SageMaker*",
        "arn:aws:sns:*:*:*Sagemaker*",
        "arn:aws:sns:*:*:*sageMaker*",
        "arn:aws:sns:*:*:*sagemaker*"
    ],
    "Condition": {
        "StringEquals": {
            "sns:Protocol": "sqs"}  
}  
}
This AWS managed policy grants permissions needed to use most features of the SageMaker Ground Truth synthetic data console. The policy is available in your AWS account. In order to use all features of the console, users must add "s3:GetObject" permissions to allow SageMaker Ground Truth synthetic data console to display data from their S3 buckets. This can be done by attaching the AmazonS3ReadOnlyAccess managed policy to their role or by adding "s3:GetObject" for specific S3 resources to their role.

Permissions details

This policy includes the following permissions.
• s3 – Allows the retrieval of objects from Amazon S3 buckets to display data in the console.
• sagemaker-groundtruth-synthetic – Allows the console to call SageMaker Ground Truth synthetic data APIs.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": [
            "sagemaker-groundtruth-synthetic:*",
            "s3:ListBucket"
         ],
         "Resource": "*"
      }
   ]
}
```

**AWS managed policy: GroundTruthSyntheticConsoleReadOnlyAccess**

This AWS managed policy grants read-only access to SageMaker Ground Truth synthetic data via the AWS Management Console. In order to use all features of the console, users must add "s3:GetObject" permissions to allow SageMaker Ground Truth synthetic data console to display data from their S3 buckets. This can be done by attaching the AmazonS3ReadOnlyAccess managed policy to their role or by adding "s3:GetObject" for specific S3 resources to their role.

**Permissions details**

This policy includes the following permissions.

• s3 – Allows the retrieval of objects from Amazon S3 buckets to display data in the console.
• sagemaker-groundtruth-synthetic – Allows the console to call SageMaker Ground Truth synthetic data ReadOnly APIs.

```json
{
   "Version": "2012-10-17",
   "Statement": [
      {
         "Effect": "Allow",
         "Action": [
            "sagemaker-groundtruth-synthetic:List*",
            "sagemaker-groundtruth-synthetic:Get*",
            "s3:ListBucket"
         ],
         "Resource": "*"
      }
   ]
}
```

**Amazon SageMaker updates to SageMaker Ground Truth managed policies**

View details about updates to AWS managed policies for Amazon SageMaker Ground Truth since this service began tracking these changes. For automatic alerts about changes to this page, subscribe to the RSS feed on the SageMaker Document history page. (p. 3695)
AWS Managed Policies for SageMaker Pipelines

These AWS managed policies add permissions required to use SageMaker Pipelines. The policies are available in your AWS account and are used by execution roles created from the SageMaker console.

Topics

- AWS managed policy: AmazonSageMakerPipelinesIntegrations (p. 3591)
- Amazon SageMaker updates to SageMaker Pipelines managed policies (p. 3593)

AWS managed policy: AmazonSageMakerPipelinesIntegrations

This AWS managed policy grants permissions commonly needed to use Callback steps and Lambda steps in SageMaker Pipelines. The policy is added to the AmazonSageMaker-ExecutionRole that is created when you onboard to Amazon SageMaker Studio. The policy can be attached to any role used for authoring or executing a pipeline.

This policy grants appropriate AWS Lambda, Amazon Simple Queue Service (Amazon SQS), Amazon EventBridge, and IAM permissions needed when building pipelines that invoke Lambda functions or include callback steps, which can be used for manual approval steps or running custom workloads.

The Amazon SQS permissions allow you to create the Amazon SQS queue needed for receiving callback messages, and also to send messages to that queue.

The Lambda permissions allow you to create, read, update, and delete the Lambda functions used in the pipeline steps, and also to invoke those Lambda functions.

This policy grants the Amazon EMR permissions needed to run a pipelines Amazon EMR step.

Permissions details

This policy includes the following permissions.

- elasticmapreduce – Read, add, and cancel steps in a running Amazon EMR cluster.
- events – Read, create, update, and add targets to an EventBridge rule named SageMakerPipelineExecutionEMRStepStatusUpdateRule.
- **iam** – Pass an IAM role to the AWS Lambda service.
- **lambda** – Create, read, update, delete, and invoke Lambda functions. These permissions are limited to functions whose name includes “sagemaker”.
- **sqs** – Create an Amazon SQS queue; send an Amazon SQS message. These permissions are limited to queues whose name includes “sagemaker”.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "lambda:CreateFunction",
        "lambda:DeleteFunction",
        "lambda:GetFunction",
        "lambda:InvokeFunction",
        "lambda:UpdateFunctionCode"
      ],
      "Resource": [
        "arn:aws:lambda:*:*:function:*sagemaker*",
        "arn:aws:lambda:*:*:function:*sageMaker*",
        "arn:aws:lambda:*:*:function:*SageMaker*"
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "sqs:CreateQueue",
        "sqs:SendMessage"
      ],
      "Resource": [
        "arn:aws:sqs:*:*:*sagemaker*",
        "arn:aws:sqs:*:*:*sageMaker*",
        "arn:aws:sqs:*:*:*SageMaker*"
      ]
    },
    {
      "Effect": "Allow",
      "Action": [
        "iam:PassRole"
      ],
      "Resource": "arn:aws:iam::*:role/**",
      "Condition": {
        "StringEquals": {
          "iam:PassedToService": [
            "lambda.amazonaws.com"
          ]
        }
      }
    },
    {
      "Effect": "Allow",
      "Action": [
        "events:DescribeRule",
        "events:PutRule",
        "events:PutTargets"
      ],
      "Resource": [
        "arn:aws:events:*:*:rule/SageMakerPipelineExecutionEMRStepStatusUpdateRule"
      ]
    }
  ]
}
```
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AWS Managed Policies for SageMaker

```json
"Action": [
    "elasticmapreduce:DescribeStep",
    "elasticmapreduce:CancelSteps",
    "elasticmapreduce:AddJobFlowSteps"
],
"Resource": [
    "arn:aws:elasticmapreduce:*:*:cluster/*"
]
}
```

Amazon SageMaker updates to SageMaker Pipelines managed policies

View details about updates to AWS managed policies for Amazon SageMaker since this service began tracking these changes. For automatic alerts about changes to this page, subscribe to the RSS feed on the SageMaker Document history page. (p. 3695)

<table>
<thead>
<tr>
<th>Policy</th>
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<th>Date</th>
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<td>AmazonSageMakerPipelinesIntegrations</td>
<td>Initial policy</td>
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<td>July 30, 2021</td>
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</table>

AWS Managed Policies for SageMaker projects and JumpStart

These AWS managed policies add permissions to use built-in Amazon SageMaker project templates and JumpStart solutions. The policies are available in your AWS account and are used by execution roles created from the SageMaker console.

SageMaker projects and JumpStart use AWS Service Catalog to provision AWS resources in customers' accounts. Some created resources need to assume an execution role. For example, if AWS Service Catalog creates a CodePipeline pipeline on behalf of a customer for a SageMaker machine learning CI/CD project, then that pipeline requires an IAM role.

The **AmazonSageMakerServiceCatalogProductsLaunchRole** role has the permissions required to launch the SageMaker portfolio of products from AWS Service Catalog. The **AmazonSageMakerServiceCatalogProductsUseRole** role has the permissions required to use the SageMaker portfolio of products from AWS Service Catalog. The **AmazonSageMakerServiceCatalogProductsLaunchRole** role passes an **AmazonSageMakerServiceCatalogProductsUseRole** role to the provisioned AWS Service Catalog product resources.

**Topics**

- AWS managed policy: AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy (p. 3594)
- AWS managed policy: AmazonSageMakerServiceCatalogProductsApiGatewayServiceRolePolicy (p. 3601)
AWS managed policy: AmazonSageMakerServiceCatalogProductsCloudformationServiceRolePolicy (p. 3602)
AWS managed policy: AmazonSageMakerServiceCatalogProductsCodeBuildServiceRolePolicy (p. 3607)
AWS managed policy: AmazonSageMakerServiceCatalogProductsCodePipelineServiceRolePolicy (p. 3614)
AWS managed policy: AmazonSageMakerServiceCatalogProductsEventsServiceRolePolicy (p. 3615)
AWS managed policy: AmazonSageMakerServiceCatalogProductsFirehoseServiceRolePolicy (p. 3616)
AWS managed policy: AmazonSageMakerServiceCatalogProductsGlueServiceRolePolicy (p. 3616)
AWS managed policy: AmazonSageMakerServiceCatalogProductsLambdaServiceRolePolicy (p. 3618)
Amazon SageMaker updates to AWS Service Catalog AWS managed policies (p. 3625)

AWS managed policy: AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy

This service role policy is used by the AWS Service Catalog service to provision products from the Amazon SageMaker portfolio. The policy grants permissions to a set of related AWS services including AWS CodePipeline, AWS CodeBuild, AWS CodeCommit, AWS Glue, AWS CloudFormation, and others.

The AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy policy is intended to be used by the AmazonSageMakerServiceCatalogProductsLaunchRole role created from the SageMaker console. The policy adds permissions to provision AWS resources for SageMaker projects and JumpStart using AWS Service Catalog to a customer's account.

Permissions details

This policy includes the following permissions.

- **apigateway** – Allows the role to call API Gateway endpoints that are tagged with sagemaker:launch-source.
- **cloudformation** – Allows AWS Service Catalog to create, update and delete CloudFormation stacks.
- **codebuild** – Allows the role assumed by AWS Service Catalog and passed to CloudFormation to create, update and delete CodeBuild projects.
- **codecommit** – Allows the role assumed by AWS Service Catalog and passed to CloudFormation to create, update and delete CodeCommit repositories.
- **codepipeline** – Allows the role assumed by AWS Service Catalog and passed to CloudFormation to create, update and delete CodePipelines.
- **codestar-connections** – Allows the role to pass AWS CodeStar connections.
- **cognito-idp** – Allows the role to create, update, and delete groups and user pools. Also allows tagging resources.
- **ecr** – Allows the role assumed by AWS Service Catalog and passed to CloudFormation to create and delete Amazon ECR repositories. Also allows tagging resources.
- **events** – Allows the role assumed by AWS Service Catalog and passed to CloudFormation to create and delete EventBridge rules. Used for tying together the various components of the CICD pipeline.
- **firehose** – Allows the role to interact with Kinesis Data Firehose streams.
- **iam** – Allows the role to interact with AWS Glue.
- **lambda** – Allows the role to pass roles prepended with AmazonSageMakerServiceCatalog. This is needed when Projects provisions a AWS Service Catalog product, as a role needs to be passed to AWS Service Catalog.
- **lambda** – Allows the role to interact with AWS Lambda. Also allows tagging resources.
• logs – Allows the role to create, delete and access log streams.
• s3 – Allows the role assumed by AWS Service Catalog and passed to CloudFormation to access Amazon S3 buckets where the Project template code is stored.
• sagemaker – Allows the role to interact with various SageMaker services. This is done both in CloudFormation during template provisioning, as well as in CodeBuild during CICD pipeline execution. Also allows tagging the following resources: endpoints, endpoint configurations, models, pipelines, projects, and model packages.
• states – Allows the role to create, delete, and update Step Functions prepended with sagemaker.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "apigateway:GET",
        "apigateway:POST",
        "apigateway:PUT",
        "apigateway:PATCH",
        "apigateway:DELETE"
      ],
      "Resource": "*",
      "Condition": {
        "StringLike": {
          "aws:ResourceTag/sagemaker:launch-source": "*"
        }
      }
    },
    {
      "Effect": "Allow",
      "Action": [
        "apigateway:POST"
      ],
      "Resource": "*",
      "Condition": {
        "ForAnyValue:StringLike": {
          "aws:TagKeys": [
            "sagemaker:launch-source"
          ]
        }
      }
    },
    {
      "Effect": "Allow",
      "Action": [
        "apigateway:PATCH"
      ],
      "Resource": [
        "arn:aws:apigateway::*:account"
      ],
      "Condition": {
        "ArnLikeIfExists": {
          "cloudformation:RoleArn": [
            "arn:aws:cloudformation:*:stack/SC-*"
          ]
        }
      }
    }
  ]
}
```
"arn:aws:sts::*:assumed-role/AmazonSageMakerServiceCatalog"

}

},
{
"Effect": "Allow",
"Action": [
"cloudformation:DescribeStackEvents",
"cloudformation:DescribeStacks"
],
"Resource": "arn:aws:cloudformation::*:stack/SC-*"
},
{
"Effect": "Allow",
"Action": [
"cloudformation:GetTemplateSummary",
"cloudformation:ValidateTemplate"
],
"Resource": "*"
},
{
"Effect": "Allow",
"Action": [
"codebuild:CreateProject",
"codebuild:DeleteProject",
"codebuild:UpdateProject"
],
"Resource": ["arn:aws:codebuild::*:project/sagemaker-*"]
},
{
"Effect": "Allow",
"Action": [
"codecommit:CreateCommit",
"codecommit:CreateRepository",
"codecommit:DeleteRepository",
"codecommit:GetRepository",
"codecommit:TagResource"
],
"Resource": ["arn:aws:codecommit::*:repository/sagemaker-*"]
},
{
"Effect": "Allow",
"Action": [
"codecommit:ListRepositories"
],
"Resource": "*"
},
{
"Effect": "Allow",
"Action": [
"codepipeline:CreatePipeline",
"codepipeline:DeletePipeline",
"codepipeline:GetPipeline",
"codepipeline:GetPipelineState",
"codepipeline:StartPipelineExecution",
"codepipeline:TagResource",
"codepipeline:UpdatePipeline"
],
"Resource": ["arn:aws:codepipeline::*:sagemaker-*"]
]
},
{
  "Effect": "Allow",
  "Action": [
    "cognito-idp:CreateUserPool",
    "cognito-idp:TagResource"
  ],
  "Resource": "*",
  "Condition": {
    "ForAnyValue:StringLike": {
      "aws:TagKeys": [
        "sagemaker:launch-source"
      ]
    }
  }
},
{
  "Effect": "Allow",
  "Action": [
    "cognito-idp:CreateGroup",
    "cognito-idp:CreateUserPoolDomain",
    "cognito-idp:CreateUserPoolClient",
    "cognito-idp:DeleteGroup",
    "cognito-idp:DeleteUserPool",
    "cognito-idp:DeleteUserPoolClient",
    "cognito-idp:DeleteUserPoolDomain",
    "cognito-idp:DescribeUserPool",
    "cognito-idp:DescribeUserPoolClient",
    "cognito-idp:UpdateUserPool",
    "cognito-idp:UpdateUserPoolClient"
  ],
  "Resource": "*",
  "Condition": {
    "StringLike": {
      "aws:ResourceTag/sagemaker:launch-source": "*"
    }
  }
},
{
  "Effect": "Allow",
  "Action": [
    "ecr:CreateRepository",
    "ecr:DeleteRepository",
    "ecr:TagResource"
  ],
  "Resource": [
    "arn:aws:ecr:*:*:repository/sagemaker-*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "events:DescribeRule",
    "events:DeleteRule",
    "events:DisableRule",
    "events:EnableRule",
    "events:PutRule",
    "events:PutTargets",
    "events:RemoveTargets"
  ],
  "Resource": [
    "arn:aws:events:*::*:rule/sagemaker-*"
  ]
},
{
  "Effect": "Allow",
  "Action": [
    "sagemaker:CreateTrainingJob",
    "sagemaker:CreateModel",
    "sagemaker:CreateEndpoint",
    "sagemaker:CreateEndpointConfig",
    "sagemaker:CreateVpcEndpoint",
    "sagemaker:CreateTrial",
    "sagemaker:CreateTrialDataset",
    "sagemaker:CreateTrialComponent",
    "sagemaker:CreateTrialOutput",
    "sagemaker:CreateS3ModelSource",
    "sagemaker:CreateS3DataSource",
    "sagemaker:CreateS3OutputPath",
    "sagemaker:CreateS3InputPath",
    "sagemaker:CreateModelPackage"
],  "Resource": "arn:aws:firehose:*:*:deliverystream/sagemaker-*"
},  
{  "Effect": "Allow",  "Action": [  "glue:CreateDatabase",  "glue:DeleteDatabase"
]},  
],  "Resource": [  "*"
]},  
{  "Effect": "Allow",  "Action": [  "glue:CreateWorkflow"
],  "Resource": [  "arn:aws:glue:*:*:workflow/sagemaker-*"
]},  
{  "Effect": "Allow",  "Action": [  "glue:CreateJob"
],  "Resource": [  "arn:aws:glue:*:*:job/sagemaker-*"
]},  
{  "Effect": "Allow",  "Action": [  "glue:CreateCrawler",  "glue:GetCrawler"
],  "Resource": [  "arn:aws:glue:*:*:crawler/sagemaker-*"
]}
}
{ "Effect": "Allow",
 "Action": [
   "glue:CreateTrigger",
   "glue:GetTrigger"
 ],
 "Resource": [
   "arn:aws:glue:*:*:trigger/sagemaker-*"
 ]},
 { "Effect": "Allow",
 "Action": [
   "iam:PassRole"
 ],
 "Resource": [
   "arn:aws:iam::*:role/service-role/AmazonSageMakerServiceCatalog"
 ]},
 { "Effect": "Allow",
 "Action": [
   "lambda:AddPermission",
   "lambda:CreateFunction",
   "lambda:DeleteFunction",
   "lambda:GetFunction",
   "lambda:GetFunctionConfiguration",
   "lambda:InvokeFunction",
   "lambda:RemovePermission"
 ],
 "Resource": [
   "arn:aws:lambda::*:function:sagemaker-*"
 ]},
 { "Effect": "Allow",
 "Action": "lambda:TagResource",
 "Resource": [
   "arn:aws:lambda::*:function:sagemaker-*"
 ],
 "Condition": {
   "ForAllValues:StringLike": {
     "aws:TagKeys": [
       "sagemaker:*"
   ]
   }
 ],
},
 { "Effect": "Allow",
 "Action": [
   "logs:CreateLogGroup",
   "logs:CreateLogStream",
   "logs:DeleteLogGroup",
   "logs:DeleteLogStream",
   "logs:DescribeLogGroups",
   "logs:DescribeLogStreams",
   "logs:PutRetentionPolicy"
 ],
 "Resource": [
   "arn:aws:logs::*:log-group:/aws/apigateway/AccessLogs/*",
   "arn:aws:logs::*:log-group:log-stream:*"
 ]},
 { "Effect": "Allow",
 "Action":

"Action": "s3:GetObject",
"Resource": "*",
"Condition": {
  "StringEquals": {
    "s3:ExistingObjectTag/servicecatalog:provisioning": "true"
  }
}
],

{"Effect": "Allow",
"Action": "s3:GetObject",
"Resource": [
  "arn:aws:s3:::sagemaker-*"
],

{"Effect": "Allow",
"Action": [
  "s3:CreateBucket",
  "s3:DeleteBucket",
  "s3:DeleteBucketPolicy",
  "s3:GetBucketPolicy",
  "s3:PutBucketAcl",
  "s3:PutBucketNotification",
  "s3:PutBucketPolicy",
  "s3:PutBucketPublicAccessBlock",
  "s3:PutBucketLogging",
  "s3:PutEncryptionConfiguration",
  "s3:PutBucketTagging",
  "s3:PutObjectTagging",
  "s3:PutBucketCORS"
],
"Resource": "arn:aws:s3:::sagemaker-*"
},

{"Effect": "Allow",
"Action": [
  "sagemaker:CreateEndpoint",
  "sagemaker:CreateEndpointConfig",
  "sagemaker:CreateModel",
  "sagemaker:CreateWorkteam",
  "sagemaker:DeleteEndpoint",
  "sagemaker:DeleteEndpointConfig",
  "sagemaker:DeleteModel",
  "sagemaker:DeleteWorkteam",
  "sagemaker:DescribeEndpoint",
  "sagemaker:DescribeEndpointConfig",
  "sagemaker:DescribeModel",
  "sagemaker:DescribeWorkteam",
  "sagemaker:CreateCodeRepository",
  "sagemaker:DescribeCodeRepository",
  "sagemaker:UpdateCodeRepository",
  "sagemaker:DeleteCodeRepository"
],
"Resource": [
  "arn:aws:sagemaker:*:*:*"
],

{"Effect": "Allow",
"Action": [
  "sagemaker:AddTags"
],
"Resource": [
  "arn:aws:sagemaker:*:*:endpoint/*",
  "arn:aws:sagemaker:*:*:endpoint-config/*"],
AWS managed policy:
AmazonSageMakerServiceCatalogProductsApiGatewayServiceRolePolicy

This policy is used by Amazon API Gateway within the AWS Service Catalog provisioned products from the Amazon SageMaker portfolio. The policy is intended to be attached to an IAM role that the AmazonSageMakerServiceCatalogProductsLaunchRole passes to the AWS resources created by API Gateway that require a role.

Permissions details

This policy includes the following permissions.

- **logs** – Create and read CloudWatch Logs groups, streams, and events; update events; describe various resources.
These permissions are limited to resources whose log group prefix starts with "aws/apigateway/".

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "logs:CreateLogDelivery",
        "logs:CreateLogGroup",
        "logs:CreateLogStream",
        "logs:DeleteLogDelivery",
        "logs:DescribeLogGroups",
        "logs:DescribeLogStreams",
        "logs:DescribeResourcePolicies",
        "logs:DescribeDestinations",
        "logs:DescribeExportTasks",
        "logs:DescribeMetricFilters",
        "logs:DescribeQueries",
        "logs:DescribeQueryDefinitions",
        "logs:DescribeSubscriptionFilters",
        "logs:getLogDelivery",
        "logs:getLogEvents",
        "logs:PutLogEvents",
        "logs:PutResourcePolicy",
        "logs:UpdateLogDelivery"
      ],
      "Resource": "arn:aws:logs:*:*:log-group:/aws/apigateway/*"
    }
  ]
}
```

**AWS managed policy:**

**AmazonSageMakerServiceCatalogProductsCloudformationServiceRolePolicy**

This policy is used by AWS CloudFormation within the AWS Service Catalog provisioned products from the Amazon SageMaker portfolio. The policy is intended to be attached to an IAM role that the AmazonSageMakerServiceCatalogProductsLaunchRole passes to the AWS resources created by AWS CloudFormation that require a role.

**Permissions details**

This policy includes the following permissions.

- **sagemaker** – Allow access to various SageMaker resources excluding domains, user-profiles, apps, and flow definitions.
- **iam** – Pass the AmazonSageMakerServiceCatalogProductsCodeBuildRole and AmazonSageMakerServiceCatalogProductsExecutionRole roles.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "sagemaker:AddAssociation",
        "sagemaker:AddTags",
        "sagemaker:AssociateTrialComponent",
```
"sagemaker:BatchDescribeModelPackage",
"sagemaker:BatchGetMetrics",
"sagemaker:BatchGetRecord",
"sagemaker:BatchPutMetrics",
"sagemaker:CreateAction",
"sagemaker:CreateAlgorithm",
"sagemaker:CreateApp",
"sagemaker:CreateAppImageConfig",
"sagemaker:CreateArtifact",
"sagemaker:CreateAutoMLJob",
"sagemaker:CreateCodeRepository",
"sagemaker:CreateCompilationJob",
"sagemaker:CreateContext",
"sagemaker:CreateDataQualityJobDefinition",
"sagemaker:CreateDeviceFleet",
"sagemaker:CreateDomain",
"sagemaker:CreateEdgePackagingJob",
"sagemaker:CreateEndpoint",
"sagemaker:CreateEndpointConfig",
"sagemaker:CreateExperiment",
"sagemaker:CreateFeatureGroup",
"sagemaker:CreateFlowDefinition",
"sagemaker:CreateHumanTaskUi",
"sagemaker:CreateHyperParameterTuningJob",
"sagemaker:CreateImage",
"sagemaker:CreateImageVersion",
"sagemaker:CreateInferenceRecommendationsJob",
"sagemaker:CreateLabelingJob",
"sagemaker:CreateLineageGroupPolicy",
"sagemaker:CreateModel",
"sagemaker:CreateModelBiasJobDefinition",
"sagemaker:CreateModelExplainabilityJobDefinition",
"sagemaker:CreateModelPackage",
"sagemaker:CreateModelPackageGroup",
"sagemaker:CreateModelQualityJobDefinition",
"sagemaker:CreateMonitoringSchedule",
"sagemaker:CreateNotebookInstance",
"sagemaker:CreateNotebookInstanceLifecycleConfig",
"sagemaker:CreatePipeline",
"sagemaker:CreatePresignedDomainUrl",
"sagemaker:CreatePresignedNotebookInstanceUrl",
"sagemaker:CreateProcessingJob",
"sagemaker:CreateProject",
"sagemaker:CreateTrainingJob",
"sagemaker:CreateTransformJob",
"sagemaker:CreateTrial",
"sagemaker:CreateTrialComponent",
"sagemaker:CreateUserProfile",
"sagemaker:CreateWorkforce",
"sagemaker:CreateWorkteam",
"sagemaker:DeleteAction",
"sagemaker:DeleteAlgorithm",
"sagemaker:DeleteApp",
"sagemaker:DeleteAppImageConfig",
"sagemaker:DeleteArtifact",
"sagemaker:DeleteAssociation",
"sagemaker:DeleteCodeRepository",
"sagemaker:DeleteContext",
"sagemaker:DeleteDataQualityJobDefinition",
"sagemaker:DeleteDeviceFleet",
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"sagemaker:DeleteEndpoint",
"sagemaker:DeleteEndpointConfig",
"sagemaker:DeleteExperiment",
"sagemaker:DeleteFeatureGroup",
"sagemaker:DeleteFlowDefinition", 3603
"sagemaker:DeleteHumanLoop",
"sagemaker:DeleteHumanTaskUi",
"sagemaker:DeleteImage",
"sagemaker:DeleteImageVersion",
"sagemaker:DeleteLineageGroupPolicy",
"sagemaker:DeleteModel",
"sagemaker:DeleteModelBiasJobDefinition",
"sagemaker:DeleteModelExplainabilityJobDefinition",
"sagemaker:DeleteModelPackage",
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"sagemaker:DeleteModelPackageGroupPolicy",
"sagemaker:DeleteModelQualityJobDefinition",
"sagemaker:DeleteMonitoringSchedule",
"sagemaker:DeleteNotebookInstance",
"sagemaker:DeleteNotebookInstanceLifecycleConfig",
"sagemaker:DeletePipeline",
"sagemaker:DeleteProject",
"sagemaker:DeleteRecord",
"sagemaker:DeleteTags",
"sagemaker:DeleteTrial",
"sagemaker:DeleteTrialComponent",
"sagemaker:DeleteUserProfile",
"sagemaker:DeleteWorkforce",
"sagemaker:DeleteWorkteam",
"sagemaker:DeregisterDevices",
"sagemaker:DescribeAction",
"sagemaker:DescribeAlgorithm",
"sagemaker:DescribeApp",
"sagemaker:DescribeAppImageConfig",
"sagemaker:DescribeArtifact",
"sagemaker:DescribeAutoMLJob",
"sagemaker:DescribeCodeRepository",
"sagemaker:DescribeCompilationJob",
"sagemaker:DescribeContext",
"sagemaker:DescribeDataQualityJobDefinition",
"sagemaker:DescribeDevice",
"sagemaker:DescribeDeviceFleet",
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"sagemaker:DescribeEndpointConfig",
"sagemaker:DescribeExperiment",
"sagemaker:DescribeFeatureGroup",
"sagemaker:DescribeFlowDefinition",
"sagemaker:DescribeHumanLoop",
"sagemaker:DescribeHumanTaskUi",
"sagemaker:DescribeHyperParameterTuningJob",
"sagemaker:DescribeImage",
"sagemaker:DescribeImageVersion",
"sagemaker:DescribeInferenceRecommendationsJob",
"sagemaker:DescribeLabelingJob",
"sagemaker:DescribeLineageGroup",
"sagemaker:DescribeModel",
"sagemaker:DescribeModelBiasJobDefinition",
"sagemaker:DescribeModelExplainabilityJobDefinition",
"sagemaker:DescribeModelPackage",
"sagemaker:DescribeModelPackageGroup",
"sagemaker:DescribeModelPackageGroupPolicy",
"sagemaker:DescribeModelQualityJobDefinition",
"sagemaker:DescribeMonitoringSchedule",
"sagemaker:DescribeNotebookInstance",
"sagemaker:DescribeNotebookInstanceLifecycleConfig",
"sagemaker:DescribePipeline",
"sagemaker:DescribePipelineDefinitionForExecution",
"sagemaker:DescribePipelineExecution",
"sagemaker:DescribeProcessingJob",
"sagemaker:DescribeProject"
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"sagemaker:ListProjects",
"sagemaker:ListSubscribedWorkteams",
"sagemaker:ListTags",
"sagemaker:ListTrainingJobs",
"sagemaker:ListTrainingJobsForHyperParameterTuningJob",
"sagemaker:ListTransformJobs",
"sagemaker:ListTrials",
"sagemaker:ListUserProfiles",
"sagemaker:ListWorkforces",
"sagemaker:ListWorkteams",
"sagemaker:PutLineageGroupPolicy",
"sagemaker:PutModelPackageGroupPolicy",
"sagemaker:PutRecord",
"sagemaker:QueryLineage",
"sagemaker:RegisterDevices",
"sagemaker:RenderUiTemplate",
"sagemaker:Search",
"sagemaker:SendHeartbeat",
"sagemaker:SendPipelineExecutionStepFailure",
"sagemaker:SendPipelineExecutionStepSuccess",
"sagemaker:StartHumanLoop",
"sagemaker:StartMonitoringSchedule",
"sagemaker:StartNotebookInstance",
"sagemaker:StartPipelineExecution",
"sagemaker:StopAutoMLJob",
"sagemaker:StopCompilationJob",
"sagemaker:StopEdgePackagingJob",
"sagemaker:StopHumanLoop",
"sagemaker:StopHyperParameterTuningJob",
"sagemaker:StopInferenceRecommendationsJob",
"sagemaker:StopLabelingJob",
"sagemaker:StopMonitoringSchedule",
"sagemaker:StopNotebookInstance",
"sagemaker:StopPipelineExecution",
"sagemaker:StopProcessingJob",
"sagemaker:StopTrainingJob",
"sagemaker:StopTransformJob",
"sagemaker:UpdateAction",
"sagemaker:UpdateAppImageConfig",
"sagemaker:UpdateArtifact",
"sagemaker:UpdateCodeRepository",
"sagemaker:UpdateContext",
"sagemaker:UpdateDeviceFleet",
"sagemaker:UpdateDevices",
"sagemaker:UpdateDomain",
"sagemaker:UpdateEndpoint",
"sagemaker:UpdateEndpointWeightsAndCapacities",
"sagemaker:UpdateExperiment",
"sagemaker:UpdateImage",
"sagemaker:UpdateModelPackage",
"sagemaker:UpdateMonitoringSchedule",
"sagemaker:UpdateNotebookInstance",
"sagemaker:UpdateNotebookInstanceLifecycleConfig",
"sagemaker:UpdatePipeline",
"sagemaker:UpdatePipelineExecution",
"sagemaker:UpdateProject",
"sagemaker:UpdateTrainingJob",
"sagemaker:UpdateTrial",
"sagemaker:UpdateTrialComponent",
"sagemaker:UpdateUserProfile",
"sagemaker:UpdateWorkforce",
"sagemaker:UpdateWorkteam"
],
"NotResource": [
  "arn:aws:sagemaker::*:*:domain/**",
  "arn:aws:sagemaker:*:*:domain/**",
  "arn:aws:sagemaker:*:*:domain/**",
]
AWS managed policy:
AmazonSageMakerServiceCatalogProductsCodeBuildServiceRolePolicy

This policy is used by AWS CodeBuild within the AWS Service Catalog provisioned products from the Amazon SageMaker portfolio. The policy is intended to be attached to an IAM role that the AmazonSageMakerServiceCatalogProductsLaunchRole passes to the AWS resources created by CodeBuild that require a role.

Permissions details

This policy includes the following permissions.

- **sagemaker** – Allow access to various SageMaker resources.
- **codecommit** – Upload CodeCommit archives to CodeBuild pipelines, get upload status, and cancel uploads; get branch and commit information. These permissions are limited to resources whose name starts with "sagemaker-".
- **ecr** – Create Amazon ECR repositories and container images; upload image layers. These permissions are limited to repositories whose name starts with "sagemaker-".
- **s3** – Create, read, and list Amazon S3 buckets. These permissions are limited to buckets whose name starts with "sagemaker-".

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": ["iam:PassRole"],
      "Resource": [
        "arn:aws:sagemaker:*:*:user-profile/*",
        "arn:aws:sagemaker:*:*:app/*",
        "arn:aws:sagemaker:*:*:flow-definition/*"
      ]
    },
    {
      "Effect": "Allow",
      "Action": ["iam:PassRole"],
      "Resource": [
        "arn:aws:iam::*:role/service-role/AmazonSageMakerServiceCatalogProductsCodeBuildRole",
        "arn:aws:iam::*:role/service-role/AmazonSageMakerServiceCatalogProductsExecutionRole"
      ]
    }
  ]
}
```
"Statement": [
{
  "Effect": "Allow",
  "Action": [
    "codecommit:CancelUploadArchive",
    "codecommit:GetBranch",
    "codecommit:GetCommit",
    "codecommit:GetUploadArchiveStatus",
    "codecommit:UploadArchive"
  ],
  "Resource": "arn:aws:codecommit:*:*:sagemaker-*"
},
{
  "Effect": "Allow",
  "Action": [
    "ecr:BatchCheckLayerAvailability",
    "ecr:BatchGetImage",
    "ecr:DescribeImageScanFindings",
    "ecr:DescribeRegistry",
    "ecr:DescribeImageReplicationStatus",
    "ecr:DescribeRepositories",
    "ecr:DescribeImageReplicationStatus",
    "ecr:GetAuthorizationToken",
    "ecr:GetDownloadUrlForLayer"
  ],
  "Resource": ["*"]
},
{
  "Effect": "Allow",
  "Action": [
    "ecr:CompleteLayerUpload",
    "ecr:CreateRepository",
    "ecr:InitiateLayerUpload",
    "ecr:PutImage",
    "ecr:UploadLayerPart"
  ],
  "Resource": ["arn:aws:ecr:*:*:repository/sagemaker-*"]
},
{
  "Effect": "Allow",
  "Action": [
    "iam:PassRole"
  ],
  "Resource": [
    "arn:aws:iam::*:role/service-role/AmazonSageMakerServiceCatalogProductsEventsRole",
    "arn:aws:iam::*:role/service-role/AmazonSageMakerServiceCatalogProductsCodePipelineRole",
    "arn:aws:iam::*:role/service-role/AmazonSageMakerServiceCatalogProductsCloudformationRole",
    "arn:aws:iam::*:role/service-role/AmazonSageMakerServiceCatalogProductsCodeBuildRole",
    "arn:aws:iam::*:role/service-role/AmazonSageMakerServiceCatalogProductsExecutionRole"
  ],
  "Condition": {
    "StringEquals": {
      "iam:PassedToService": [
        "events.amazonaws.com",
        "codepipeline.amazonaws.com",
        "cloudformation.amazonaws.com",
        "codebuild.amazonaws.com",
        "sagemaker.amazonaws.com"
      ]
    }
  }
]
["Effect": "Allow",
"Action": [
  "logs:CreateLogDelivery",
  "logs:CreateLogGroup",
  "logs:CreateLogStream",
  "logs:DeleteLogDelivery",
  "logs:DescribeLogGroups",
  "logs:DescribeLogStreams",
  "logs:DescribeResourcePolicies",
  "logs:DescribeDestinations",
  "logs:DescribeExportTasks",
  "logs:DescribeMetricFilters",
  "logs:DescribeQueries",
  "logs:DescribeQueryDefinitions",
  "logs:DescribeSubscriptionFilters",
  "logs:GetLogDelivery",
  "logs:GetLogEvents",
  "logs:ListLogDeliveries",
  "logs:PutLogEvents",
  "logs:PutResourcePolicy",
  "logs:UpdateLogDelivery"
],
"Resource": "arn:aws:logs:*:*:log-group:/aws/codebuild/*"
},
{
"Effect": "Allow",
"Action": [
  "s3:CreateBucket",
  "s3:DeleteBucket",
  "s3:GetBucketAcl",
  "s3:GetBucketCors",
  "s3:GetBucketLocation",
  "s3:ListAllMyBuckets",
  "s3:ListBucket",
  "s3:ListBucketMultipartUploads",
  "s3:PutBucketCors",
  "s3:AbortMultipartUpload",
  "s3:DeleteObject",
  "s3:GetObject",
  "s3:GetObjectVersion",
  "s3:PutObject"
],
"Resource": [
  "arn:aws:s3:::aws-glue-*",
  "arn:aws:s3:::sagemaker-*"
]
},
{
"Effect": "Allow",
"Action": [
  "sagemaker:AddAssociation",
  "sagemaker:AddTags",
  "sagemaker:AssociateTrialComponent",
  "sagemaker:BatchDescribeModelPackage",
  "sagemaker:BatchGetMetrics",
  "sagemaker:BatchGetRecord",
  "sagemaker:BatchPutMetrics",
  "sagemaker:CreateAction",
  "sagemaker:CreateAlgorithm",
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  "sagemaker:DeleteAppImageConfig",
  "sagemaker:DeleteAppImageConfig"
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"sagemaker:CreateCodeRepository",
"sagemaker:CreateCompilationJob",
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"sagemaker:CreateEndpointConfig",
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"sagemaker:CreateImageVersion",
"sagemaker:CreateInferenceRecommendationsJob",
"sagemaker:CreateLabelingJob",
"sagemaker:CreateLineageGroupPolicy",
"sagemaker:CreateModel",
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"sagemaker:CreateModelExplainabilityJobDefinition",
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"sagemaker:CreatePresignedNotebookInstanceUrl",
"sagemaker:CreateProcessingJob",
"sagemaker:CreateProject",
"sagemaker:CreateTrainingJob",
"sagemaker:CreateTransformJob",
"sagemaker:CreateTrial",
"sagemaker:CreateTrialComponent",
"sagemaker:CreateUserProfile",
"sagemaker:CreateWorkforce",
"sagemaker:CreateWorkteam",
"sagemaker:DeleteAction",
"sagemaker:DeleteAlgorithm",
"sagemaker:DeleteApp",
"sagemaker:DeleteAppImageConfig",
"sagemaker:DeleteArtifact",
"sagemaker:DeleteAssociation",
"sagemaker:DeleteCodeRepository",
"sagemaker:DeleteContext",
"sagemaker:DeleteDataQualityJobDefinition",
"sagemaker:DeleteDeviceFleet",
"sagemaker:DeleteDomain",
"sagemaker:DeleteEndpoint",
"sagemaker:DeleteEndpointConfig",
"sagemaker:DeleteExperiment",
"sagemaker:DeleteFeatureGroup",
"sagemaker:DeleteFlowDefinition",
"sagemaker:DeleteHumanLoop",
"sagemaker:DeleteHumanTaskUi",
"sagemaker:DeleteImage",
"sagemaker:DeleteImageVersion",
"sagemaker:DeleteLineageGroupPolicy",
"sagemaker:DeleteModel",
"sagemaker:DeleteModelBiasJobDefinition",
"sagemaker:DeleteModelExplainabilityJobDefinition"
"sagemaker:DeleteModelPackage",
"sagemaker:DeleteModelPackageGroup",
"sagemaker:DeleteModelPackageGroupPolicy",
"sagemaker:DeleteModelQualityJobDefinition",
"sagemaker:DeleteMonitoringSchedule",
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"sagemaker:DeleteNotebookInstanceLifecycleConfig",
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"sagemaker:DeleteTrial",
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"sagemaker:DescribeArtifact",
"sagemaker:DescribeAutoMLJob",
"sagemaker:DescribeCodeRepository",
"sagemaker:DescribeCompilationJob",
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"sagemaker:DescribeTransformJob",
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"sagemaker:DescribeTrialComponent",
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"sagemaker:DescribeWorkforce",
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"sagemaker:GetModelPackageGroupPolicy",
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"sagemaker:listTrainingJobsForHyperParameterTuningJob",
"sagemaker:listTransformJobs",
"sagemaker:listTrialComponents",
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"sagemaker:ListWorkteams",
"sagemaker:PutLineageGroupPolicy",
"sagemaker:PutModelPackageGroupPolicy",
"sagemaker:PutRecord",
"sagemaker:QueryLineage",
"sagemaker:RegisterDevices",
"sagemaker:RenderUiTemplate",
"sagemaker:Search",
"sagemaker:SendHeartbeat",
"sagemaker:SendPipelineExecutionStepFailure",
"sagemaker:SendPipelineExecutionStepSuccess",
"sagemaker:StartHumanLoop",
"sagemaker:StartMonitoringSchedule",
"sagemaker:StartNotebookInstance",
"sagemaker:StartPipelineExecution",
"sagemaker:StopAutoMLJob",
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"sagemaker:StopEdgePackagingJob",
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"sagemaker:StopLabelingJob",
"sagemaker:StopMonitoringSchedule",
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"sagemaker:StopTrainingJob",
"sagemaker:StopTransformJob",
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"sagemaker:UpdateArtifact",
"sagemaker:UpdateCodeRepository",
"sagemaker:UpdateContext",
"sagemaker:UpdateDeviceFleet",
"sagemaker:UpdateDevices",
"sagemaker:UpdateDomain",
"sagemaker:UpdateEndpoint",
"sagemaker:UpdateEndpointWeightsAndCapacities",
"sagemaker:UpdateExperiment",
"sagemaker:UpdateImage",
"sagemaker:UpdateModelPackage",
"sagemaker:UpdateMonitoringSchedule",
"sagemaker:UpdateNotebookInstance",
"sagemaker:UpdateNotebookInstanceLifecycleConfig",
"sagemaker:UpdatePipeline",
"sagemaker:UpdatePipelineExecution",
"sagemaker:UpdateProject",
"sagemaker:UpdateTrainingJob",
"sagemaker:UpdateTrial",
"sagemaker:UpdateTrialComponent",
"sagemaker:UpdateUserProfile",
"sagemaker:UpdateWorkforce",
"sagemaker:UpdateWorkteam"
]

"Resource": [
  "arn:aws:sagemaker:*:*:endpoint/**",
  "arn:aws:sagemaker:*:*:endpoint-config/**",
  "arn:aws:sagemaker:*:*:model/**",
  "arn:aws:sagemaker:*:*:pipeline/**",
  "arn:aws:sagemaker:*:*:project/**",
  "arn:aws:sagemaker:*:*:model-package/**
]
}
**AWS managed policy:**

AmazonSageMakerServiceCatalogProductsCodePipelineServiceRolePolicy

This policy is used by AWS CodePipeline within the AWS Service Catalog provisioned products from the Amazon SageMaker portfolio. The policy is intended to be attached to an IAM role that the AmazonSageMakerServiceCatalogProductsLaunchRole passes to the AWS resources created by CodePipeline that require a role.

**Permissions details**

This policy includes the following permissions.

- **cloudformation** – Create, read, delete, and update CloudFormation stacks; create, read, delete, and execute change sets; set stack policy. These permissions are limited to resources whose name starts with "sagemaker-".
- **s3** – Create, read, list, and delete Amazon S3 buckets; add, read, and delete objects from the buckets; read and set the CORS configuration; read the access control list (ACL); and read the AWS Region the bucket resides in.

  These permissions are limited to buckets whose name starts with "sagemaker-" or "aws-glue-".
- **iam** – Pass the AmazonSageMakerServiceCatalogProductsCloudformationRole role.
- **codebuild** – Get CodeBuild build information and start builds. These permissions are limited to project and build resources whose name starts with "sagemaker-".
- **codecommit** – Upload CodeCommit archives to CodeBuild pipelines, get upload status, and cancel uploads; get branch and commit information.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "cloudformation:CreateChangeSet",
        "cloudformation:CreateStack",
        "cloudformation:DescribeChangeSet",
        "cloudformation:DescribeStack",
        "cloudformation:DeleteChangeSet",
        "cloudformation:DeleteStack",
        "cloudformation:DescribeStacks",
        "cloudformation:ExecuteChangeSet",
        "cloudformation:SetStackPolicy",
        "cloudformation:UpdateStack"
      ],
      "Resource": "arn:aws:cloudformation::*:stack/sagemaker-*"
    },
    {
      "Effect": "Allow",
      "Action": [
        "s3:AbortMultipartUpload",
        "s3:DeleteObject",
        "s3:GetObject",
        "s3:GetObjectVersion",
        "s3:PutObject"
      ],
      "Resource": [
        "arn:aws:s3:::sagemaker-*"
      ]
    }]
}
AWS managed policy:
AmazonSageMakerServiceCatalogProductsEventsServiceRolePolicy

This policy is used by Amazon EventBridge within the AWS Service Catalog provisioned products from the Amazon SageMaker portfolio. The policy is intended to be attached to an IAM role that the AmazonSageMakerServiceCatalogProductsLaunchRole passes to the AWS resources created by EventBridge that require a role.

Permissions details

This policy includes the following permissions.

- codepipeline – Start a CodeBuild execution. These permissions are limited to pipelines whose name starts with "sagemaker-".
AWS managed policy:
AmazonSageMakerServiceCatalogProductsFirehoseServiceRolePolicy

This policy is used by Amazon Kinesis Data Firehose within the AWS Service Catalog provisioned products from the Amazon SageMaker portfolio. The policy is intended to be attached to an IAM role that the AmazonSageMakerServiceCatalogProductsLaunchRole passes to the AWS resources created by Kinesis Data Firehose that require a role.

Permissions details

This policy includes the following permissions.

• firehose – Send Kinesis Data Firehose records. These permissions are limited to resources whose delivery stream name starts with "sagemaker-".

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "VisualEditor0",
      "Effect": "Allow",
      "Action": [
        "firehose:PutRecord",
        "firehose:PutRecordBatch"
      ],
      "Resource": "arn:aws:firehose:*:*:deliverystream/sagemaker-*"
    }
  ]
}
```

AWS managed policy:
AmazonSageMakerServiceCatalogProductsGlueServiceRolePolicy

This policy is used by AWS Glue within the AWS Service Catalog provisioned products from the Amazon SageMaker portfolio. The policy is intended to be attached to an IAM role that the AmazonSageMakerServiceCatalogProductsLaunchRole passes to the AWS resources created by Glue that require a role.

Permissions details

This policy includes the following permissions.

• glue – Create, read, and delete AWS Glue partitions, tables, and table versions. These permissions are limited to those resources whose name starts with "sagemaker-". Create and read AWS Glue databases. These permissions are limited to databases whose name is "default", "global_temp", or starts with "sagemaker-". Get user defined functions.

• s3 – Create, read, list, and delete Amazon S3 buckets; add, read, and delete objects from the buckets; read and set the CORS configuration; read the access control list (ACL), and read the AWS Region the bucket resides in. These permissions are limited to buckets whose name starts with "sagemaker-" or "aws-glue-".

• logs – Create, read, and delete CloudWatch Logs log group, streams, and deliveries; and create a resource policy. These permissions are limited to resources whose name prefix starts with "aws/glue/".

```json
{
}
```
"Version": "2012-10-17",
"Statement": [
{ "Effect": "Allow",
  "Action": [
    "glue:BatchCreatePartition",
    "glue:BatchDeletePartition",
    "glue:BatchDeleteTable",
    "glue:BatchDeleteTableVersion",
    "glue:BatchGetPartition",
    "glue:CreateDatabase",
    "glue:CreatePartition",
    "glue:CreateTable",
    "glue:DeletePartition",
    "glue:DeleteTable",
    "glue:DeleteTableVersion",
    "glue:GetDatabase",
    "glue:GetPartition",
    "glue:GetPartitions",
    "glue:GetTable",
    "glue:GetTables",
    "glue:GetTableVersion",
    "glue:GetTableVersions",
    "glue:SearchTables",
    "glue:UpdatePartition",
    "glue:UpdateTable",
    "glue:GetUserDefinedFunctions"
  ],
  "Resource": [
    "arn:aws:glue::*:*:catalog",
    "arn:aws:glue::*:*:database/default",
    "arn:aws:glue::*:*:database/global_temp",
    "arn:aws:glue::*:*:database/sagemaker-*",
    "arn:aws:glue::*:*:table/sagemaker-*",
    "arn:aws:glue::*:*:tableVersion/sagemaker-*"
  ]},
{ "Effect": "Allow",
  "Action": [
    "s3:CreateBucket",
    "s3:DeleteBucket",
    "s3:GetBucketAcl",
    "s3:GetBucketCors",
    "s3:GetBucketLocation",
    "s3:ListAllMyBuckets",
    "s3:ListBucket",
    "s3:ListBucketMultipartUploads",
    "s3:PutBucketCors"
  ],
  "Resource": [
    "arn:aws:s3:::aws-glue-*",
    "arn:aws:s3:::sagemaker-*"
  ]},
{ "Effect": "Allow",
  "Action": [
    "s3:AbortMultipartUpload",
    "s3:DeleteObject",
    "s3:GetObject",
    "s3:GetObjectVersion",
    "s3:PutObject"
  ],
  "Resource": [
    "arn:aws:s3:::aws-glue-*"
  ]}
]
AWS managed policy:  
AmazonSageMakerServiceCatalogProductsLambdaServiceRolePolicy

This policy is used by AWS Lambda within the AWS Service Catalog provisioned products from the Amazon SageMaker portfolio. The policy is intended to be attached to an IAM role that the AmazonSageMakerServiceCatalogProductsLaunchRole passes to the AWS resources created by Lambda that require a role.

Permissions details

This policy includes the following permissions.

- **sagemaker** – Allow access to various SageMaker resources.
- **ecr** – Create and delete Amazon ECR repositories; create, read, and delete container images; upload image layers. These permissions are limited to repositories whose name starts with "sagemaker-".
- **events** – Create, read, and delete Amazon EventBridge rules; and create and remove targets. These permissions are limited to rules whose name starts with "sagemaker-".
- **s3** – Create, read, list, and delete Amazon S3 buckets; add, read, and delete objects from the buckets; read and set the CORS configuration; read the access control list (ACL), and read the AWS Region the bucket resides in.
  
  These permissions are limited to buckets whose name starts with "sagemaker-" or "aws-glue-".
- **iam** – Pass the AmazonSageMakerServiceCatalogProductsExecutionRole role.
- **logs** – Create, read, and delete CloudWatch Logs log group, streams, and deliveries; and create a resource policy.
  
  These permissions are limited to resources whose name prefix starts with "aws/lambda/".

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
            "Action": [
                "ecr:DescribeImages",
                ...
            ],
            "Resource": "arn:aws:logs:::sagemaker-*"
        },
        {
            "Effect": "Allow",
            "Action": [
                "logs:CreateLogDelivery",
                "logs:CreateLogGroup",
                "logs:CreateLogStream",
                "logs:DeleteLogDelivery",
                "logs:Describe*",
                "logs:GetLogDelivery",
                "logs:GetLogEvents",
                "logs:ListLogDeliveries",
                "logs:GetResourcePolicy",
                "logs:UpdateLogDelivery"
            ],
            "Resource": "arn:aws:logs:::*:log-group:/aws/glue/**"
        }
    ]
}
```
"ecr:BatchDeleteImage",
"ecr:CompleteLayerUpload",
"ecr:CreateRepository",
"ecr:DeleteRepository",
"ecr:InitiateLayerUpload",
"ecr:PutImage",
"ecr:UploadLayerPart"
],
"Resource": [
"arn:aws:ecr:*:*:repository/sagemaker-*"
],
},
{
"Effect": "Allow",
"Action": [
"events:DeleteRule",
"events:DescribeRule",
"events:PutRule",
"events:PutTargets",
"events:RemoveTargets"
],
"Resource": [
"arn:aws:events:*:*:rule/sagemaker-*"
],
}
{
"Effect": "Allow",
"Action": [
"s3:CreateBucket",
"s3:DeleteBucket",
"s3:GetBucketAcl",
"s3:GetBucketCors",
"s3:GetBucketLocation",
"s3:ListAllMyBuckets",
"s3:GetBucket",
"s3:ListBucketMultipartUploads",
"s3:PutBucketCors"
],
"Resource": [
"arn:aws:s3:::aws-glue-*",
"arn:aws:s3:::sagemaker-*"
],
}
{
"Effect": "Allow",
"Action": [
"s3:AbortMultipartUpload",
"s3:DeleteObject",
"s3:GetObject",
"s3:GetObjectVersion",
"s3:PutObject"
],
"Resource": [
"arn:aws:s3:::aws-glue-*",
"arn:aws:s3:::sagemaker-*"
],
}
{
"Effect": "Allow",
"Action": [
"sagemaker:AddAssociation",
"sagemaker:AddTags",
"sagemaker:AssociateTrialComponent",
"sagemaker:BatchDescribeModelPackage",
"sagemaker:BatchGetMetrics",
"sagemaker:BatchGetRecord",
"sagemaker:CreateModel",
"sagemaker:CreateEndpoint",
"sagemaker:CreateEndpointConfig",
"sagemaker:CreateFeatureGroup",
"sagemaker:CreateImage",
"sagemaker:CreateInferenceInstance",
"sagemaker:CreateInferenceInstanceUsageReport",
"sagemaker:CreateLabelAlgorithmJob",
"sagemaker:CreateLabelingJob",
"sagemaker:CreateModel",
"sagemaker:CreateModelDataCrossValidationGroup",
"sagemaker:CreateModelGroup",
"sagemaker:CreateModelPackage",
"sagemaker:CreateOptimizerJob",
"sagemaker:CreatePredictor",
"sagemaker:CreateProfileJobDefinition",
"sagemaker:CreateRepository",
"sagemaker:CreateTrial",
"sagemaker:CreateTrialComponent",
"sagemaker:CreateTrainingJob",
"sagemaker:DeleteAssociation",
"sagemaker:DeleteModel",
"sagemaker:DeleteModelGroup",
"sagemaker:DeleteModelPackage",
"sagemaker:DeleteOptimizerJob",
"sagemaker:DeletePredictor",
"sagemaker:DeleteProfileJobDefinition",
"sagemaker:DeleteRepository",
"sagemaker:DeleteTrial",
"sagemaker:DeleteTrialComponent",
"sagemaker:DeleteTrainingJob",
"sagemaker:DescribeAssociation",
"sagemaker:DescribeModel",
"sagemaker:DescribeModelDataCrossValidationGroup",
"sagemaker:DescribeModelGroup",
"sagemaker:DescribeModelPackage",
"sagemaker:DescribeOptimizerJob",
"sagemaker:DescribePredictor",
"sagemaker:DescribeProfileJobDefinition",
"sagemaker:DescribeRepository",
"sagemaker:DescribeTrial",
"sagemaker:DescribeTrialComponent",
"sagemaker:DescribeTrainingJob",
"sagemaker:DownloadProfileJobDefinitionOutput",
"sagemaker:Infer",
"sagemaker:ListAssociation",
"sagemaker:ListModelDataCrossValidationGroups",
"sagemaker:ListModelGroups",
"sagemaker:ListModelPackages",
"sagemaker:ListOptimizerJobs",
"sagemaker:ListPredictorEndpoints",
"sagemaker:ListPredictorEndpointsForUserProfile",
"sagemaker:ListPredictors",
"sagemaker:ListProfileJobDefinitions",
"sagemaker:ListRepositories",
"sagemaker:ListSoFModels",
"sagemaker:ListSoFProfiles",
"sagemaker:ListSoFTrainingJobs",
"sagemaker:ListSoFStatistics",
"sagemaker:ListTrials",
"sagemaker:ListTrialsComponents",
"sagemaker:ListTrainingJobs",
"sagemaker:StartProfileJobDefinition",
"sagemaker:TagResource",
"sagemaker:UntagResource",
"sagemaker:UpdateAssociation",
"sagemaker:UpdateModel",
"sagemaker:UpdateModelDataCrossValidationGroup",
"sagemaker:UpdateModelGroup",
"sagemaker:UpdateModelPackage",
"sagemaker:UpdateOptimizerJob",
"sagemaker:UpdatePredictor",
"sagemaker:UpdateProfileJobDefinition",
"sagemaker:UpdateRepository",
"sagemaker:UpdateTrial",
"sagemaker:UpdateTrialComponent",
"sagemaker:UpdateTrainingJob",
"sagemaker:UploadProfileJobDefinitionOutput",
"sagemaker:UploadProfileDataToPredictorEndpoint"
],
"Resource": [
"arn:aws:sagemaker:*:*:model/*",
"arn:aws:sagemaker:*:*:model-package/*",
"arn:aws:sagemaker:*:*:optimizer-job/*",
"arn:aws:sagemaker:*:*:predictor/*",
"arn:aws:sagemaker:*:*:profile-job-definition/*",
"arn:aws:sagemaker:*:*:repository/*",
"arn:aws:sagemaker:*:*:trial/*",
"arn:aws:sagemaker:*:*:trial-component/*",
"arn:aws:sagemaker:*:*:training-job/*"
],
"Condition": 
"StringEquals:
  "sagemaker:AWS::Region",
  ["REGION_NAME"]
]
"sagemaker:BatchPutMetrics",
"sagemaker:CreateAction",
"sagemaker:CreateAlgorithm",
"sagemaker:CreateApp",
"sagemaker:CreateAppImageConfig",
"sagemaker:CreateArtifact",
"sagemaker:CreateAutoMLJob",
"sagemaker:CreateCodeRepository",
"sagemaker:CreateCompilationJob",
"sagemaker:CreateContext",
"sagemaker:CreateDataQualityJobDefinition",
"sagemaker:CreateDeviceFleet",
"sagemaker:CreateDomain",
"sagemaker:CreateEdgePackagingJob",
"sagemaker:CreateEndpoint",
"sagemaker:CreateEndpointConfig",
"sagemaker:CreateExperiment",
"sagemaker:CreateFeatureGroup",
"sagemaker:CreateFlowDefinition",
"sagemaker:CreateHumanTaskUi",
"sagemaker:CreateHyperParameterTuningJob",
"sagemaker:CreateImage",
"sagemaker:CreateImageVersion",
"sagemaker:CreateInferenceRecommendationsJob",
"sagemaker:CreateLabelingJob",
"sagemaker:CreateLineageGroupPolicy",
"sagemaker:CreateModel",
"sagemaker:CreateModelBiasJobDefinition",
"sagemaker:CreateModelExplainabilityJobDefinition",
"sagemaker:CreateModelPackage",
"sagemaker:CreateModelPackageGroup",
"sagemaker:CreateModelQualityJobDefinition",
"sagemaker:CreateMonitoringSchedule",
"sagemaker:CreateNotebookInstance",
"sagemaker:CreateNotebookInstanceLifecycleConfig",
"sagemaker:CreatePipeline",
"sagemaker:CreatePresignedDomainUrl",
"sagemaker:CreatePresignedNotebookInstanceUrl",
"sagemaker:CreateProcessingJob",
"sagemaker:CreateProject",
"sagemaker:CreateTrainingJob",
"sagemaker:CreateTransformJob",
"sagemaker:CreateTrial",
"sagemaker:CreateTrialComponent",
"sagemaker:CreateUserProfile",
"sagemaker:CreateWorkforce",
"sagemaker:CreateWorkteam",
"sagemaker:DeleteAction",
"sagemaker:DeleteAlgorithm",
"sagemaker:DeleteApp",
"sagemaker:DeleteAppImageConfig",
"sagemaker:DeleteArtifact",
"sagemaker:DeleteAssociation",
"sagemaker:DeleteCodeRepository",
"sagemaker:DeleteContext",
"sagemaker:DeleteDataQualityJobDefinition",
"sagemaker:DeleteDeviceFleet",
"sagemaker:DeleteDomain",
"sagemaker:DeleteEndpoint",
"sagemaker:DeleteEndpointConfig",
"sagemaker:DeleteExperiment",
"sagemaker:DeleteFeatureGroup",
"sagemaker:DeleteFlowDefinition",
"sagemaker:DeleteHumanLoop",
"sagemaker:DeleteHumanTaskUi",
"sagemaker:DeleteImage"
"sagemaker:DeleteImageVersion",
"sagemaker:DeleteLineageGroupPolicy",
"sagemaker:DeleteModel",
"sagemaker:DeleteModelBiasJobDefinition",
"sagemaker:DeleteModelExplainabilityJobDefinition",
"sagemaker:DeleteModelPackage",
"sagemaker:DeleteModelPackageGroup",
"sagemaker:DeleteModelPackageGroupPolicy",
"sagemaker:DeleteModelQualityJobDefinition",
"sagemaker:DeleteMonitoringSchedule",
"sagemaker:DeleteNotebookInstance",
"sagemaker:DeleteNotebookInstanceLifecycleConfig",
"sagemaker:DeletePipeline",
"sagemaker:DeleteProject",
"sagemaker:DeleteRecord",
"sagemaker:DeleteTags",
"sagemaker:DeleteTrial",
"sagemaker:DeleteTrialComponent",
"sagemaker:DeleteUserProfile",
"sagemaker:DeleteWorkforce",
"sagemaker:DeleteWorkteam",
"sagemaker:DeregisterDevices",
"sagemaker:DescribeAction",
"sagemaker:DescribeAlgorithm",
"sagemaker:DescribeApp",
"sagemaker:DescribeAppImageConfig",
"sagemaker:DescribeArtifact",
"sagemaker:DescribeAutoMLJob",
"sagemaker:DescribeCodeRepository",
"sagemaker:DescribeCompilationJob",
"sagemaker:DescribeContext",
"sagemaker:DescribeDataQualityJobDefinition",
"sagemaker:DescribeDevice",
"sagemaker:DescribeDeviceFleet",
"sagemaker:DescribeDomain",
"sagemaker:DescribeEdgePackagingJob",
"sagemaker:DescribeEndpoint",
"sagemaker:DescribeEndpointConfig",
"sagemaker:DescribeExperiment",
"sagemaker:DescribeFeatureGroup",
"sagemaker:DescribeFlowDefinition",
"sagemaker:DescribeHumanLoop",
"sagemaker:DescribeHumanTaskUi",
"sagemaker:DescribeHyperParameterTuningJob",
"sagemaker:DescribeImage",
"sagemaker:DescribeImageVersion",
"sagemaker:DescribeInferenceRecommendationsJob",
"sagemaker:DescribeLabelingJob",
"sagemaker:DescribeLineageGroup",
"sagemaker:DescribeModel",
"sagemaker:DescribeModelBiasJobDefinition",
"sagemaker:DescribeModelExplainabilityJobDefinition",
"sagemaker:DescribeModelPackage",
"sagemaker:DescribeModelPackageGroup",
"sagemaker:DescribeModelQualityJobDefinition",
"sagemaker:DescribeMonitoringSchedule",
"sagemaker:DescribeNotebookInstance",
"sagemaker:DescribeNotebookInstanceLifecycleConfig",
"sagemaker:DescribePipeline",
"sagemaker:DescribePipelineDefinitionForExecution",
"sagemaker:DescribePipelineExecution",
"sagemaker:DescribeProcessingJob",
"sagemaker:DescribeProject",
"sagemaker:DescribeSubscribedWorkteam",
"sagemaker:DescribeTrainingJob",
"sagemaker:DescribeTransformJob"
"sagemaker:DescribeTrial",
"sagemaker:DescribeTrialComponent",
"sagemaker:DescribeUserProfile",
"sagemaker:DescribeWorkforce",
"sagemaker:DescribeWorkteam",
"sagemaker:DisableSagemakerServicecatalogPortfolio",
"sagemaker:DisassociateTrialComponent",
"sagemaker:EnableSagemakerServicecatalogPortfolio",
"sagemaker:GetDeviceFleetReport",
"sagemaker:GetDeviceRegistration",
"sagemaker:GetLineageGroupPolicy",
"sagemaker:GetModelPackageGroupPolicy",
"sagemaker:GetRecord",
"sagemaker:GetSagemakerServicecatalogPortfolioStatus",
"sagemaker:GetSearchSuggestions",
"sagemaker:InvokeEndpoint",
"sagemaker:InvokeEndpointAsync",
"sagemaker:ListActions",
"sagemaker:ListAlgorithms",
"sagemaker:ListAppImageConfigs",
"sagemaker:ListApps",
"sagemaker:ListArtifacts",
"sagemaker:ListAssociations",
"sagemaker:ListAutoMLJobs",
"sagemaker:ListCandidatesForAutoMLJob",
"sagemaker:ListCodeRepositories",
"sagemaker:ListCompilationJobs",
"sagemaker:ListContexts",
"sagemaker:ListDataQualityJobDefinitions",
"sagemaker:ListDeviceFleets",
"sagemaker:ListDevices",
"sagemaker:ListDomains",
"sagemaker:ListEdgePackagingJobs",
"sagemaker:ListEndpointConfigs",
"sagemaker:ListEndpoints",
"sagemaker:ListExperiments",
"sagemaker:ListFeatureGroups",
"sagemaker:ListFlowDefinitions",
"sagemaker:ListHumanLoops",
"sagemaker:ListHumanTaskUIs",
"sagemaker:ListHyperParameterTuningJobs",
"sagemaker:ListImageVersions",
"sagemaker:ListImages",
"sagemaker:ListInferenceRecommendationsJobs",
"sagemaker:ListLabelingJobs",
"sagemaker:ListLabelingJobsForWorkteam",
"sagemaker:ListLineageGroups",
"sagemaker:ListModelBiasJobDefinitions",
"sagemaker:ListModelExplainabilityJobDefinitions",
"sagemaker:ListModelMetadata",
"sagemaker:ListModelPackageGroups",
"sagemaker:ListModelPackages",
"sagemaker:ListModelQualityJobDefinitions",
"sagemaker:ListModels",
"sagemaker:ListMonitoringExecutions",
"sagemaker:ListMonitoringSchedules",
"sagemaker:ListNotebookInstanceLifecycleConfigs",
"sagemaker:ListNotebookInstances",
"sagemaker:ListPipelineExecutionSteps",
"sagemaker:ListPipelineExecutions",
"sagemaker:ListPipelineParametersForExecution",
"sagemaker:ListPipelines",
"sagemaker:ListProcessingJobs",
"sagemaker:ListProjects",
"sagemaker:ListSubscribedWorkteams",
"sagemaker:ListTags"
"sagemaker:ListTrainingJobs",
"sagemaker:ListTrainingJobsForHyperParameterTuningJob",
"sagemaker:ListTransformJobs",
"sagemaker:ListTrialComponents",
"sagemaker:ListTrials",
"sagemaker:ListUserProfiles",
"sagemaker:ListWorkforces",
"sagemaker:ListWorkteams",
"sagemaker:PutLineageGroupPolicy",
"sagemaker:PutModelPackageGroupPolicy",
"sagemaker:PutRecord",
"sagemaker:QueryLineage",
"sagemaker:RegisterDevices",
"sagemaker:RenderUiTemplate",
"sagemaker:Search",
"sagemaker:SendHeartbeat",
"sagemaker:SendPipelineExecutionStepFailure",
"sagemaker:SendPipelineExecutionStepSuccess",
"sagemaker:StartHumanLoop",
"sagemaker:StartMonitoringSchedule",
"sagemaker:StartNotebookInstance",
"sagemaker:StartPipelineExecution",
"sagemaker:StopAutoMLJob",
"sagemaker:StopCompilationJob",
"sagemaker:StopEdgePackagingJob",
"sagemaker:StopHumanLoop",
"sagemaker:StopHyperParameterTuningJob",
"sagemaker:StopInferenceRecommendationsJob",
"sagemaker:StopLabelingJob",
"sagemaker:StopMonitoringSchedule",
"sagemaker:StopNotebookInstance",
"sagemaker:StopPipelineExecution",
"sagemaker:StopProcessingJob",
"sagemaker:StopTrainingJob",
"sagemaker:StopTransformJob",
"sagemaker:UpdateAction",
"sagemaker:UpdateAppImageConfig",
"sagemaker:UpdateArtifact",
"sagemaker:UpdateCodeRepository",
"sagemaker:UpdateContext",
"sagemaker:UpdateDeviceFleet",
"sagemaker:UpdateDevices",
"sagemaker:UpdateDomain",
"sagemaker:UpdateEndpoint",
"sagemaker:UpdateEndpointWeightsAndCapacities",
"sagemaker:UpdateExperiment",
"sagemaker:UpdateImage",
"sagemaker:UpdateModelPackage",
"sagemaker:UpdateMonitoringSchedule",
"sagemaker:UpdateNotebookInstance",
"sagemaker:UpdateNotebookInstanceLifecycleConfig",
"sagemaker:UpdatePipeline",
"sagemaker:UpdatePipelineExecution",
"sagemaker:UpdateProject",
"sagemaker:UpdateTrainingJob",
"sagemaker:UpdateTrial",
"sagemaker:UpdateTrialComponent",
"sagemaker:UpdateUserProfile",
"sagemaker:UpdateWorkforce",
"sagemaker:UpdateWorkteam"
]

"Resource": [
  "arn:aws:sagemaker:us-east-1:*:*:action/*",
  "arn:aws:sagemaker:us-east-1:*:*:algorithm/*",
  "arn:aws:sagemaker:us-east-1:*:*:app-image-config/*",
  "arn:aws:sagemaker:us-east-1:*:*:artifact/*",
  "arn:aws:sagemaker:us-east-1:*:*:endpoint/*",
  "arn:aws:sagemaker:us-east-1:*:*:endpoint-config/*",
  "arn:aws:sagemaker:us-east-1:*:*:endpoint-input/*",
  "arn:aws:sagemaker:us-east-1:*:*:endpoint-output/*",
  "arn:aws:sagemaker:us-east-1:*:*:instance/*",
  "arn:aws:sagemaker:us-east-1:*:*:interaction-tasks/*",
  "arn:aws:sagemaker:us-east-1:*:*:job/*",
  "arn:aws:sagemaker:us-east-1:*:*:iteration/*",
  "arn:aws:sagemaker:us-east-1:*:*:labeling-job/*",
  "arn:aws:sagemaker:us-east-1:*:*:labeling-job-config/*",
  "arn:aws:sagemaker:us-east-1:*:*:metadata-set/*",
  "arn:aws:sagemaker:us-east-1:*:*:model-package/*",
  "arn:aws:sagemaker:us-east-1:*:*:notebook-instance/*",
  "arn:aws:sagemaker:us-east-1:*:*:notebook-instance-lifecycle-config/*",
  "arn:aws:sagemaker:us-east-1:*:*:pipeline/*",
  "arn:aws:sagemaker:us-east-1:*:*:pipeline-execution/*",
  "arn:aws:sagemaker:us-east-1:*:*:project/*",
  "arn:aws:sagemaker:us-east-1:*:*:project-lifecycle-config/*",
  "arn:aws:sagemaker:us-east-1:*:*:source-configuration/*",
  "arn:aws:sagemaker:us-east-1:*:*:trial/*",
  "arn:aws:sagemaker:us-east-1:*:*:trial-component/*",
  "arn:aws:sagemaker:us-east-1:*:*:user-profile/*",
  "arn:aws:sagemaker:us-east-1:*:*:workflow/*",
  "arn:aws:sagemaker:us-east-1:*:*:workforce/*",
  "arn:aws:sagemaker:us-east-1:*:*:workteam/*",
  "arn:aws:sagemaker:us-east-1:*:*:work-async-queue/*",
  "arn:aws:sagemaker:us-east-1:*:*:work-mechanism/*",
  "arn:aws:sagemaker:us-east-1:*:*:work-request/*"]
}
"arn:aws:sagemaker:*:*:automl-job/**",
"arn:aws:sagemaker:*:*:code-repository/**",
"arn:aws:sagemaker:*:*:compilation-job/**",
"arn:aws:sagemaker:*:*:context/**",
"arn:aws:sagemaker:*:*:data-quality-job-definition/**",
"arn:aws:sagemaker:*:*:device-fleet/*/device/**",
"arn:aws:sagemaker:*:*:device-fleet/**",
"arn:aws:sagemaker:*:*:edge-packaging-job/**",
"arn:aws:sagemaker:*:*:endpoint/**",
"arn:aws:sagemaker:*:*:endpoint-config/**",
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"arn:aws:sagemaker:*:*:experiment-trial/**",
"arn:aws:sagemaker:*:*:experiment-trial-component/**",
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"arn:aws:sagemaker:*:*:model/**",
"arn:aws:sagemaker:*:*:model-bias-job-definition/**",
"arn:aws:sagemaker:*:*:model-explainability-job-definition/**",
"arn:aws:sagemaker:*:*:model-package/**",
"arn:aws:sagemaker:*:*:model-package-group/**",
"arn:aws:sagemaker:*:*:model-quality-job-definition/**",
"arn:aws:sagemaker:*:*:monitoring-schedule/**",
"arn:aws:sagemaker:*:*:notebook-instance/**",
"arn:aws:sagemaker:*:*:notebook-instance-lifecycle-config/**",
"arn:aws:sagemaker:*:*:pipeline/**",
"arn:aws:sagemaker:*:*:pipeline/*execution/**",
"arn:aws:sagemaker:*:*:processing-job/**",
"arn:aws:sagemaker:*:*:project/**",
"arn:aws:sagemaker:*:*:training-job/**",
"arn:aws:sagemaker:*:*:transform-job/**",
"arn:aws:sagemaker:*:*:workforce/**",
"arn:aws:sagemaker:*:*:workteam/**"

],
{
"Effect": "Allow",
"Action": [
"iam:PassRole"
],
"Resource": [
"arn:aws:iam::*:service-role/AmazonSageMakerServiceCatalogProductsExecutionRole"
]
},
{
"Effect": "Allow",
"Action": [
"logs:CreateLogDelivery",
"logs:CreateLogGroup",
"logs:CreateLogStream",
"logs:DeleteLogDelivery",
"logs:DescribeLogGroups",
"logs:DescribeLogStreams",
"logs:DescribeResourcePolicies",
"logs:DescribeDestinations",
"logs:DescribeExportTasks",
"logs:DescribeMetricFilters",
"logs:DescribeQueries",
"logs:DescribeQueryDefinitions",
"logs:DescribeSubscriptionFilters",
"logs:GetLogDelivery",
"logs:PutLogDelivery"
]
}
Amazon SageMaker updates to AWS Service Catalog AWS managed policies

View details about updates to AWS managed policies for Amazon SageMaker since this service began tracking these changes. For automatic alerts about changes to this page, subscribe to the RSS feed on the SageMaker Document history page. (p. 3695)

<table>
<thead>
<tr>
<th>Policy</th>
<th>Version</th>
<th>Change</th>
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<tr>
<td>AmazonSageMakerServiceCatalogProductsGlueServiceRolePolicy</td>
<td>2</td>
<td>Add permission for glue:GetUserDefinedFunctions.</td>
<td>August 26, 2022</td>
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<tr>
<td>AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy</td>
<td>7</td>
<td>Add permission for sagemaker:AddTags.</td>
<td>August 2, 2022</td>
</tr>
<tr>
<td>AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy</td>
<td>6</td>
<td>Add permission for lambda:TagResource.</td>
<td>July 14, 2022</td>
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<tr>
<td>AmazonSageMakerServiceCatalogProductsLogServiceRolePolicy</td>
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<td>Initial policy</td>
<td>April 4, 2022</td>
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<tr>
<td>AmazonSageMakerServiceCatalogProductsLogServiceRolePolicy</td>
<td>1</td>
<td>Initial policy</td>
<td>March 24, 2022</td>
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<tr>
<td>AmazonSageMakerServiceCatalogProductsCloudformationServiceRolePolicy</td>
<td>1</td>
<td>Initial policy</td>
<td>March 24, 2022</td>
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<tr>
<td>AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy</td>
<td>5</td>
<td>Add new permission for ecr-idp:TagResource.</td>
<td>March 21, 2022</td>
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<tr>
<td>AmazonSageMakerServiceCatalogProductsCodeBuildServiceRolePolicy</td>
<td>1</td>
<td>Initial policy</td>
<td>February 22, 2022</td>
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<tr>
<td>AmazonSageMakerServiceCatalogProductsCodePipelineServiceRolePolicy</td>
<td>1</td>
<td>Initial policy</td>
<td>February 22, 2022</td>
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<tr>
<td>AmazonSageMakerServiceCatalogProductsEventsServiceRolePolicy</td>
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<td>AmazonSageMakerServiceCatalogProductsFirehoseServiceRolePolicy</td>
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<td>February 22, 2022</td>
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<tr>
<td>AmazonSageMakerServiceCatalogProductsGlueServiceRolePolicy</td>
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<td>Initial policy</td>
<td>February 22, 2022</td>
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<tr>
<td>AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy</td>
<td>4</td>
<td>Add permissions for cognito-idp:TagResource and s3:PutBucketCORS.</td>
<td>February 16, 2022</td>
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<td>AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy</td>
<td>3</td>
<td>Add new permissions for sagemaker. Create, read, update, and delete SageMaker Images.</td>
<td>September 15, 2021</td>
</tr>
<tr>
<td>AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy</td>
<td>2</td>
<td>Add permissions for sagemaker and codestar-connections.</td>
<td>July 1, 2021</td>
</tr>
</tbody>
</table>
### SageMaker Updates to AWS Managed Policies

View details about updates to AWS managed policies for SageMaker since this service began tracking these changes. For automatic alerts about changes to this page, subscribe to the RSS feed on the SageMaker document history page.

<table>
<thead>
<tr>
<th>Policy</th>
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<th>Date</th>
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<tr>
<td>AmazonSageMakerAdmin-ServiceCatalogProductsServiceRolePolicy</td>
<td>1</td>
<td>Initial policy</td>
<td>November 27, 2020</td>
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<tr>
<td>AmazonSageMakerFullAccess</td>
<td>23</td>
<td>Add glue:UpdateTable.</td>
<td>June 29, 2022</td>
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<tr>
<td>AmazonSageMakerFullAccess</td>
<td>22</td>
<td>Add cloudformation:ListStackResources.</td>
<td>May 1, 2022</td>
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<tr>
<td>AmazonSageMakerFullAccess</td>
<td>21</td>
<td>Add sns:Publish permissions for endpoints with Async Inference enabled.</td>
<td>September 8, 2021</td>
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<tr>
<td>AmazonSageMakerFullAccess</td>
<td>20</td>
<td>Update iam:PassRole resources and permissions.</td>
<td>July 15, 2021</td>
</tr>
<tr>
<td>AmazonSageMakerReadOnly</td>
<td>10</td>
<td>New API BatchGetRecord added for SageMaker Feature Store.</td>
<td>June 10, 2021</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SageMaker started tracking changes for its AWS managed policies.</td>
<td>June 1, 2021</td>
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</table>

### Troubleshooting Amazon SageMaker Identity and Access

Use the following information to help you diagnose and fix common issues that you might encounter when working with SageMaker and IAM.

**Topics**
I Am Not Authorized to Perform an Action in SageMaker

If the AWS Management Console tells you that you're not authorized to perform an action, then you must contact your administrator for assistance. Your administrator is the person that provided you with your user name and password.

The following example error occurs when the mateojackson IAM user tries to use the console to view details about a training job but does not have sagemaker:sagemaker:DescribeTrainingJob permissions.

User: arn:aws:iam::123456789012:user/mateojackson is not authorized to perform: sagemaker:DescribeTrainingJob on resource: my-example-widget

In this case, Mateo asks his administrator to update his policies to allow him to access the TrainingJob resource using the sagemaker:DescribeTrainingJob action.

I Am Not Authorized to Perform iam:PassRole

If you receive an error that you're not authorized to perform the iam:PassRole action, your policies must be updated to allow you to pass a role to SageMaker.

Some AWS services allow you to pass an existing role to that service instead of creating a new service role or service-linked role. To do this, you must have permissions to pass the role to the service.

The following example error occurs when an IAM user named marymajor tries to use the console to perform an action in SageMaker. However, the action requires the service to have permissions that are granted by a service role. Mary does not have permissions to pass the role to the service.

User: arn:aws:iam::123456789012:user/marymajor is not authorized to perform: iam:PassRole

In this case, Mary's policies must be updated to allow her to perform the iam:PassRole action.

If you need help, contact your AWS administrator. Your administrator is the person who provided you with your sign-in credentials.

I Want to View My Access Keys

After you create your IAM user access keys, you can view your access key ID at any time. However, you can't view your secret access key again. If you lose your secret key, you must create a new access key pair.

Access keys consist of two parts: an access key ID (for example, AKIAIOSFODNN7EXAMPLE) and a secret access key (for example, wJalrXUttnFEMI/K7MDENG/bPxRfiCYEXAMPLEKEY). Like a user name and password, you must use both the access key ID and secret access key together to authenticate your requests. Manage your access keys as securely as you do your user name and password.

Important
Do not provide your access keys to a third party, even to help find your canonical user ID. By doing this, you might give someone permanent access to your account.
When you create an access key pair, you are prompted to save the access key ID and secret access key in a secure location. The secret access key is available only at the time you create it. If you lose your secret access key, you must add new access keys to your IAM user. You can have a maximum of two access keys. If you already have two, you must delete one key pair before creating a new one. To view instructions, see Managing access keys in the IAM User Guide.

I'm an Administrator and Want to Allow Others to Access SageMaker

To allow others to access SageMaker, you must create an IAM entity (user or role) for the person or application that needs access. They will use the credentials for that entity to access AWS. You must then attach a policy to the entity that grants them the correct permissions in SageMaker.

To get started right away, see Creating your first IAM delegated user and group in the IAM User Guide.

I Want to Allow People Outside of My AWS Account to Access My SageMaker Resources

You can create a role that users in other accounts or people outside of your organization can use to access your resources. You can specify who is trusted to assume the role. For services that support resource-based policies or access control lists (ACLs), you can use those policies to grant people access to your resources.

To learn more, consult the following:

- To learn whether SageMaker supports these features, see How Amazon SageMaker Works with IAM (p. 3505).
- To learn how to provide access to your resources across AWS accounts that you own, see Providing access to an IAM user in another AWS account that you own in the IAM User Guide.
- To learn how to provide access to your resources to third-party AWS accounts, see Providing access to AWS accounts owned by third parties in the IAM User Guide.
- To learn how to provide access through identity federation, see Providing access to externally authenticated users (identity federation) in the IAM User Guide.
- To learn the difference between using roles and resource-based policies for cross-account access, see How IAM roles differ from resource-based policies in the IAM User Guide.

Logging and Monitoring

You can monitor Amazon SageMaker using Amazon CloudWatch, which collects raw data and processes it into readable, near real-time metrics. These statistics are kept for 15 months, so that you can access historical information and gain a better perspective on how your web application or service is performing. You can also set alarms that watch for certain thresholds and send notifications or take actions when those thresholds are met. For more information, see Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663).

Amazon CloudWatch Logs enables you to monitor, store, and access your log files from Amazon EC2 instances, AWS CloudTrail, and other sources. You can collect and track metrics, create customized dashboards, and set alarms that notify you or take actions when a specified metric reaches a threshold that you specify. CloudWatch Logs can monitor information in the log files and notify you when certain thresholds are met. You can also archive your log data in highly durable storage. For more information, see Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675).
Compliance Validation for Amazon SageMaker

Third-party auditors assess the security and compliance of Amazon SageMaker as part of multiple AWS compliance programs. These include SOC, PCI, FedRAMP, HIPAA, and others.

For a list of AWS services in scope of specific compliance programs, see AWS Services in Scope by Compliance Program. For general information, see AWS Compliance Programs.

You can download third-party audit reports using AWS Artifact. For more information, see Downloading Reports in AWS Artifact.

Your compliance responsibility when using Amazon SageMaker is determined by the sensitivity of your data, your company's compliance objectives, and applicable laws and regulations. AWS provides the following resources to help with compliance:

- **Security and Compliance Quick Start Guides** – These deployment guides discuss architectural considerations and provide steps for deploying security- and compliance-focused baseline environments on AWS.
- **Architecting for HIPAA Security and Compliance Whitepaper** – This whitepaper describes how companies can use AWS to create HIPAA-compliant applications.
- **AWS Compliance Resources** – This collection of workbooks and guides might apply to your industry and location.
- **AWS Config** – This AWS service assesses how well your resource configurations comply with internal practices, industry guidelines, and regulations.
- **AWS Security Hub** – This AWS service provides a comprehensive view of your security state within AWS that helps you check your compliance with security industry standards and best practices.

Resilience in Amazon SageMaker

The AWS global infrastructure is built around AWS Regions and Availability Zones. AWS Regions provide multiple physically separated and isolated Availability Zones, which are connected with low-latency, high-throughput, and highly redundant networking. With Availability Zones, you can design and operate applications and databases that automatically fail over between Availability Zones without interruption. Availability Zones are more highly available, fault tolerant, and scalable than traditional single or multiple data center infrastructures.

For more information about AWS Regions and Availability Zones, see AWS Global Infrastructure.

In addition to the AWS global infrastructure, Amazon SageMaker offers several features to help support your data resiliency and backup needs.
Infrastructure Security in Amazon SageMaker

As a managed service, Amazon SageMaker is protected by the AWS global network security procedures that are described in the Amazon Web Services: Overview of Security Processes whitepaper.

You use AWS published API calls to access Amazon SageMaker through the network. Clients must support Transport Layer Security (TLS) 1.0 or later. We recommend TLS 1.2 or later. Clients must also support cipher suites with perfect forward secrecy (PFS) such as Ephemeral Diffie-Hellman (DHE) or Elliptic Curve Ephemeral Diffie-Hellman (ECDHE). Most modern systems such as Java 7 and later support these modes.

Additionally, requests must be signed by using an access key ID and a secret access key that is associated with an IAM principal. Or you can use the AWS Security Token Service (AWS STS) to generate temporary security credentials to sign requests.

Topics
- SageMaker Scans AWS Marketplace Training and Inference Containers for Security Vulnerabilities (p. 3630)
- Connect to Resources From Within a VPC (p. 3630)
- Run Training and Inference Containers in Internet-Free Mode (p. 3634)
- Connect to SageMaker Through a VPC Interface Endpoint (p. 3635)
- Give SageMaker Access to Resources in your Amazon VPC (p. 3644)

SageMaker Scans AWS Marketplace Training and Inference Containers for Security Vulnerabilities

To meet our security requirements, algorithms and model packages listed in AWS Marketplace are scanned for Common Vulnerabilities and Exposures (CVE). CVE is a list of publicly known information about security vulnerability and exposure. The National Vulnerability Database (NVD) provides CVE details such as severity, impact rating, and fix information. Both CVE and NVD are available for public consumption and free for security tools and services to use. For more information, see http://cve.mitre.org/about/faqs.html#what_is_cve.

Connect to Resources From Within a VPC

Amazon SageMaker Studio and SageMaker notebook instances allow direct internet access by default. This allows you to download popular packages and notebooks, customize your development environment, and work efficiently. However, this could provide an additional avenue for unauthorized access to your data. For example, if you install malicious code on your computer in the form of a publicly available notebook or a publicly available source code library, it could access your data. You can choose to restrict which traffic can access the internet by launching your Amazon SageMaker Studio and SageMaker notebook instances in a Amazon Virtual Private Cloud (Amazon VPC) of your choosing.

An Amazon Virtual Private Cloud is a virtual network dedicated to your AWS account. With an Amazon VPC, you can control the network access and internet connectivity of your Amazon SageMaker Studio and notebook instances. You can disable direct internet access to add an additional layer of security.

The following topics describe how to connect your SageMaker Studio instances and notebook instances to resources in a VPC.

Topics
Connect SageMaker Studio Notebooks in a VPC to External Resources

The following topic gives information on how to connect Studio Notebooks in a VPC to external resources.

Default communication with the internet

By default, SageMaker Studio provides a network interface that allows communication with the internet through a VPC managed by SageMaker. Traffic to AWS services like Amazon S3 and CloudWatch goes through an internet gateway, as does traffic that accesses the SageMaker API and SageMaker runtime. Traffic between the domain and your Amazon EFS volume goes through the VPC that you specified when you onboarded to Studio or called the CreateDomain API. The following diagram shows the default configuration.

VPC only communication with the internet

To prevent SageMaker from providing internet access to your Studio notebooks, you can disable internet access by specifying the VPC only network access type when you onboard to Studio or call the CreateDomain API. As a result, you won't be able to run a Studio notebook unless your VPC has an interface endpoint to the SageMaker API and runtime, or a NAT gateway with internet access, and your security groups allow outbound connections. The following diagram shows a configuration for using VPC-only mode.
Requirements to use VPC only mode

When you choose *VpcOnly*, follow these steps:

1. Ensure your subnets have the required number of IP addresses needed. The expected number of IP addresses needed per user can vary based on use case. We recommend between 2 and 4 IP addresses per user. The total IP address capacity for a Studio domain is the sum of available IP addresses for each subnet provided when the domain is created. Ensure that your estimated IP address usage does not exceed the capacity supported by the number of subnets you provide. Additionally, using subnets distributed across many availability zones can aid in IP address availability. For more information, see [VPC and subnet sizing for IPv4](#).

   **Note**
   You can configure only subnets with a default tenancy VPC in which your instance runs on shared hardware. For more information on the tenancy attribute for VPCs, see [Dedicated Instances](#).

2. Set up one or more security groups with inbound and outbound rules that together allow the following traffic:
   - **NFS traffic over TCP on port 2049** between the domain and the Amazon EFS volume.
   - **TCP traffic within the security group.** This is required for connectivity between the JupyterServer app and the KernelGateway apps. You must allow access to at least ports in the range 8192–65535.

3. If you want to allow internet access, you must use a **NAT gateway** with access to the internet, for example through an internet gateway.

4. If you don’t want to allow internet access, create interface VPC endpoints (AWS PrivateLink) to allow Studio to access the following services with the corresponding service names. You must also associate the security groups for your VPC with these endpoints.
   - **SageMaker API**: `com.amazonaws.us-east-1.sagemaker.api`
   - **SageMaker runtime**: `com.amazonaws.us-east-1.sagemaker.runtime`. This is required to run Studio notebooks and to train and host models.
   - **Amazon S3**: `com.amazonaws.us-east-1.s3`
   - To use SageMaker Projects: `com.amazonaws.us-east-1.servicecatalog`.
   - Any other AWS services you require.
Note
For a customer working within VPC mode, company firewalls can cause connection issues with SageMaker Studio or between JupyterServer and the KernelGateway. Make the following checks if you encounter one of these issues when using SageMaker Studio from behind a firewall.

- Check that the Studio URL is in your networks allowlist.
- Check that the websocket connections are not blocked. Jupyter uses websocket under the hood. If the KernelGateway application is InService, JupyterServer may not be able to connect to the KernelGateway. You should see this problem when opening System Terminal as well.

For more information
- Securing Amazon SageMaker Studio connectivity using a private VPC.
- Security groups for your VPC
- Connect to SageMaker Through a VPC Interface Endpoint (p. 3635)
- VPC with public and private subnets (NAT)

Connect a Notebook Instance in a VPC to External Resources

The following topic gives information on how to connect your notebook instance in a VPC to external resources.

Default communication with the internet

When your notebook allows direct internet access, SageMaker provides a network interface that allows the notebook to communicate with the internet through a VPC managed by SageMaker. Traffic within your VPC’s CIDR goes through elastic network interface created in your VPC. All the other traffic goes through the network interface created by SageMaker, which is essentially through the public internet. Traffic to gateway VPC endpoints like Amazon S3 and DynamoDB goes through the public internet, while traffic to interface VPC interface endpoints still goes through your VPC. If you want to use gateway VPC endpoints, you might want to disable direct internet access.

VPC communication with the internet

To disable direct internet access, you can specify a VPC for your notebook instance. By doing so, you prevent SageMaker from providing internet access to your notebook instance. As a result, the notebook instance can’t train or host models unless your VPC has an interface endpoint (AWS PrivateLink) or a NAT gateway and your security groups allow outbound connections.

For information about creating a VPC interface endpoint to use AWS PrivateLink for your notebook instance, see Connect to a Notebook Instance Through a VPC Interface Endpoint (p. 3641). For information about setting up a NAT gateway for your VPC, see VPC with Public and Private Subnets (NAT) in the Amazon Virtual Private Cloud User Guide. For information about security groups, see Security Groups for Your VPC. For more information about networking configurations in each networking mode and configuring network on premise, see Understanding Amazon SageMaker notebook instance networking configurations and advanced routing options.

Security and Shared Notebook Instances

A SageMaker notebook instance is designed to work best for an individual user. It is designed to give data scientists and other users the most power for managing their development environment.

A notebook instance user has root access for installing packages and other pertinent software. We recommend that you exercise judgement when granting individuals access to notebook instances that are attached to a VPC that contains sensitive information. For example, you might grant a user access to a notebook instance with an IAM policy, as shown in the following example:
Run Training and Inference Containers in Internet-Free Mode

SageMaker training and deployed inference containers are internet-enabled by default. This allows containers to access external services and resources on the public internet as part of your training and inference workloads. However, this could provide an avenue for unauthorized access to your data. For example, a malicious user or code that you accidentally install on the container (in the form of a publicly available source code library) could access your data and transfer it to a remote host.

If you use an Amazon VPC by specifying a value for the VpcConfig parameter when you call CreateTrainingJob, CreateHyperParameterTuningJob, or CreateModel, you can protect your data and resources by managing security groups and restricting internet access from your VPC. However, this comes at the cost of additional network configuration, and has the risk of configuring your network incorrectly. If you do not want SageMaker to provide external network access to your training or inference containers, you can enable network isolation.

Network Isolation

You can enable network isolation when you create your training job or model by setting the value of the EnableNetworkIsolation parameter to True when you call CreateTrainingJob, CreateHyperParameterTuningJob, or CreateModel.

Note
Network isolation is required to run training jobs and models using resources from AWS Marketplace.

If you enable network isolation, the containers can't make any outbound network calls, even to other AWS services such as Amazon S3. Additionally, no AWS credentials are made available to the container runtime environment. In the case of a training job with multiple instances, network inbound and outbound traffic is limited to the peers of each training container. SageMaker still performs download and upload operations against Amazon S3 using your SageMaker execution role in isolation from the training or inference container.

The following managed SageMaker containers do not support network isolation because they require access to Amazon S3:

- Chainer
- SageMaker Reinforcement Learning

Network isolation with a VPC

Network isolation can be used in conjunction with a VPC. In this scenario, the download and upload of customer data and model artifacts are routed through your VPC subnet. However, the training and
inference containers themselves continue to be isolated from the network, and do not have access to any resource within your VPC or on the internet.

Connect to SageMaker Through a VPC Interface Endpoint

You can connect directly to the SageMaker API or to the SageMaker Runtime through an interface endpoint in your Virtual Private Cloud (VPC) instead of connecting over the internet. When you use a VPC interface endpoint, communication between your VPC and the SageMaker API or Runtime is conducted entirely and securely within the AWS network.

The SageMaker API and Runtime support Amazon Virtual Private Cloud (Amazon VPC) interface endpoints that are powered by AWS PrivateLink. Each VPC endpoint is represented by one or more Elastic Network Interfaces with private IP addresses in your VPC subnets.

The VPC interface endpoint connects your VPC directly to the SageMaker API or Runtime without an internet gateway, NAT device, VPN connection, or AWS Direct Connect connection. The instances in your VPC don't need public IP addresses to communicate with the SageMaker API or Runtime.

You can create an interface endpoint to connect to SageMaker or to SageMaker Runtime with either the AWS console or AWS Command Line Interface (AWS CLI) commands. For instructions, see Creating an Interface Endpoint.

After you have created a VPC endpoint, you can use the following example CLI commands that use the endpoint-url parameter to specify interface endpoints to the SageMaker API or Runtime:

```bash
aws sagemaker list-notebook-instances --endpoint-url VPC_Endpoint_ID.api.sagemaker.Region.vpce.amazonaws.com
aws sagemaker list-training-jobs --endpoint-url VPC_Endpoint_ID.api.sagemaker.Region.vpce.amazonaws.com
aws sagemaker-runtime invoke-endpoint --endpoint-url VPC_Endpoint_ID.runtime.sagemaker.Region.vpce.amazonaws.com --endpoint-name Endpoint_Name --body "Endpoint_Body" --content-type "Content_Type" "Output_File"
```

If you enable private DNS hostnames for your VPC endpoint, you don't need to specify the endpoint URL. The SageMaker API DNS hostname that the CLI and SageMaker SDK use by default (https://api.sagemaker.Region.amazonaws.com) resolves to your VPC endpoint. Similarly, the SageMaker Runtime DNS hostname that the CLI and SageMaker Runtime SDK use by default (https://runtime.sagemaker.Region.amazonaws.com) resolves to your VPC endpoint.

The SageMaker API and Runtime support VPC endpoints in all AWS Regions where both Amazon VPC and SageMaker are available. SageMaker supports making calls to all of its Operations inside your VPC. The result AuthorizedUrl from the CreatePresignedNotebookInstanceUrl is not supported by AWS PrivateLink. For information about how to enable AWS PrivateLink for the authorized URL that users use to connect to a notebook instance, see Connect to a Notebook Instance Through a VPC Interface Endpoint (p. 3641).

To learn more about AWS PrivateLink, see the AWS PrivateLink documentation. Refer to PrivateLink Pricing for the price of VPC endpoints. To learn more about VPC and endpoints, see Amazon VPC. For information about how to use identity-based AWS Identity and Access Management policies to restrict access to the SageMaker API and runtime, see Control Access to the SageMaker API by Using Identity-based Policies (p. 3525).
Create a VPC Endpoint Policy for SageMaker

You can create a policy for Amazon VPC endpoints for SageMaker to specify the following:

- The principal that can perform actions.
- The actions that can be performed.
- The resources on which actions can be performed.

For more information, see Controlling Access to Services with VPC Endpoints in the Amazon VPC User Guide.

**Note**

VPC endpoint policies aren't supported for Federal Information Processing Standard (FIPS) SageMaker runtime endpoints for `runtime_InvokeEndpoint`.

The following example VPC endpoint policy specifies that all users who have access to the VPC interface endpoint are allowed to invoke the SageMaker hosted endpoint named `myEndpoint`.

```json
{
  "Statement": [
    {
      "Action": "sagemaker:InvokeEndpoint",
      "Effect": "Allow",
      "Principal": "*"
    }
  ]
}
```

In this example, the following are denied:

- Other SageMaker API actions, such as `sagemaker:CreateEndpoint` and `sagemaker:CreateTrainingJob`.
- Invoking SageMaker hosted endpoints other than `myEndpoint`.

**Note**

In this example, users can still take other SageMaker API actions from outside the VPC. For information about how to restrict API calls to those from within the VPC, see Control Access to the SageMaker API by Using Identity-based Policies (p. 3525).

Create a VPC Endpoint Policy for Amazon SageMaker Feature Store

To create a VPC Endpoint for Amazon SageMaker Feature Store, use the following endpoint template, substituting your `VPC_Endpoint_ID.api` and `Region`:

`VPC_Endpoint_ID.api.featurestore-runtime.sagemaker.Region.vpce.amazonaws.com`

Connect to SageMaker Studio Through an Interface VPC Endpoint

You can connect to Amazon SageMaker Studio from your Amazon Virtual Private Cloud (Amazon VPC) through an interface endpoint in your VPC instead of connecting over the internet. When you use an
interface VPC endpoint (interface endpoint), communication between your VPC and Studio is conducted entirely and securely within the AWS network.

SageMaker Studio supports interface endpoints that are powered by AWS PrivateLink. Each interface endpoint is represented by one or more Elastic network interfaces with private IP addresses in your VPC subnets.

Studio supports interface endpoints in all AWS Regions where both Amazon SageMaker and Amazon VPC are available.

Topics
- Create a VPC Endpoint (p. 3637)
- Create a VPC Endpoint Policy for SageMaker Studio (p. 3637)
- Allow Access Only from Within Your VPC (p. 3638)

Create a VPC Endpoint

You can create an interface endpoint to connect to Studio with either the AWS console or the AWS Command Line Interface (AWS CLI). For instructions, see Creating an interface endpoint. Make sure that you create interface endpoints for all of the subnets in your VPC from which you want to connect to Studio.

When you create an interface endpoint, ensure that the security groups on your endpoint allow inbound access for HTTPS traffic from the security groups associated with SageMaker Studio. For more information, see Control access to services with VPC endpoints.

Note
In addition to creating an interface endpoint to connect to SageMaker Studio, create an interface endpoint to connect to the Amazon SageMaker API. When users call CreatePresignedDomainUrl to get the URL to connect to Studio, that call goes through the interface endpoint used to connect to the SageMaker API.

When you create the interface endpoint, specify aws.sagemaker.Region.studio as the service name. After you create the interface endpoint, enable private DNS for your endpoint. When you connect to SageMaker Studio from within the VPC using the SageMaker API, the AWS CLI, or the console, you connect through the interface endpoint instead of the public internet. You also need to set up a custom DNS with private hosted zones for the Amazon VPC endpoint so SageMaker Studio can access the SageMaker API using the api.sagemaker.$region.amazonaws.com endpoint rather than using the VPC endpoint URL. For instructions on setting up a private hosted zone, see Working with private hosted zones.

Create a VPC Endpoint Policy for SageMaker Studio

You can attach an Amazon VPC endpoint policy to the interface VPC endpoints that you use to connect to SageMaker Studio. The endpoint policy controls access to Studio. You can specify the following:

- The principal that can perform actions.
- The actions that can be performed.
- The resources on which actions can be performed.

To use a VPC endpoint with SageMaker Studio, your endpoint policy must allow the CreateApp operation on the KernelGateway app type. This allows traffic that is routed to through the VPC endpoint to call the CreateApp API. The following example VPC endpoint policy shows how to allow the CreateApp operation.

```
"Statement": [  
  
  
  
  ]
}

For more information, see Controlling access to services with VPC endpoints.

The following example of a VPC endpoint policy specifies that all users that have access to the endpoint are allowed to access the user profiles in the SageMaker Studio domain with the specified domain ID. Access to other domains is denied.

```
{
  "Statement": [
    
    
    
  ]
}
```

Allow Access Only from Within Your VPC

Users outside your VPC can connect to SageMaker Studio over the internet even if you set up an interface endpoint in your VPC.

To allow access to only connections made from within your VPC, create an AWS Identity and Access Management (IAM) policy to that effect. Add that policy to every IAM user, group, or role used to access Studio. This feature is only supported in IAM mode, and is not supported in IAM Identity Center mode. The following examples demonstrate how to create such policies.

**Important**
If you apply an IAM policy similar to one of the following examples, users can't access SageMaker Studio or the specified SageMaker APIs through the SageMaker console. To access Studio, users must use a presigned URL or call the SageMaker APIs directly.

**Example 1: Allow connections only within the subnet of an interface endpoint**

The following policy allows connections only to callers within the subnet where you created the interface endpoint.

```
{
  "Id": "sagemaker-studio-example-1",
  "Version": "2012-10-17",
  "Statement": [
    
    
    
    ]
}
```
Example 2: Allow connections only through interface endpoints using `aws:sourceVpce`

The following policy allows connections only to those made through the interface endpoints specified by the `aws:sourceVpce` condition key. For example, the first interface endpoint could allow access through the SageMaker Studio Control Panel. The second interface endpoint could allow access through the SageMaker API.

```json
{
"Id": "sagemaker-studio-example-2",
"Version": "2012-10-17",
"Statement": [
{
 "Sid": "Enable SageMaker Studio Access",
 "Effect": "Allow",
 "Action": [
 "sagemaker:CreatePresignedDomainUrl",
 "sagemaker:DescribeUserProfile"
 ],
 "Resource": "*",
 "Condition": {
 "ForAnyValue:StringEquals": {
 "aws:sourceVpce": [
 "vpce-111bbccc",
 "vpce-111bbddd"
 ]
 }
 }
]
}
```

This policy includes the `DescribeUserProfile` action. Typically you call `DescribeUserProfile` to make sure that the status of the user profile is `InService` before you try to connect to the domain. For example:

```bash
aws sagemaker describe-user-profile \
   --domain-id domain-id \
   --user-profile-name profile-name
```

Response:

```json
{
 "DomainId": "domain-id",
 "UserProfileName": "profile-name",
 "HomeEfsFileSystemUid": "200001",
 "Status": "InService",
 "LastModifiedTime": 1605418785.555,
 "CreationTime": 1605418477.297
}
```

```bash
aws sagemaker create-presigned-domain-url
```
Connect to SageMaker Through a VPC Interface Endpoint

---

**Response:**

```
{
  "AuthorizedUrl": "https://domain-id.studio.us-west-2.sagemaker.aws/auth?token=AuthToken"
}
```

For both of these calls, if you are using a version of the AWS SDK that was released before August 13, 2018, you must specify the endpoint URL in the call. For example, the following example shows a call to `create-presigned-domain-url`:

```
aws sagemaker create-presigned-domain-url
   --domain-id domain-id \ 
   --user-profile-name profile-name \ 
   --endpoint-url vpc-endpoint-id.api.sagemaker.Region.vpce.amazonaws.com
```

**Example 3: Allow connections from IP addresses using `aws:SourceIp`**

The following policy allows connections only from the specified range of IP addresses using the `aws:SourceIp` condition key.

```
{
  "Id": "sagemaker-studio-example-3",
  "Version": "2012-10-17",
  "Statement": [ 
    { 
      "Sid": "Enable SageMaker Studio Access",
      "Effect": "Allow",
      "Action": [ 
        "sagemaker:CreatePresignedDomainUrl",
        "sagemaker:DescribeUserProfile"
      ],
      "Resource": "*",
      "Condition": { 
        "IpAddress": { 
          "aws:SourceIp": [ 
            "192.0.2.0/24",
            "203.0.113.0/24"
          ]
        }
      }
    }
  ]
}
```

**Example 4: Allow connections from IP addresses through an interface endpoint using `aws:VpcSourceIp`**

If you are accessing SageMaker Studio through an interface endpoint, you can use the `aws:VpcSourceIp` condition key to allow connections only from the specified range of IP addresses within the subnet where you created the interface endpoint as shown in the following policy:

```
{
  "Id": "sagemaker-studio-example-4",
  "Version": "2012-10-17",
  "Statement": [ 
    { 
      "Sid": "Enable SageMaker Studio Access",
      "Effect": "Allow",
      "Action": [ 
        "sagemaker:CreatePresignedDomainUrl",
        "sagemaker:DescribeUserProfile"
      ],
      "Resource": "*",
      "Condition": { 
        "IpAddress": { 
          "aws:SourceIp": [ 
            "192.0.2.0/24",
            "203.0.113.0/24"
          ]
        } 
      }
    }
  ]
}
```
Connect to a Notebook Instance Through a VPC Interface Endpoint

You can connect to your notebook instance from your VPC through an interface endpoint in your Virtual Private Cloud (VPC) instead of connecting over the public internet. When you use a VPC interface endpoint, communication between your VPC and the notebook instance is conducted entirely and securely within the AWS network.

SageMaker notebook instances support Amazon Virtual Private Cloud (Amazon VPC) interface endpoints that are powered by AWS PrivateLink. Each VPC endpoint is represented by one or more Elastic Network Interfaces with private IP addresses in your VPC subnets.

Note
Before you create an interface VPC endpoint to connect to a notebook instance, create an interface VPC endpoint to connect to the SageMaker API. That way, when users call CreatePresignedNotebookInstanceUrl to get the URL to connect to the notebook instance, that call also goes through the interface VPC endpoint. For information, see Connect to SageMaker Through a VPC Interface Endpoint (p. 3635).

You can create an interface endpoint to connect to your notebook instance with either the AWS console or AWS Command Line Interface (AWS CLI) commands. For instructions, see Creating an Interface Endpoint. Make sure that you create an interface endpoint for all of the subnets in your VPC from which you want to connect to the notebook instance.

When you create the interface endpoint, specify aws.sagemaker.region.notebook as the service name. After you create a VPC endpoint, enable private DNS for your VPC endpoint. Anyone using the SageMaker API, the AWS CLI, or the console to connect to the notebook instance from within the VPC connects to the notebook instance through the VPC endpoint instead of the public internet.

SageMaker notebook instances support VPC endpoints in all AWS Regions where both Amazon VPC and SageMaker are available.

Topics
- Connect Your Private Network to Your VPC (p. 3642)
- Create a VPC Endpoint Policy for SageMaker Notebook Instances (p. 3642)
- Restrict Access to Connections from Within Your VPC (p. 3642)
Connect Your Private Network to Your VPC

To connect to your notebook instance through your VPC, you either have to connect from an instance that is inside the VPC, or connect your private network to your VPC by using an AWS Virtual Private Network (AWS VPN) or AWS Direct Connect. For information about AWS VPN, see VPN Connections in the Amazon Virtual Private Cloud User Guide. For information about AWS Direct Connect, see Creating a Connection in the AWS Direct Connect User Guide.

Create a VPC Endpoint Policy for SageMaker Notebook Instances

You can create a policy for Amazon VPC endpoints for SageMaker notebook instances to specify the following:

- The principal that can perform actions.
- The actions that can be performed.
- The resources on which actions can be performed.

For more information, see Controlling Access to Services with VPC Endpoints in the Amazon VPC User Guide.

The following example of a VPC endpoint policy specifies that all users that have access to the endpoint are allowed to access the notebook instance named myNotebookInstance.

```
{
  "Statement": [
    {
      "Action": "sagemaker:CreatePresignedNotebookInstanceUrl",
      "Effect": "Allow",
      "Principal": "*"
    }
  ]
}
```

Access to other notebook instances is denied.

Restrict Access to Connections from Within Your VPC

Even if you set up an interface endpoint in your VPC, individuals outside the VPC can connect to the notebook instance over the internet.

Important

If you apply an IAM policy similar to one of the following, users can't access the specified SageMaker APIs or the notebook instance through the console.

To restrict access to only connections made from within your VPC, create an AWS Identity and Access Management policy that restricts access to only calls that come from within your VPC. Then add that policy to every AWS Identity and Access Management user, group, or role used to access the notebook instance.

Note

This policy allows connections only to callers within a subnet where you created an interface endpoint.

```
{
  "Id": "notebook-example-1",
  "Version": "2012-10-17",
  "Statement": [
```
Connect to SageMaker Through a VPC Interface Endpoint

If you want to restrict access to the notebook instance to only connections made using the interface endpoint, use the `aws:SourceVpce` condition key instead of `aws:SourceVpc`:

```json
{
  "Id": "notebook-example-1",
  "Version": "2012-10-17",
  "Statement": [
    {
      "Sid": "Enable Notebook Access",
      "Effect": "Allow",
      "Action": [
        "sagemaker:CreatePresignedNotebookInstanceUrl",
        "sagemaker:DescribeNotebookInstance"
      ],
      "Resource": "*",
      "Condition": {
        "ForAnyValue:StringEquals": {
          "aws:SourceVpce": [
            "vpce-111bbccc",
            "vpce-111bbddd"
          ]
        }
      }
    }
  ]
}
```

Both of these policy examples assume that you have also created an interface endpoint for the SageMaker API. For more information, see Connect to SageMaker Through a VPC Interface Endpoint (p. 3635). In the second example, one of the values for `aws:SourceVpce` is the ID of the interface endpoint for the notebook instance. The other is the ID of the interface endpoint for the SageMaker API.

The policy examples here include `DescribeNotebookInstance`, because typically you would call `DescribeNotebookInstance` to make sure that the `NotebookInstanceStatus` is `InService` before you try to connect to it. For example:

```bash
aws sagemaker describe-notebook-instance
  --notebook-instance-name myNotebookInstance
```

```json
{
  "NotebookInstanceArn":
```
"NotebookInstanceName": "myNotebookInstance",
"NotebookInstanceStatus": "InService",
"Url": "mynotebookinstance.notebook.us-west-2.sagemaker.aws",
"InstanceType": "ml.m4.xlarge",
"RoleArn": "arn:aws:iam::1234567890ab:role/service-role/AmazonSageMaker-
ExecutionRole-12345678T123456",
"LastModifiedTime": 1540334777.501,
"CreationTime": 1523050674.078,
"DirectInternetAccess": "Disabled"
}

aws sagemaker create-presigned-notebook-instance-url --notebook-instance-name
myNotebookInstance

{
  "AuthorizedUrl": "https://mynotebookinstance.notebook.us-west-2.sagemaker.aws?
authToken=AuthToken"
}

**Note**
The presigned url generated can be used from anywhere on the internet.

For both of these calls, if you did not enable private DNS hostnames for your VPC endpoint, or if you
are using a version of the AWS SDK that was released before August 13, 2018, you must specify the
endpoint URL in the call. For example, the call to create-presigned-notebook-instance-url is:

```bash
aws sagemaker create-presigned-notebook-instance-url
--notebook-instance-name myNotebookInstance
--endpoint-url VPC_Endpoint_ID.api.sagemaker.Region.vpce.amazonaws.com
```

**Connect Your Private Network to Your VPC**

To call the SageMaker API and runtime through your VPC, you have to connect from an instance that is
inside the VPC or connect your private network to your VPC by using an AWS Virtual Private Network
(AWS VPN) or AWS Direct Connect. For information about AWS VPN, see **VPN Connections** in the Amazon
Virtual Private Cloud User Guide. For information about AWS Direct Connect, see **Creating a Connection** in
the AWS Direct Connect User Guide.

**Give SageMaker Access to Resources in your Amazon VPC**

SageMaker runs the following job types in an Amazon Virtual Private Cloud by default.

- Processing
- Training
- Model hosting
- Batch transform
- Amazon SageMaker Clarify
- SageMaker Compilation

However, containers for these jobs access AWS resources—such as the Amazon Simple Storage Service
(Amazon S3) buckets where you store training data and model artifacts—over the internet.

To control access to your data and job containers, we recommend that you create a private VPC
and configure it so that they aren't accessible over the internet. For information about creating and
configuring a VPC, see Getting Started With Amazon VPC in the Amazon VPC User Guide. Using a VPC helps to protect your job containers and data because you can configure your VPC so that it is not connected to the internet. Using a VPC also allows you to monitor all network traffic in and out of your job containers by using VPC flow logs. For more information, see VPC Flow Logs in the Amazon VPC User Guide.

You specify your private VPC configuration when you create jobs by specifying subnets and security groups. When you specify the subnets and security groups, SageMaker creates elastic network interfaces that are associated with your security groups in one of the subnets. Network interfaces allow your job containers to connect to resources in your VPC. For information about network interfaces, see Elastic Network Interfaces in the Amazon VPC User Guide.

**Topics**
- Give SageMaker Processing Jobs Access to Resources in Your Amazon VPC (p. 3645)
- Give SageMaker Training Jobs Access to Resources in Your Amazon VPC (p. 3648)
- Give SageMaker Hosted Endpoints Access to Resources in Your Amazon VPC (p. 3650)
- Give Batch Transform Jobs Access to Resources in Your Amazon VPC (p. 3653)
- Give Amazon SageMaker Clarify Jobs Access to Resources in Your Amazon VPC (p. 3656)
- Give SageMaker Compilation Jobs Access to Resources in Your Amazon VPC (p. 3659)

**Give SageMaker Processing Jobs Access to Resources in Your Amazon VPC**

To control access to your data and processing jobs, we recommend that you create a private Amazon VPC and configure it so that your jobs aren't accessible over the public internet. For information about creating and configuring a VPC, see Getting Started With Amazon VPC in the Amazon VPC User Guide. Using a VPC helps to protect your processing containers and data because you can configure your VPC so that it is not connected to the internet. Using a VPC also allows you to monitor all network traffic in and out of your processing containers by using VPC flow logs. For more information, see VPC Flow Logs in the Amazon VPC User Guide.

This document explains how to add Amazon VPC configurations for processing jobs.

**Configure a Processing Job for Amazon VPC Access**

To specify subnets and security groups in your private VPC, use the NetworkConfig.VpcConfig request parameter of the CreateProcessingJob API, or provide this information when you create a processing job in the SageMaker console. SageMaker uses this information to create network interfaces and attach them to your processing containers. The network interfaces provide your processing containers with a network connection within your VPC that is not connected to the internet. They also enable your processing job to connect to resources in your private VPC.

The following is an example of the VpcConfig parameter that you include in your call to CreateProcessingJob:

```json
VpcConfig: {
    "Subnets": [
        "subnet-0123456789abcdef0",
        "subnet-0123456789abcdef1",
        "subnet-0123456789abcdef2"
    ],
    "SecurityGroupIds": [
        "sg-0123456789abcdef0"
    ]
}
```
Configure Your Private VPC for SageMaker Processing

When configuring the private VPC for your SageMaker processing jobs, use the following guidelines. For information about setting up a VPC, see Working with VPCs and Subnets in the Amazon VPC User Guide.

Topics

• Ensure That Subnets Have Enough IP Addresses (p. 3646)
• Create an Amazon S3 VPC Endpoint (p. 3646)
• Use a Custom Endpoint Policy to Restrict Access to S3 (p. 3646)
• Configure Route Tables (p. 3647)
• Configure the VPC Security Group (p. 3647)
• Connect to Resources Outside Your VPC (p. 3647)

Ensure That Subnets Have Enough IP Addresses

Your VPC subnets should have at least two private IP addresses for each instance in a processing job. For more information, see VPC and Subnet Sizing for IPv4 in the Amazon VPC User Guide.

Create an Amazon S3 VPC Endpoint

If you configure your VPC so that processing containers don't have access to the internet, they can't connect to the Amazon S3 buckets that contain your data unless you create a VPC endpoint that allows access. By creating a VPC endpoint, you allow your processing containers to access the buckets where you store your data. We recommend that you also create a custom policy that allows only requests from your private VPC to access to your S3 buckets. For more information, see Endpoints for Amazon S3.

To create an S3 VPC endpoint:

1. Open the Amazon VPC console at https://console.aws.amazon.com/vpc/.
2. In the navigation pane, choose Endpoints, then choose Create Endpoint
3. For Service Name, choose com.amazonaws.region.s3, where region is the name of the region where your VPC resides.
4. For VPC, choose the VPC you want to use for this endpoint.
5. For Configure route tables, select the route tables to be used by the endpoint. The VPC service automatically adds a route to each route table you select that points any S3 traffic to the new endpoint.
6. For Policy, choose Full Access to allow full access to the S3 service by any user or service within the VPC. Choose Custom to restrict access further. For information, see Use a Custom Endpoint Policy to Restrict Access to S3 (p. 3646).

Use a Custom Endpoint Policy to Restrict Access to S3

The default endpoint policy allows full access to S3 for any user or service in your VPC. To further restrict access to S3, create a custom endpoint policy. For more information, see Using Endpoint Policies for Amazon S3. You can also use a bucket policy to restrict access to your S3 buckets to only traffic that comes from your Amazon VPC. For information, see Using Amazon S3 Bucket Policies.

Restrict Package Installation on the Processing Container

The default endpoint policy allows users to install packages from the Amazon Linux and Amazon Linux 2 repositories on the processing container. If you don't want users to install packages from that repository, create a custom endpoint policy that explicitly denies access to the Amazon Linux and Amazon Linux 2 repositories. The following is an example of a policy that denies access to these repositories:
Give SageMaker Access to Resources in your Amazon VPC

```json
{
  "Statement": [
    {
      "Sid": "AmazonLinuxAMIRepositoryAccess",
      "Principal": "*",
      "Action": [
        "s3:GetObject"
      ],
      "Effect": "Deny",
      "Resource": [
        "arn:aws:s3:::packages.*.amazonaws.com/*",
        "arn:aws:s3:::repo.*.amazonaws.com/*"
      ]
    }
  ]
}
{
  "Statement": [
    {
      "Sid": "AmazonLinux2AMIRepositoryAccess",
      "Principal": "*",
      "Action": [
        "s3:GetObject"
      ],
      "Effect": "Deny",
      "Resource": [
        "arn:aws:s3:::amazonlinux.*.amazonaws.com/*"
      ]
    }
  ]
}
```

Configure Route Tables

Use default DNS settings for your endpoint route table, so that standard Amazon S3 URLs (for example, http://s3-aws-region.amazonaws.com/MyBucket) resolve. If you don't use default DNS settings, ensure that the URLs that you use to specify the locations of the data in your processing jobs resolve by configuring the endpoint route tables. For information about VPC endpoint route tables, see Routing for Gateway Endpoints in the Amazon VPC User Guide.

Configure the VPC Security Group

In distributed processing, you must allow communication between the different containers in the same processing job. To do that, configure a rule for your security group that allows inbound connections between members of the same security group. For more information, see Security Group Rules.

Connect to Resources Outside Your VPC

If you configure your VPC so that it doesn't have internet access, processing jobs that use that VPC do not have access to resources outside your VPC. If your processing job needs access to resources outside your VPC, provide access with one of the following options:

- If your processing job needs access to an AWS service that supports interface VPC endpoints, create an endpoint to connect to that service. For a list of services that support interface endpoints, see VPC Endpoints in the Amazon VPC User Guide. For information about creating an interface VPC endpoint, see Interface VPC Endpoints (AWS PrivateLink) in the Amazon VPC User Guide.

- If your processing job needs access to an AWS service that doesn't support interface VPC endpoints or to a resource outside of AWS, create a NAT gateway and configure your security groups to allow outbound connections. For information about setting up a NAT gateway for your VPC, see Scenario 2: VPC with Public and Private Subnets (NAT) in the Amazon Virtual Private Cloud User Guide.
Give SageMaker Training Jobs Access to Resources in Your Amazon VPC

**Note**
For training jobs, you can configure only subnets with a default tenancy VPC in which your instance runs on shared hardware. For more information on the tenancy attribute for VPCs, see [Dedicated Instances](#).

**Configure a Training Job for Amazon VPC Access**

To specify subnets and security groups in your private VPC, use the `VpcConfig` request parameter of the `CreateTrainingJob` API, or provide this information when you create a training job in the SageMaker console. SageMaker uses this information to create network interfaces and attach them to your training containers. The network interfaces provide your training containers with a network connection within your VPC that is not connected to the internet. They also enable your training job to connect to resources in your private VPC.

The following is an example of the `VpcConfig` parameter that you include in your call to `CreateTrainingJob`:

```
VpcConfig: {
  "Subnets": [
    "subnet-0123456789abcdef0",
    "subnet-0123456789abcdef1",
    "subnet-0123456789abcdef2"
  ],
  "SecurityGroupIds": [
    "sg-0123456789abcdef0"
  ]
}
```

**Configure Your Private VPC for SageMaker Training**

When configuring the private VPC for your SageMaker training jobs, use the following guidelines. For information about setting up a VPC, see [Working with VPCs and Subnets](#) in the Amazon VPC User Guide.

**Topics**
- Ensure That Subnets Have Enough IP Addresses (p. 3648)
- Create an Amazon S3 VPC Endpoint (p. 3648)
- Use a Custom Endpoint Policy to Restrict Access to S3 (p. 3649)
- Configure Route Tables (p. 3650)
- Configure the VPC Security Group (p. 3650)
- Connect to Resources Outside Your VPC (p. 3650)

**Ensure That Subnets Have Enough IP Addresses**

Your VPC subnets should have at least two private IP addresses for each instance in a training job. For more information, see [VPC and Subnet Sizing for IPv4](#) in the Amazon VPC User Guide.

**Create an Amazon S3 VPC Endpoint**

If you configure your VPC so that training containers don't have access to the internet, they can't connect to the Amazon S3 buckets that contain your training data unless you create a VPC endpoint that allows access. By creating a VPC endpoint, you allow your training containers to access the buckets where you store your data and model artifacts. We recommend that you also create a custom policy that allows only requests from your private VPC to access to your S3 buckets. For more information, see [Endpoints for Amazon S3](#).
To create an S3 VPC endpoint:

1. Open the Amazon VPC console at https://console.aws.amazon.com/vpc/.
2. In the navigation pane, choose Endpoints, then choose Create Endpoint.
3. For Service Name, search for com.amazonaws.region.s3, where region is the name of the region where your VPC resides.
4. Choose the Gateway type.
5. For VPC, choose the VPC you want to use for this endpoint.
6. For Configure route tables, select the route tables to be used by the endpoint. The VPC service automatically adds a route to each route table you select that points any S3 traffic to the new endpoint.
7. For Policy, choose Full Access to allow full access to the S3 service by any user or service within the VPC. Choose Custom to restrict access further. For information, see Use a Custom Endpoint Policy to Restrict Access to S3 (p. 3649).

Use a Custom Endpoint Policy to Restrict Access to S3

The default endpoint policy allows full access to S3 for any user or service in your VPC. To further restrict access to S3, create a custom endpoint policy. For more information, see Using Endpoint Policies for Amazon S3. You can also use a bucket policy to restrict access to your S3 buckets to only traffic that comes from your Amazon VPC. For information, see Using Amazon S3 Bucket Policies.

Restrict Package Installation on the Training Container

The default endpoint policy allows users to install packages from the Amazon Linux and Amazon Linux 2 repositories on the training container. If you don't want users to install packages from that repository, create a custom endpoint policy that explicitly denies access to the Amazon Linux and Amazon Linux 2 repositories. The following is an example of a policy that denies access to these repositories:

```json
{
  "Statement": [
    {
      "Sid": "AmazonLinuxAMIRepositoryAccess",
      "Principal": "*",
      "Action": [
        "s3:GetObject"
      ],
      "Effect": "Deny",
      "Resource": [
        "arn:aws:s3:::packages.*.amazonaws.com/*",
        "arn:aws:s3:::repo.*.amazonaws.com/*"
      ]
    }
  ]
}

{
  "Statement": [
    {
      "Sid": "AmazonLinux2AMIRepositoryAccess",
      "Principal": "*",
      "Action": [
        "s3:GetObject"
      ],
      "Effect": "Deny",
      "Resource": [
        "arn:aws:s3:::amazonlinux.*.amazonaws.com/*"
      ]
    }
  ]
}
```
Give SageMaker Access to Resources in your Amazon VPC

Configure Route Tables

Use default DNS settings for your endpoint route table, so that standard Amazon S3 URLs (for example, http://s3-aws-region.amazonaws.com/MyBucket) resolve. If you don't use default DNS settings, ensure that the URLs that you use to specify the locations of the data in your training jobs resolve by configuring the endpoint route tables. For information about VPC endpoint route tables, see Routing for Gateway Endpoints in the Amazon VPC User Guide.

Configure the VPC Security Group

In distributed training, you must allow communication between the different containers in the same training job. To do that, configure a rule for your security group that allows inbound connections between members of the same security group. For EFA-enabled instances, ensure that both inbound and outbound connections allow all traffic from the same security group. For information, see Security Group Rules in the Amazon Virtual Private Cloud User Guide.

Connect to Resources Outside Your VPC

If you configure your VPC so that it doesn't have internet access, training jobs that use that VPC do not have access to resources outside your VPC. If your training job needs access to resources outside your VPC, provide access with one of the following options:

- If your training job needs access to an AWS service that supports interface VPC endpoints, create an endpoint to connect to that service. For a list of services that support interface endpoints, see VPC Endpoints in the Amazon Virtual Private Cloud User Guide. For information about creating an interface VPC endpoint, see Interface VPC Endpoints (AWS PrivateLink) in the Amazon Virtual Private Cloud User Guide.
- If your training job needs access to an AWS service that doesn't support interface VPC endpoints or to a resource outside of AWS, create a NAT gateway and configure your security groups to allow outbound connections. For information about setting up a NAT gateway for your VPC, see Scenario 2: VPC with Public and Private Subnets (NAT) in the Amazon Virtual Private Cloud User Guide.

Give SageMaker Hosted Endpoints Access to Resources in Your Amazon VPC

Configure a Model for Amazon VPC Access

To specify subnets and security groups in your private VPC, use the VpcConfig request parameter of the CreateModel API, or provide this information when you create a model in the SageMaker console. SageMaker uses this information to create network interfaces and attach them to your model containers. The network interfaces provide your model containers with a network connection within your VPC that is not connected to the internet. They also enable your model to connect to resources in your private VPC.

**Note**
You must create at least two subnets in different availability zones in your private VPC, even if you have only one hosting instance.

The following is an example of the VpcConfig parameter that you include in your call to CreateModel:

```json
VpcConfig: {
    "Subnets": [
        "subnet-0123456789abcdef0",
        "subnet-0123456789abcdef1",
        "subnet-0123456789abcdef2"
    ],
}
```
"SecurityGroupIds": [
  "sg-0123456789abcdef0"
]
}

## Configure Your Private VPC for SageMaker Hosting

When configuring the private VPC for your SageMaker models, use the following guidelines. For information about setting up a VPC, see [Working with VPCs and Subnets](https://docs.aws.amazon.com/vpc/userguide) in the *Amazon VPC User Guide*.

### Topics
- **Ensure That Subnets Have Enough IP Addresses** (p. 3651)
- **Create an Amazon S3 VPC Endpoint** (p. 3651)
- **Use a Custom Endpoint Policy to Restrict Access to Amazon S3** (p. 3651)
- **Add Permissions for Endpoint Access for Containers Running in a VPC to Custom IAM Policies** (p. 3652)
- **Configure Route Tables** (p. 3653)
- **Connect to Resources Outside Your VPC** (p. 3653)

### Ensure That Subnets Have Enough IP Addresses

Your VPC subnets should have at least two private IP addresses for each model instance. For more information, see [VPC and Subnet Sizing for IPv4](https://docs.aws.amazon.com/vpc/userguide) in the *Amazon VPC User Guide*.

### Create an Amazon S3 VPC Endpoint

If you configure your VPC so that model containers don't have access to the internet, they can't connect to the Amazon S3 buckets that contain your data unless you create a VPC endpoint that allows access. By creating a VPC endpoint, you allow your model containers to access the buckets where you store your data and model artifacts. We recommend that you also create a custom policy that allows only requests from your private VPC to access to your S3 buckets. For more information, see [Endpoints for Amazon S3](https://docs.aws.amazon.com/s3/v2/endpoint_overview).

**To create an Amazon S3 VPC endpoint:**

1. Open the Amazon VPC console at [https://console.aws.amazon.com/vpc/](https://console.aws.amazon.com/vpc/).
2. In the navigation pane, choose **Endpoints**, then choose **Create Endpoint**.
3. For **Service Name**, choose com.amazonaws.region.s3, where *region* is the name of the AWS Region where your VPC resides.
4. For **VPC**, choose the VPC that you want to use for this endpoint.
5. For **Configure route tables**, choose the route tables for the endpoint to use. The VPC service automatically adds a route to each route table that you choose that points Amazon S3 traffic to the new endpoint.
6. For **Policy**, choose **Full Access** to allow full access to the Amazon S3 service by any user or service within the VPC. To restrict access further, choose **Custom**. For more information, see [Use a Custom Endpoint Policy to Restrict Access to Amazon S3](https://docs.aws.amazon.com/s3/v2/endpoint_overview) (p. 3651).

### Use a Custom Endpoint Policy to Restrict Access to Amazon S3

The default endpoint policy allows full access to Amazon Simple Storage Service (Amazon S3) for any user or service in your VPC. To further restrict access to Amazon S3, create a custom endpoint policy. For more information, see [Using Endpoint Policies for Amazon S3](https://docs.aws.amazon.com/s3/v2/endpoint_overview).

You can also use a bucket policy to restrict access to your S3 buckets to only traffic that comes from your Amazon VPC. For information, see [Using Amazon S3 Bucket Policies](https://docs.aws.amazon.com/s3/v2/endpoint_overview).
Restrict Package Installation on the Model Container with a Custom Endpoint Policy

The default endpoint policy allows users to install packages from the Amazon Linux and Amazon Linux 2 repositories on the model container. If you don't want users to install packages from those repositories, create a custom endpoint policy that explicitly denies access to the Amazon Linux and Amazon Linux 2 repositories. The following is an example of a policy that denies access to these repositories:

```json
{
    "Statement": [
        {
            "Sid": "AmazonLinuxAMIRepositoryAccess",
            "Principal": "*",
            "Action": ["s3:GetObject"],
            "Effect": "Deny",
            "Resource": ["arn:aws:s3:::packages.*.amazonaws.com/*", "arn:aws:s3:::repo.*.amazonaws.com/*"]
        }
    ]
}
{
    "Statement": [
        {
            "Sid": "AmazonLinux2AMIRepositoryAccess",
            "Principal": "*",
            "Action": ["s3:GetObject"],
            "Effect": "Deny",
            "Resource": ["arn:aws:s3:::amazonlinux.*.amazonaws.com/*"]
        }
    ]
}
```

Add Permissions for Endpoint Access for Containers Running in a VPC to Custom IAM Policies

The SageMakerFullAccess managed policy includes the permissions that you need to use models configured for Amazon VPC access with an endpoint. These permissions allow SageMaker to create an elastic network interface and attach it to model containers running in a VPC. If you use your own IAM policy, you must add the following permissions to that policy to use models configured for VPC access.

```json
{
    "Version": "2012-10-17",
    "Statement": [
        {
            "Effect": "Allow",
        ]
    ]
}
```
For more information about the SageMakerFullAccess managed policy, see AWS managed policy: AmazonSageMakerFullAccess (p. 3572).

Configure Route Tables

Use default DNS settings for your endpoint route table, so that standard Amazon S3 URLs (for example, http://s3-aws-region.amazonaws.com/MyBucket) resolve. If you don't use default DNS settings, ensure that the URLs that you use to specify the locations of the data in your models resolve by configuring the endpoint route tables. For information about VPC endpoint route tables, see Routing for Gateway Endpoints in the Amazon VPC User Guide.

Connect to Resources Outside Your VPC

If you configure your VPC so that it doesn't have internet access, models that use that VPC do not have access to resources outside your VPC. If your model needs access to resources outside your VPC, provide access with one of the following options:

- If your model needs access to an AWS service that supports interface VPC endpoints, create an endpoint to connect to that service. For a list of services that support interface endpoints, see VPC Endpoints in the Amazon VPC User Guide. For information about creating an interface VPC endpoint, see Interface VPC Endpoints (AWS PrivateLink) in the Amazon VPC User Guide.

- If your model needs access to an AWS service that doesn't support interface VPC endpoints or to a resource outside of AWS, create a NAT gateway and configure your security groups to allow outbound connections. For information about setting up a NAT gateway for your VPC, see Scenario 2: VPC with Public and Private Subnets (NAT) in the Amazon Virtual Private Cloud User Guide.

Give Batch Transform Jobs Access to Resources in Your Amazon VPC

To control access to your data and batch transform jobs, we recommend that you create a private Amazon VPC and configure it so that your jobs aren't accessible over the public internet. You specify your private VPC configuration when you create a model by specifying subnets and security groups. You then specify the same model when you create a batch transform job. When you specify the subnets and security groups, SageMaker creates elastic network interfaces that are associated with your security groups in one of the subnets. Network interfaces allow your model containers to connect to resources in your VPC. For information about network interfaces, see Elastic Network Interfaces in the Amazon VPC User Guide.

This document explains how to add Amazon VPC configurations for batch transform jobs.

Configure a Batch Transform Job for Amazon VPC Access

To specify subnets and security groups in your private VPC, use the VpcConfig request parameter of the CreateModel API, or provide this information when you create a model in the SageMaker console. Then specify the same model in the ModelName request parameter of the CreateTransformJob API, or in the Model name field when you create a transform job in the SageMaker console. SageMaker uses this information to create network interfaces and attach them to your model containers. The network interfaces provide your model containers with a network connection within your VPC that is not connected to the internet. They also enable your transform job to connect to resources in your private VPC.

The following is an example of the VpcConfig parameter that you include in your call to CreateModel:
If you are creating a model using the CreateModel API operation, the IAM execution role that you use to create your model must include the permissions described in CreateModel API: Execution Role Permissions (p. 3552), including the following permissions required for a private VPC.

When creating a model in the console, if you select Create a new role in the Model Settings section, the AmazonSageMakerFullAccess policy used to create the role already contains these permissions. If you select Enter a custom IAM role ARN or Use existing role, the role ARN that you specify must have an execution policy attached with the following permissions.

```json
{
   "Effect": "Allow",
   "Action": [
      "ec2:CreateNetworkInterface",
      "ec2:DeleteNetworkInterface",
      "ec2:DescribeNetworkInterfaces",
      "ec2:DescribeVpcs",
      "ec2:DescribeDhcpOptions",
      "ec2:DescribeSecurityGroups"
   ]
}
```

### Configure Your Private VPC for SageMaker Batch Transform

When configuring the private VPC for your SageMaker batch transform jobs, use the following guidelines. For information about setting up a VPC, see Working with VPCs and Subnets in the Amazon VPC User Guide.

**Topics**

- Ensure That Subnets Have Enough IP Addresses (p. 3654)
- Create an Amazon S3 VPC Endpoint (p. 3654)
- Use a Custom Endpoint Policy to Restrict Access to S3 (p. 3655)
- Configure Route Tables (p. 3656)
- Configure the VPC Security Group (p. 3656)
- Connect to Resources Outside Your VPC (p. 3656)

**Ensure That Subnets Have Enough IP Addresses**

Your VPC subnets should have at least two private IP addresses for each instance in a transform job. For more information, see VPC and Subnet Sizing for IPv4 in the Amazon VPC User Guide.

**Create an Amazon S3 VPC Endpoint**

If you configure your VPC so that model containers don't have access to the internet, they can't connect to the Amazon S3 buckets that contain your data unless you create a VPC endpoint that allows access. By creating a VPC endpoint, you allow your model containers to access the buckets where you store your data.
data and model artifacts. We recommend that you also create a custom policy that allows only requests from your private VPC to access to your S3 buckets. For more information, see Endpoints for Amazon S3.

To create an S3 VPC endpoint:

1. Open the Amazon VPC console at https://console.aws.amazon.com/vpc/.
2. In the navigation pane, choose Endpoints, then choose Create Endpoint.
3. For Service Name, choose com.amazonaws.region.s3, where region is the name of the region where your VPC resides.
4. For VPC, choose the VPC you want to use for this endpoint.
5. For Configure route tables, select the route tables to be used by the endpoint. The VPC service automatically adds a route to each route table you select that points any S3 traffic to the new endpoint.
6. For Policy, choose Full Access to allow full access to the S3 service by any user or service within the VPC. Choose Custom to restrict access further. For information, see Use a Custom Endpoint Policy to Restrict Access to S3 (p. 3655).

Use a Custom Endpoint Policy to Restrict Access to S3

The default endpoint policy allows full access to S3 for any user or service in your VPC. To further restrict access to S3, create a custom endpoint policy. For more information, see Using Endpoint Policies for Amazon S3. You can also use a bucket policy to restrict access to your S3 buckets to only traffic that comes from your Amazon VPC. For information, see Using Amazon S3 Bucket Policies.

Restrict Package Installation on the Model Container

The default endpoint policy allows users to install packages from the Amazon Linux and Amazon Linux 2 repositories on the training container. If you don't want users to install packages from that repository, create a custom endpoint policy that explicitly denies access to the Amazon Linux and Amazon Linux 2 repositories. The following is an example of a policy that denies access to these repositories:

```
{
  "Statement": [
    {
      "Sid": "AmazonLinuxAMIRepositoryAccess",
      "Principal": "*",
      "Action": [
        "s3:GetObject"
      ],
      "Effect": "Deny",
      "Resource": [
        "arn:aws:s3:::packages.*.amazonaws.com/*",
        "arn:aws:s3:::repo.*.amazonaws.com/*"
      ]
    }
  ]
}
{
  "Statement": [
    {
      "Sid": "AmazonLinux2AMIRepositoryAccess",
      "Principal": "*",
      "Action": [
        "s3:GetObject"
      ],
      "Effect": "Deny",
      "Resource": [
        "arn:aws:s3:::amazonlinux.*.amazonaws.com/*"
      ]
    }
  ]
}
```

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Configure Route Tables

Use default DNS settings for your endpoint route table, so that standard Amazon S3 URLs (for example, http://s3-aws-region.amazonaws.com/MyBucket) resolve. If you don't use default DNS settings, ensure that the URLs that you use to specify the locations of the data in your batch transform jobs resolve by configuring the endpoint route tables. For information about VPC endpoint route tables, see Routing for Gateway Endpoints in the Amazon VPC User Guide.

Configure the VPC Security Group

In distributed batch transform, you must allow communication between the different containers in the same batch transform job. To do that, configure a rule for your security group that allows inbound and outbound connections between members of the same security group. Members of the same security group should be able to communicate with each other across all ports. For more information, see Security Group Rules.

Connect to Resources Outside Your VPC

If you configure your VPC so that it doesn't have internet access, batch transform jobs that use that VPC do not have access to resources outside your VPC. If your batch transform job needs access to resources outside your VPC, provide access with one of the following options:

- If your batch transform job needs access to an AWS service that supports interface VPC endpoints, create an endpoint to connect to that service. For a list of services that support interface endpoints, see VPC Endpoints in the Amazon VPC User Guide. For information about creating an interface VPC endpoint, see Interface VPC Endpoints (AWS PrivateLink) in the Amazon VPC User Guide.
- If your batch transform job needs access to an AWS service that doesn't support interface VPC endpoints or to a resource outside of AWS, create a NAT gateway and configure your security groups to allow outbound connections. For information about setting up a NAT gateway for your VPC, see Scenario 2: VPC with Public and Private Subnets (NAT) in the Amazon Virtual Private Cloud User Guide.

Give Amazon SageMaker Clarify Jobs Access to Resources in Your Amazon VPC

To control access to your data and SageMaker Clarify jobs, we recommend that you create a private Amazon VPC and configure it so that your jobs aren't accessible over the public internet. For information about creating and configuring an Amazon VPC for processing jobs, see Give SageMaker Processing Jobs Access to Resources in Your Amazon VPC.

This document explains how to add additional Amazon VPC configurations that meet the requirements for SageMaker Clarify jobs.

Topics

- Configure a SageMaker Clarify Job for Amazon VPC Access (p. 3656)
- Configure Your Private Amazon VPC for SageMaker Clarify jobs (p. 3658)

Configure a SageMaker Clarify Job for Amazon VPC Access

You need to specify subnets and security groups when configuring your private Amazon VPC for SageMaker Clarify jobs and to enable the job to get inferences from the SageMaker model when computing post-training bias metrics and feature contributions that help explain model predictions.
SageMaker Developer Guide

Give SageMaker Access to Resources in your Amazon VPC

Topics

- SageMaker Clarify Job Amazon VPC Subnets and Security Groups (p. 3657)
- Configure a Model Amazon VPC for Inference (p. 3657)

SageMaker Clarify Job Amazon VPC Subnets and Security Groups

Subnets and security groups in your private Amazon VPC can be assigned to a SageMaker Clarify job in various ways, depending on how you create the job.

- **SageMaker console:** Provide this information when you create the job in the SageMaker Dashboard. From the Processing menu, choose Processing jobs, then choose Create processing job. Select the VPC option in the Network panel and provide the subnets and security groups using the drop-down lists. Make sure network isolation option provided in this panel is set to disabled.

- **SageMaker API:** Use the NetworkConfig.VpcConfig request parameter of the CreateProcessingJob API, as shown in the following example:

  ```json
  "NetworkConfig": {
    "VpcConfig": {
      "Subnets": [
        "subnet-0123456789abcdef0",
        "subnet-0123456789abcdef1",
        "subnet-0123456789abcdef2"
      ],
      "SecurityGroupIds": [
        "sg-0123456789abcdef0"
      ]
    }
  }
  ```

- **SageMaker Python SDK:** Use the NetworkConfig parameter of the SageMakerClarifyProcessor API or Processor API, as shown in the following example:

  ```python
  from sagemaker.network import NetworkConfig
  network_config = NetworkConfig(
    subnets=[
      "subnet-0123456789abcdef0",
      "subnet-0123456789abcdef1",
      "subnet-0123456789abcdef2",
    ],
    security_group_ids=[
      "sg-0123456789abcdef0",
    ],
  )
  ```

SageMaker uses the information to create network interfaces and attach them to the SageMaker Clarify job. The network interfaces provide a SageMaker Clarify job with a network connection within your Amazon VPC that is not connected to the public internet. They also enable the SageMaker Clarify job to connect to resources in your private Amazon VPC.

Configure a Model Amazon VPC for Inference

In order to compute post-training bias metrics and explainability, the SageMaker Clarify job needs to get inferences from the SageMaker model that is specified by the model_name parameter of the analysis configuration for the SageMaker Clarify processing job. Alternatively, if you use the SageMakerClarifyProcessor API in the SageMaker Python SDK, the job needs to get the model_name specified by the ModelConfig class. To accomplish this, the SageMaker Clarify job creates an ephemeral endpoint with the model, known as a shadow endpoint, and then applies the Amazon VPC configuration of the model to the shadow endpoint.

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**Note**
The network isolation option of both the SageMaker Clarify job and the model must be disabled (by default the option is disabled) so that the SageMaker Clarify job can communicate with the shadow endpoint.

To specify subnets and security groups in your private Amazon VPC to the SageMaker model, use the VpcConfig request parameter of the CreateModel API or provide this information when you create the model using the SageMaker dashboard in the console. The following is an example of the VpcConfig parameter that you include in your call to CreateModel:

```json
"VpcConfig": {
  "Subnets": ["subnet-0123456789abcdef0", "subnet-0123456789abcdef1", "subnet-0123456789abcdef2"],
  "SecurityGroupIds": ["sg-0123456789abcdef0"]
}
```

You can specify the number of instances of the shadow endpoint to launch with the initial_instance_count parameter of the analysis configuration for the SageMaker Clarify processing job. Alternatively, if you use the SageMakerClarifyProcessor API in the SageMaker Python SDK, the job needs to get the instance_count specified by the ModelConfig class.

**Note**
Even if you only request one instance when creating the shadow endpoint, you need at least two subnets in the model's ModelConfig in distinct availability zones. Otherwise the shadow endpoint creation fails with the following error:

```
ClientError: Error hosting endpoint sagemaker-clarify-endpoint-XXX: Failed. Reason: Unable to locate at least 2 availability zone(s) with the requested instance type YYY that overlap with SageMaker subnets.
```

If your model requires model files in Amazon S3, then the model Amazon VPC needs to have an Amazon S3 VPC endpoint. For more information about creating and configuring an Amazon VPC for SageMaker models, see [Give SageMaker Hosted Endpoints Access to Resources in Your Amazon VPC](p. 3650).

### Configure Your Private Amazon VPC for SageMaker Clarify jobs

In general, you can follow the steps in [Configure Your Private VPC for SageMaker Processing](p. 3650) to configure your private Amazon VPC for SageMaker Clarify jobs. Here are some highlights and special requirements for SageMaker Clarify jobs.

**Topics**

- [Connect to Resources Outside Your Amazon VPC](p. 3658)
- [Configure the Amazon VPC Security Group](p. 3659)

### Connect to Resources Outside Your Amazon VPC

If you configure your Amazon VPC so that it does not have public internet access, then some additional setup is required to grant SageMaker Clarify jobs access to resources and services outside of your Amazon VPC. For example, an Amazon S3 VPC endpoint is required because a SageMaker Clarify job needs to load a dataset from an S3 bucket as well as save the analysis results to an S3 bucket. For more information, see [Create an Amazon S3 VPC Endpoint](p. 3650) for the creation guide. In addition, if a SageMaker Clarify job needs to get inferences from the shadow endpoint, then it needs to call several more AWS services.
Create an Amazon SageMaker API service VPC endpoint: The SageMaker Clarify job needs to call the Amazon SageMaker API service to manipulate the shadow endpoint, or to describe a SageMaker model for Amazon VPC validation. You can follow the guidance provided in the Securing all Amazon SageMaker API calls with AWS PrivateLink blog to create an Amazon SageMaker API VPC endpoint that allows the SageMaker Clarify job to make the service calls. Note that the service name of Amazon SageMaker API service is com.amazonaws.region.sagemaker.api, where region is the name of the Region where your Amazon VPC resides.

Create an Amazon SageMaker Runtime VPC Endpoint: The SageMaker Clarify job needs to call the Amazon SageMaker runtime service, which routes the invocations to the shadow endpoint. The setup steps are similar to those for the Amazon SageMaker API service. Note that the service name of Amazon SageMaker Runtime service is com.amazonaws.region.sagemaker.runtime, where region is the name of the Region where your Amazon VPC resides.

Configure the Amazon VPC Security Group

SageMaker Clarify jobs support distributed processing when two or more processing instances are specified in one of the following ways:

- **SageMaker console**: The Instance count is specified in the Resource configuration part of the Job settings panel on the Create processing job page.
- **SageMaker API**: The InstanceCount is specified when you create the job with the CreateProcessingJob API.
- **SageMaker Python SDK**: The instance_count is specified when using the SageMakerClarifyProcessor API or the Processor API.

In distributed processing, you must allow communication between the different instances in the same processing job. To do that, configure a rule for your security group that allows inbound connections between members of the same security group. For information, see Security group rules.

Give SageMaker Compilation Jobs Access to Resources in Your Amazon VPC

Note
For compilation jobs, you can configure only subnets with a default tenancy VPC in which your job runs on shared hardware. For more information on the tenancy attribute for VPCs, see Dedicated Instances.

Configure a Compilation Job for Amazon VPC Access

To specify subnets and security groups in your private VPC, use the VpcConfig request parameter of the CreateCompilationJob API, or provide this information when you create a compilation job in the SageMaker console. SageMaker Neo uses this information to create network interfaces and attach them to your compilation jobs. The network interfaces provide compilation jobs with a network connection within your VPC that is not connected to the internet. They also enable your compilation job to connect to resources in your private VPC. The following is an example of the VpcConfig parameter that you include in your call to CreateCompilationJob:

```json
VpcConfig: {"Subnets": [
  "subnet-0123456789abcdef0",
  "subnet-0123456789abcdef1",
  "subnet-0123456789abcdef2"
],
  "SecurityGroupIds": ["sg-0123456789abcdef0"]
}
```
Configure Your Private VPC for SageMaker Compilation

When configuring the private VPC for your SageMaker compilation jobs, use the following guidelines. For information about setting up a VPC, see Working with VPCs and Subnets in the Amazon VPC User Guide.

Topics

- Ensure That Subnets Have Enough IP Addresses (p. 3660)
- Create an Amazon S3 VPC Endpoint (p. 3660)
- Use a Custom Endpoint Policy to Restrict Access to S3 (p. 3660)
- Configure Route Tables (p. 3661)
- Configure the VPC Security Group (p. 3662)

Ensure That Subnets Have Enough IP Addresses

Your VPC subnets should have at least two private IP addresses for each instance in a compilation job. For more information, see VPC and Subnet Sizing for IPv4 in the Amazon VPC User Guide.

Create an Amazon S3 VPC Endpoint

If you configure your VPC to block access to the internet, SageMaker Neo can’t connect to the Amazon S3 buckets that contain your models unless you create a VPC endpoint that allows access. By creating a VPC endpoint, you allow your SageMaker Neo compilation jobs to access the buckets where you store your data and model artifacts. We recommend that you also create a custom policy that allows only requests from your private VPC to access to your S3 buckets. For more information, see Endpoints for Amazon S3.

To create an S3 VPC endpoint:

1. Open the Amazon VPC console at https://console.aws.amazon.com/vpc/.
2. In the navigation pane, choose Endpoints, then choose Create Endpoint
3. For Service Name, search for com.amazonaws.region.s3, where region is the name of the region where your VPC resides.
4. Choose the Gateway type.
5. For VPC, choose the VPC you want to use for this endpoint.
6. For Configure route tables, select the route tables to be used by the endpoint. The VPC service automatically adds a route to each route table you select that points any S3 traffic to the new endpoint.
7. For Policy, choose Full Access to allow full access to the S3 service by any user or service within the VPC. Choose Custom to restrict access further. For information, see Use a Custom Endpoint Policy to Restrict Access to S3 (p. 3649).

Use a Custom Endpoint Policy to Restrict Access to S3

The default endpoint policy allows full access to S3 for any user or service in your VPC. To further restrict access to S3, create a custom endpoint policy. For more information, see Using Endpoint Policies for Amazon S3. You can also use a bucket policy to restrict access to your S3 buckets to only traffic that comes from your Amazon VPC. For information, see Using Amazon S3 Bucket Policies. The following is a sample customized policy:

```json

```
Give SageMaker Access to Resources in your Amazon VPC

Add Permissions for Compilation Job Running in a Amazon VPC to Custom IAM Policies

The SageMakerFullAccess managed policy includes the permissions that you need to use models configured for Amazon VPC access with an endpoint. These permissions allow SageMaker Neo to create an elastic network interface and attach it to compilation job running in a Amazon VPC. If you use your own IAM policy, you must add the following permissions to that policy to use models configured for Amazon VPC access.

```
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Action": [
        "ec2:DescribeVpcEndpoints",
        "ec2:DescribeDhcpOptions",
        "ec2:DescribeVpcs",
        "ec2:DescribeSubnets",
        "ec2:DescribeSecurityGroups",
        "ec2:DescribeNetworkInterfaces",
        "ec2:DeleteNetworkInterfacePermission",
        "ec2:DeleteNetworkInterface",
        "ec2:CreateNetworkInterfacePermission",
        "ec2:CreateNetworkInterface",
        "ec2:ModifyNetworkInterfaceAttribute"
      ],
      "Resource": "*
    }
  ]
}
```

For more information about the SageMakerFullAccess managed policy, see AWS managed policy: AmazonSageMakerFullAccess (p. 3572).

Configure Route Tables

Use default DNS settings for your endpoint route table, so that standard Amazon S3 URLs (for example, http://s3-aws-region.amazonaws.com/MyBucket) resolve. If you don't use default DNS settings, ensure that the URLs that you use to specify the locations of the data in your compilation jobs resolve by configuring the endpoint route tables. For information about VPC endpoint route tables, see Routing for Gateway Endpoints in the Amazon VPC User Guide.
Configure the VPC Security Group

In your security group for the compilation job, you must allow outbound communication to your Amazon S3 Amazon VPC endpoints and the subnet CIDR ranges used for the compilation job. For information, see Security Group Rules and Control access to services with Amazon VPC endpoints.
Monitor Amazon SageMaker

Monitoring is an important part of maintaining the reliability, availability, and performance of SageMaker and your other AWS solutions. AWS provides the following monitoring tools to watch SageMaker, report when something is wrong, and take automatic actions when appropriate:

- **Amazon CloudWatch** monitors your AWS resources and the applications that you run on AWS in real time. You can collect and track metrics, create customized dashboards, and set alarms that notify you or take actions when a specified metric reaches a threshold that you specify. For example, you can have CloudWatch track CPU usage or other metrics of your Amazon EC2 instances and automatically launch new instances when needed. For more information, see the [Amazon CloudWatch User Guide](#).

- **Amazon CloudWatch Logs** enables you to monitor, store, and access your log files from EC2 instances, AWS CloudTrail, and other sources. CloudWatch Logs can monitor information in the log files and notify you when certain thresholds are met. You can also archive your log data in highly durable storage. For more information, see the [Amazon CloudWatch Logs User Guide](#).

- **AWS CloudTrail** captures API calls and related events made by or on behalf of your AWS account and delivers the log files to an Amazon S3 bucket that you specify. You can identify which users and accounts called AWS, the source IP address from which the calls were made, and when the calls occurred. For more information, see the [AWS CloudTrail User Guide](#).

- **CloudWatch Events** delivers a near real-time stream of system events that describe changes in AWS resources. Create CloudWatch Events rules react to a status change in a SageMaker training, hyperparameter tuning, or batch transform job

Topics

- Monitor Amazon SageMaker with Amazon CloudWatch (p. 3663)
- Log Amazon SageMaker Events with Amazon CloudWatch (p. 3675)
- Log Amazon SageMaker API Calls with AWS CloudTrail (p. 3676)
- Monitoring user resource access from Amazon SageMaker Studio (p. 3679)
- Automating Amazon SageMaker with Amazon EventBridge (p. 3681)

Monitor Amazon SageMaker with Amazon CloudWatch

You can monitor Amazon SageMaker using Amazon CloudWatch, which collects raw data and processes it into readable, near real-time metrics. These statistics are kept for 15 months, so that you can access historical information and gain a better perspective on how your web application or service is performing. However, the Amazon CloudWatch console limits the search to metrics that were updated in the last 2 weeks. This limitation ensures that the most current jobs are shown in your namespace. To graph metrics without using a search, specify its exact name in the source view. You can also set alarms that watch for certain thresholds, and send notifications or take actions when those thresholds are met. For more information, see the [Amazon CloudWatch User Guide](#).

SageMaker Metrics and Dimensions

- SageMaker Endpoint Invocation Metrics (p. 3664)
- SageMaker Multi-Model Endpoint Metrics (p. 3665)
- SageMaker Jobs and Endpoint Metrics (p. 3667)
- SageMaker Ground Truth Metrics (p. 3670)
SageMaker Endpoint Invocation Metrics

The AWS/SageMaker namespace includes the following request metrics from calls to `InvokeEndpoint`. Metrics are available at a 1-minute frequency.

For information about how long CloudWatch metrics are retained for, see `GetMetricStatistics` in the Amazon CloudWatch API Reference.

### Endpoint Invocation Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Invocation4XXErrors</td>
<td>The number of <code>InvokeEndpoint</code> requests where the model returned a 4xx HTTP response code. For each 4xx response, 1 is sent; otherwise, 0 is sent.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>Invocation5XXErrors</td>
<td>The number of <code>InvokeEndpoint</code> requests where the model returned a 5xx HTTP response code. For each 5xx response, 1 is sent; otherwise, 0 is sent.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>Invocations</td>
<td>The number of <code>InvokeEndpoint</code> requests sent to a model endpoint.</td>
</tr>
<tr>
<td></td>
<td>To get the total number of requests sent to a model endpoint, use the Sum statistic.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>InvocationsPerInstance</td>
<td>The number of invocations sent to a model, normalized by <code>InstanceCount</code> in each ProductionVariant. 1/<code>numberOfInstances</code> is sent as the value on each request, where <code>numberOfInstances</code> is the number of active instances for the ProductionVariant behind the endpoint at the time of the request.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum</td>
</tr>
<tr>
<td>ModelLatency</td>
<td>The interval of time taken by a model to respond as viewed from SageMaker. This interval includes the local communication times taken to send the request and to fetch the response from the container of a model and the time taken to complete the inference in the container.</td>
</tr>
<tr>
<td></td>
<td>Units: Microseconds</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
</tbody>
</table>
| OverheadLatency      | The interval of time added to the time taken to respond to a client request by SageMaker overheads. This interval is measured from the time SageMaker
Multi-Model Endpoint Metrics

### Metric Description

**Metric**: ModelLatency

- **Description**: The interval of time that an invocation request has waited for the target model to be downloaded, or loaded, or both in order to perform inference.

- **Units**: Microseconds

- **Valid statistics**: Average, Sum, Min, Max, Sample Count

**Metric**: ModelSetupTime

- **Description**: The time it takes to launch new compute resources for a serverless endpoint.

- **Units**: Microseconds

- **Valid statistics**: Average, Min, Max, Sample Count, Percentiles

**Dimensions for Endpoint Invocation Metrics**

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EndpointName,</td>
<td>Filters endpoint invocation metrics for a ProductionVariant of the</td>
</tr>
<tr>
<td>VariantName</td>
<td>specified endpoint and variant.</td>
</tr>
</tbody>
</table>

### SageMaker Multi-Model Endpoint Metrics

The AWS/SageMaker namespace includes the following model loading metrics from calls to `InvokeEndpoint`.

- **Metrics are available at a 1-minute frequency.**

For information about how long CloudWatch metrics are retained for, see `GetMetricStatistics` in the *Amazon CloudWatch API Reference*.

**Multi-Model Endpoint Model Loading Metrics**

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ModelLoadingWaitTime</td>
<td>The interval of time that an invocation request has waited for the target</td>
</tr>
<tr>
<td></td>
<td>model to be downloaded, or loaded, or both in order to perform inference.</td>
</tr>
<tr>
<td></td>
<td><strong>Units</strong>: Microseconds</td>
</tr>
<tr>
<td></td>
<td><strong>Valid statistics</strong>: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>ModelUnloadingTime</td>
<td>The interval of time that it took to unload the model through the container's</td>
</tr>
<tr>
<td></td>
<td>UnloadModel API call.</td>
</tr>
<tr>
<td></td>
<td><strong>Units</strong>: Microseconds</td>
</tr>
<tr>
<td></td>
<td><strong>Valid statistics</strong>: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>ModelDownloadingTime</td>
<td>The interval of time that it took to download the model from Amazon Simple</td>
</tr>
<tr>
<td></td>
<td>Storage Service (Amazon S3).</td>
</tr>
</tbody>
</table>
### Multi-Model Endpoint Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ModelLoadingTime</td>
<td>The interval of time that it took to load the model through the container's LoadModel API call.</td>
</tr>
<tr>
<td></td>
<td>Units: Microseconds</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
<tr>
<td>ModelCacheHit</td>
<td>The number of InvokeEndpoint requests sent to the multi-model endpoint for which the model was already loaded.</td>
</tr>
<tr>
<td></td>
<td>The Average statistic shows the ratio of requests for which the model was already loaded.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum, Sample Count</td>
</tr>
</tbody>
</table>

### Dimensions for Multi-Model Endpoint Model Loading Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EndpointName, VariantName</td>
<td>Filters endpoint invocation metrics for a ProductionVariant of the specified endpoint and variant.</td>
</tr>
</tbody>
</table>

The /aws/sagemaker/Endpoints namespaces include the following instance metrics from calls to InvokeEndpoint.

Metrics are available at a 1-minute frequency.

For information about how long CloudWatch metrics are retained for, see GetMetricStatistics in the Amazon CloudWatch API Reference.

### Multi-Model Endpoint Model Instance Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>LoadedModelCount</td>
<td>The number of models loaded in the containers of the multi-model endpoint. This metric is emitted per instance.</td>
</tr>
<tr>
<td></td>
<td>The Average statistic with a period of 1 minute tells you the average number of models loaded per instance.</td>
</tr>
<tr>
<td></td>
<td>The Sum statistic tells you the total number of models loaded across all instances in the endpoint.</td>
</tr>
<tr>
<td></td>
<td>The models that this metric tracks are not necessarily unique because a model might be loaded in multiple containers at the endpoint.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
</tbody>
</table>
Dimensions for Multi-Model Endpoint Model Loading Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EndpointName,</td>
<td>Filters endpoint invocation metrics for a ProductionVariant of the</td>
</tr>
<tr>
<td>VariantName</td>
<td>specified endpoint and variant.</td>
</tr>
</tbody>
</table>

SageMaker Jobs and Endpoint Metrics

The /aws/sagemaker/ProcessingJobs, /aws/sagemaker/TrainingJobs, /aws/sagemaker/TransformJobs, and /aws/sagemaker/Endpoints namespaces include the following metrics for the training jobs and endpoint instances.

Metrics are available at a 1-minute frequency.

**Note**
Amazon CloudWatch supports high-resolution custom metrics and its finest resolution is 1 second. However, the finer the resolution, the shorter the lifespan of the CloudWatch metrics. For the 1-second frequency resolution, the CloudWatch metrics are available for 3 hours. For more information about the resolution and the lifespan of the CloudWatch metrics, see GetMetricStatistics in the Amazon CloudWatch API Reference.

**Tip**
If you want to profile your training job with a finer resolution down to 100-millisecond (0.1 second) granularity and store the training metrics indefinitely in Amazon S3 for custom analysis at any time, consider using Amazon SageMaker Debugger. SageMaker Debugger provides built-in rules to automatically detect common training issues; it detects hardware resource utilization issues (such as CPU, GPU, and I/O bottlenecks) and non-converging model issues (such as overfit, vanishing gradients, and exploding tensors). SageMaker Debugger also provides visualizations through Studio and its profiling report. To explore the Debugger visualizations, see SageMaker Debugger Insights Dashboard Walkthrough, Debugger Profiling Report Walkthrough, and Analyze Data Using the SMDebug Client Library.

Processing Job, Training Job, Batch Transform Job, and Endpoint Instance Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPUUtilization</td>
<td>The sum of each individual CPU core's utilization. The CPU utilization of</td>
</tr>
<tr>
<td></td>
<td>each core range is 0–100. For example, if there are four CPUs, the</td>
</tr>
<tr>
<td></td>
<td>CPUUtilization range is 0%–400%. For processing jobs, the value is the</td>
</tr>
<tr>
<td></td>
<td>CPU utilization of the processing container on the instance.</td>
</tr>
<tr>
<td></td>
<td>For training jobs, the value is the CPU utilization of the algorithm</td>
</tr>
<tr>
<td></td>
<td>container on the instance.</td>
</tr>
<tr>
<td></td>
<td>For batch transform jobs, the value is the CPU utilization of the transform</td>
</tr>
<tr>
<td></td>
<td>container on the instance.</td>
</tr>
<tr>
<td></td>
<td>For endpoint variants, the value is the sum of the CPU utilization of the</td>
</tr>
<tr>
<td></td>
<td>primary and supplementary containers on the instance.</td>
</tr>
<tr>
<td></td>
<td><strong>Note</strong> For multi-instance jobs, each instance reports CPU utilization</td>
</tr>
<tr>
<td></td>
<td>metrics. However, the default view in CloudWatch shows the average CPU</td>
</tr>
<tr>
<td></td>
<td>utilization across all instances.</td>
</tr>
</tbody>
</table>

Units: Percent
<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MemoryUtilization</td>
<td>The percentage of memory that is used by the containers on an instance. This value range is 0%–100%. For processing jobs, the value is the memory utilization of the processing container on the instance. For training jobs, the value is the memory utilization of the algorithm container on the instance. For batch transform jobs, the value is the memory utilization of the transform container on the instance. For endpoint variants, the value is the sum of the memory utilization of the primary and supplementary containers on the instance. Units: Percent</td>
</tr>
<tr>
<td>GPUUtilization</td>
<td>The percentage of GPU units that are used by the containers on an instance. The value can range between 0%–100% and is multiplied by the number of GPUs. For example, if there are four GPUs, the GPUUtilization range is 0%–400%. For processing jobs, the value is the GPU utilization of the processing container on the instance. For training jobs, the value is the GPU utilization of the algorithm container on the instance. For batch transform jobs, the value is the GPU utilization of the transform container on the instance. For endpoint variants, the value is the sum of the GPU utilization of the primary and supplementary containers on the instance. Units: Percent</td>
</tr>
</tbody>
</table>

**Note**
For multi-instance jobs, each instance reports memory utilization metrics. However, the default view in CloudWatch shows the average memory utilization across all instances.

For multi-instance jobs, each instance reports GPU utilization metrics. However, the default view in CloudWatch shows the average GPU utilization across all instances.
<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPUMemoryUtilization</td>
<td>The percentage of GPU memory used by the containers on an instance. The value range is 0–100 and is multiplied by the number of GPUs. For example, if there are four GPUs, the GPUMemoryUtilization range is 0%–400%. For processing jobs, the value is the GPU memory utilization of the processing container on the instance. For training jobs, the value is the GPU memory utilization of the algorithm container on the instance. For batch transform jobs, the value is the GPU memory utilization of the transform container on the instance. For endpoint variants, the value is the sum of the GPU memory utilization of the primary and supplementary containers on the instance. Note For multi-instance jobs, each instance reports GPU memory utilization metrics. However, the default view in CloudWatch shows the average GPU memory utilization across all instances. Units: Percent</td>
</tr>
<tr>
<td>DiskUtilization</td>
<td>The percentage of disk space used by the containers on an instance uses. This value range is 0%–100%. This metric is not supported for batch transform jobs. For processing jobs, the value is the disk space utilization of the processing container on the instance. For training jobs, the value is the disk space utilization of the algorithm container on the instance. For endpoint variants, the value is the sum of the disk space utilization of the primary and supplementary containers on the instance. Units: Percent Note For multi-instance jobs, each instance reports disk utilization metrics. However, the default view in CloudWatch shows the average disk utilization across all instances.</td>
</tr>
</tbody>
</table>

Dimensions for Processing Job, Training Job and Batch Transform Job Instance Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Host</td>
<td>For processing jobs, the value for this dimension has the format [processing-job-name]/algo-[instance-number-in-cluster]. Use this dimension to filter instance metrics for the specified processing job and instance. This dimension format is present only in the /aws/sagemaker/ProcessingJobs namespace. For training jobs, the value for this dimension has the format [training-job-name]/algo-[instance-number-in-cluster]. Use this dimension to filter instance metrics for the specified training job and instance. This dimension format is present only in the /aws/sagemaker/TrainingJobs namespace.</td>
</tr>
</tbody>
</table>
Amazon SageMaker Developer Guide

Ground Truth Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>For batch transform jobs, the value for this dimension has the format [transform-job-name]/[instance-id]. Use this dimension to filter instance metrics for the specified batch transform job and instance. This dimension format is present only in the /aws/sagemaker/TransformJobs namespace.</td>
<td></td>
</tr>
</tbody>
</table>

### SageMaker Ground Truth Metrics

**Ground Truth Metrics**

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
</table>
| **ActiveWorkers** | A single active worker on a private work team submitted, released, or declined a task. To get the total number of active workers, use the Sum statistic. Ground Truth attempts to deliver each individual ActiveWorkers event once. If this delivery is unsuccessful, this metric may not report the total number of active workers.  
Units: None  
Valid statistics: Sum, Sample Count |
| **DatasetObjectsAutoAnnotated** | The number of dataset objects auto-annotated in a labeling job. This metric is only emitted when automated labeling is enabled. To view the labeling job progress, use the Max metric.  
Units: None  
Valid statistics: Max |
| **DatasetObjectsHumanAnnotated** | The number of dataset objects annotated by a human in a labeling job. To view the labeling job progress, use the Max metric.  
Units: None  
Valid statistics: Max |
| **DatasetObjectsLabelingFailed** | The number of dataset objects that failed labeling in a labeling job. To view the labeling job progress, use the Max metric.  
Units: None  
Valid statistics: Max |
| **JobsFailed** | A single labeling job failed. To get the total number of labeling jobs that failed, use the Sum statistic.  
Units: None  
Valid statistics: Sum, Sample Count |
| **JobsSucceeded** | A single labeling job succeeded. To get the total number of labeling jobs that succeeded, use the Sum statistic.  
Units: None |
<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>JobsStopped</td>
<td>A single labeling job was stopped. To get the total number of labeling jobs that were stopped, use the Sum statistic.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum, Sample Count</td>
</tr>
<tr>
<td>TasksAccepted</td>
<td>A single task was accepted by a worker. To get the total number of tasks accepted by workers, use the Sum statistic. Ground Truth attempts to deliver each individual TaskAccepted event once. If this delivery is unsuccessful, this metric may not report the total number of tasks accepted.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum, Sample Count</td>
</tr>
<tr>
<td>TasksDeclined</td>
<td>A single task was declined by a worker. To get the total number of tasks declined by workers, use the Sum statistic. Ground Truth attempts to deliver each individual TasksDeclined event once. If this delivery is unsuccessful, this metric may not report the total number of tasks declined.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum, Sample Count</td>
</tr>
<tr>
<td>TasksReturned</td>
<td>A single task was returned. To get the total number of tasks returned, use the Sum statistic. Ground Truth attempts to deliver each individual TasksReturned event once. If this delivery is unsuccessful, this metric may not report the total number of tasks returned.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum, Sample Count</td>
</tr>
<tr>
<td>TasksSubmitted</td>
<td>A single task was submitted/completed by a private worker. To get the total number of tasks submitted by workers, use the Sum statistic. Ground Truth attempts to deliver each individual TasksSubmitted event once. If this delivery is unsuccessful, this metric may not report the total number of tasks submitted.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum, Sample Count</td>
</tr>
<tr>
<td>TimeSpent</td>
<td>Time spent on a task completed by a private worker. This metric does not include time when a worker paused or took a break. Ground Truth attempts to deliver each TimeSpent event once. If this delivery is unsuccessful, this metric may not report the total amount of time spent.</td>
</tr>
<tr>
<td></td>
<td>Units: Seconds</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Sum, Sample Count</td>
</tr>
</tbody>
</table>
### Metric Description

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>TotalDatasetObjectsLabeled</td>
<td>The number of dataset objects labeled successfully in a labeling job. To view the labeling job progress, use the Max metric.</td>
</tr>
<tr>
<td>Units: None</td>
<td>Valid statistics: Max</td>
</tr>
</tbody>
</table>

### Dimensions for Dataset Object Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>LabelingJobName</td>
<td>Filters dataset object count metrics for a labeling job.</td>
</tr>
</tbody>
</table>

### Amazon SageMaker Feature Store Metrics

#### Feature Store Consumption Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ConsumedReadRequestsUnits</td>
<td>The number of consumed read units over the specified time period. You can retrieve the consumed read units for a feature store runtime operation and its corresponding feature group.</td>
</tr>
<tr>
<td>Units: None</td>
<td>Valid statistics: All</td>
</tr>
<tr>
<td>ConsumedWriteRequestsUnits</td>
<td>The number of consumed write units over the specified time period. You can retrieve the consumed write units for a feature store runtime operation and its corresponding feature group.</td>
</tr>
<tr>
<td>Units: None</td>
<td>Valid statistics: All</td>
</tr>
</tbody>
</table>

### Dimensions for Feature Store Consumption Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>FeatureGroupName, OperationName</td>
<td>Filters feature store runtime consumption metrics of the feature group and the operation that you've specified.</td>
</tr>
</tbody>
</table>

#### Feature Store Operational Metrics

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Invocations</td>
<td>The number of requests made to the feature store runtime operations over the specified time period.</td>
</tr>
<tr>
<td>Units: None</td>
<td></td>
</tr>
<tr>
<td>Metric</td>
<td>Description</td>
</tr>
<tr>
<td>---------------------</td>
<td>-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Operation4XXErrors</td>
<td>The number of requests made to the Feature Store runtime operations where the operation returned a 4xx HTTP response code. For each 4xx response, 1 is sent; otherwise, 0 is sent.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>Operation5XXErrors</td>
<td>The number of requests made to the feature store runtime operations where the operation returned a 5xx HTTP response code. For each 5xx response, 1 is sent; otherwise, 0 is sent.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>ThrottledRequests</td>
<td>The number of requests made to the feature store runtime operations where the request got throttled. For each throttled request, 1 is sent; otherwise, 0 is sent.</td>
</tr>
<tr>
<td></td>
<td>Units: None</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>Latency</td>
<td>The time interval to process requests made to the Feature Store runtime operations. This interval is measured from the time SageMaker receives the request until it returns a response to the client.</td>
</tr>
<tr>
<td></td>
<td>Units: Microseconds</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count, Percentiles</td>
</tr>
</tbody>
</table>

**Dimensions for Feature Store Operational Metrics**

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>FeatureGroupName, OperationName</td>
<td>Filters feature store runtime operational metrics of the feature group and the operation that you've specified. You can use these dimensions for non batch operations, such as GetRecord, PutRecord, and DeleteRecord.</td>
</tr>
<tr>
<td>OperationName</td>
<td>Filters feature store runtime operational metrics for the operation that you've specified. You can use this dimension for batch operations such as BatchGetRecord.</td>
</tr>
</tbody>
</table>

**SageMaker Pipelines Metrics**

The AWS/Sagemaker/ModelBuildingPipeline namespace includes the following metrics for pipeline executions.

Two categories of Pipelines execution metrics are available:

- **Execution Metrics across All Pipelines** – Account level pipeline execution metrics (for all pipelines in the current account)
• **Execution Metrics by Pipeline** – Pipeline execution metrics per pipeline

Metrics are available at a 1-minute frequency.

**Pipelines Execution Metrics**

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ExecutionStarted</td>
<td>The number of pipeline executions that started.</td>
</tr>
<tr>
<td></td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>ExecutionFailed</td>
<td>The number of pipeline executions that failed.</td>
</tr>
<tr>
<td></td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>ExecutionSucceeded</td>
<td>The number of pipeline executions that succeeded.</td>
</tr>
<tr>
<td></td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>ExecutionStopped</td>
<td>The number of pipeline executions that stopped.</td>
</tr>
<tr>
<td></td>
<td>Units: Count</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>ExecutionDuration</td>
<td>The duration in milliseconds that the pipeline execution ran.</td>
</tr>
<tr>
<td></td>
<td>Units: Milliseconds</td>
</tr>
<tr>
<td></td>
<td>Valid statistics: Average, Sum Min Max Sample Count</td>
</tr>
</tbody>
</table>

**Dimensions for Execution Metrics by Pipeline**

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PipelineName</td>
<td>Filters pipeline execution metrics for a specified pipeline.</td>
</tr>
</tbody>
</table>

**Pipelines Step Metrics**

The AWS/Sagemaker/ModelBuildingPipeline namespace includes the following metrics for pipeline steps.

Metrics are available at a 1-minute frequency.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>StepStarted</td>
<td>The number of steps that started.</td>
</tr>
<tr>
<td></td>
<td>Units: Count</td>
</tr>
</tbody>
</table>
### Metric Description

<table>
<thead>
<tr>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>StepFailed</td>
<td>The number of steps that failed.</td>
</tr>
<tr>
<td>Units: Count</td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>StepSucceeded</td>
<td>The number of steps that succeeded.</td>
</tr>
<tr>
<td>Units: Count</td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>StepStopped</td>
<td>The number of steps that stopped.</td>
</tr>
<tr>
<td>Units: Count</td>
<td>Valid statistics: Average, Sum</td>
</tr>
<tr>
<td>StepDuration</td>
<td>The duration in milliseconds that the step ran.</td>
</tr>
<tr>
<td>Units: Milliseconds</td>
<td>Valid statistics: Average, Sum, Min, Max, Sample Count</td>
</tr>
</tbody>
</table>

### Dimensions for Pipelines Step Metrics

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>PipelineName</td>
<td>Filters step metrics for a specified pipeline and step.</td>
</tr>
<tr>
<td>StepName</td>
<td>Filters step metrics for a specified pipeline and step.</td>
</tr>
</tbody>
</table>

---

**Log Amazon SageMaker Events with Amazon CloudWatch**

To help you debug your compilation jobs, processing jobs, training jobs, endpoints, transform jobs, notebook instances, and notebook instance lifecycle configurations, anything an algorithm container, a model container, or a notebook instance lifecycle configuration sends to `stdout` or `stderr` is also sent to Amazon CloudWatch Logs. In addition to debugging, you can use these for progress analysis.

**Logs**

The following table lists all of the logs provided by Amazon SageMaker.

<table>
<thead>
<tr>
<th>Log Group Name</th>
<th>Log Stream Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>/aws/sagemaker/CompilationJobs</td>
<td>[compilation-job-name]</td>
</tr>
</tbody>
</table>
## Log Group Name | Log Stream Name
---|---
/aws/sagemaker/Endpoints/[EndpointName] | [production-variant-name]/[instance-id]
/aws/sagemaker/groundtruth/WorkerActivity | aws/sagemaker/groundtruth/worker-activity/[requester-AWS-Id]-[region]/[timestamp]
/aws/sagemaker/LabelingJobs | [labeling-job-name]
/aws/sagemaker/NotebookInstances | [notebook-instance-name]/[LifecycleConfigHook]
/aws/sagemaker/NotebookInstances | [notebook-instance-name]/jupyter.log
/aws/sagemaker/ProcessingJobs | [processing-job-name]/[hostname]-[epoch_timestamp]
/aws/sagemaker/studio | [domain-id]/[user-profile-name]/[app-type]/[app-name]
/aws/sagemaker/studio | [domain-id]/domain-shared/rstudioserverpro/default
/aws/sagemaker/TrainingJobs | [training-job-name]/algo-[instance-number-in-cluster]-[epoch_timestamp]
/aws/sagemaker/TransformJobs | [transform-job-name]/[instance-id]-[epoch_timestamp]
/aws/sagemaker/TransformJobs | [transform-job-name]/[instance-id]-[epoch_timestamp]/data-log
/aws/sagemaker/TransformJobs | [transform-job-name]/[instance-id]-[epoch_timestamp]/[container-name provided in SageMaker model] (For Inference Pipelines)

**Note**
1. The /aws/sagemaker/NotebookInstances/[LifecycleConfigHook] log stream is created when you create a notebook instance with a lifecycle configuration. For more information, see Customize a Notebook Instance Using a Lifecycle Configuration Script (p. 299).
2. For Inference Pipelines, if you don’t provide container names, the platform uses **container-1, container-2**, and so on, corresponding to the order provided in the SageMaker model.

For more information about logging events with CloudWatch logging, see [What is Amazon CloudWatch Logs?](https://docs.aws.amazon.com/AmazonCloudWatch/latest/logs/log_group_and_stream_names.html) in the *Amazon CloudWatch User Guide*.

---

**Log Amazon SageMaker API Calls with AWS CloudTrail**

Amazon SageMaker is integrated with AWS CloudTrail, a service that provides a record of actions taken by a user, role, or an AWS service in SageMaker. CloudTrail captures all API calls for SageMaker, with the exception of `InvokeEndpoint` and `InvokeEndpointAsync`, as events. The calls captured include calls from the SageMaker console and code calls to the SageMaker API operations. If you create a trail, you can enable continuous delivery of CloudTrail events to an Amazon S3 bucket, including events for
SageMaker. If you don't configure a trail, you can still view the most recent events in the CloudTrail console in **Event history**. Using the information collected by CloudTrail, you can determine the request that was made to SageMaker, the IP address from which the request was made, who made the request, when it was made, and additional details.

To learn more about CloudTrail, see the [AWS CloudTrail User Guide](https://docs.aws.amazon.com/AmazonCloudWatch/latest/monitoring/aws-cloud-trail.html).

By default, log data is stored in CloudWatch Logs indefinitely. However, you can configure how long to store log data in a log group. For information, see [Change Log Data Retention in CloudWatch Logs](https://docs.aws.amazon.com/AmazonCloudWatch/latest/logs/retention-change-log.html) in the Amazon CloudWatch Logs User Guide.

### SageMaker Information in CloudTrail

CloudTrail is enabled on your AWS account when you create the account. When activity occurs in Amazon SageMaker, that activity is recorded in a CloudTrail event along with other AWS service events in **Event history**. You can view, search, and download recent events in your AWS account. For more information, see [Viewing Events with CloudTrail Event History](https://docs.aws.amazon.com/AmazonCloudWatch/latest/logs/cloudtrail-view-events.html).

For an ongoing record of events in your AWS account, including events for Amazon SageMaker, create a trail. A **trail** enables CloudTrail to deliver log files to an Amazon S3 bucket. By default, when you create a trail in the console, the trail applies to all AWS Regions. The trail logs events from all Regions in the AWS partition and delivers the log files to the Amazon S3 bucket that you specify. Additionally, you can configure other AWS services to further analyze and act upon the event data collected in CloudTrail logs. For more information, see the following:

- **Overview for Creating a Trail**
- **CloudTrail Supported Services and Integrations**
- **Configuring Amazon SNS Notifications for CloudTrail**
- **Receiving CloudTrail Log Files from Multiple Regions** and **Receiving CloudTrail Log Files from Multiple Accounts**

All SageMaker actions, with the exception of **InvokeEndpoint** and **InvokeEndpointAsync**, are logged by CloudTrail and are documented in the **Operations**. For example, calls to the **CreateTrainingJob**, **CreateEndpoint** and **CreateNotebookInstance** actions generate entries in the CloudTrail log files.

Every event or log entry contains information about who generated the request. The identity information helps you determine the following:

- Whether the request was made with root or AWS Identity and Access Management (IAM) user credentials.
- Whether the request was made with temporary security credentials for a role or federated user.
- Whether the request was made by another AWS service.

For more information, see the [CloudTrail userIdentity Element](https://docs.aws.amazon.com/AmazonCloudWatch/latest/logs/cloudtrail-view-events.html).

### Operations Performed by Automatic Model Tuning

SageMaker supports logging non-API service events to your CloudTrail log files for automatic model tuning jobs. These events are related to your tuning jobs but, are not the direct result of a customer request to the public AWS API. For example, when you create a hyperparameter tuning job by calling **CreateHyperParameterTuningJob**, SageMaker creates training jobs to evaluate various combinations of hyperparameters to find the best result. Similarly, when you call **StopHyperParameterTuningJob** to stop a hyperparameter tuning job, SageMaker might stop any of the associated running training...
jobs. Non-API events for your tuning jobs are logged to CloudTrail to help you improve governance, compliance, and operational and risk auditing of your AWS account.

Log entries that result from non-API service events have an eventType of AwsServiceEvent instead of AwsApiCall.

Understanding SageMaker Log File Entries

A trail is a configuration that enables delivery of events as log files to an S3 bucket that you specify. CloudTrail log files contain one or more log entries. An event represents a single request from any source and includes information about the requested action, the date and time of the action, request parameters, and so on. CloudTrail log files are not an ordered stack trace of the public API calls, so they do not appear in any specific order.

The following examples a log entry for the CreateEndpoint action, which creates an endpoint to deploy a trained model.

```json
{
  "eventVersion": "1.05",
  "userIdentity": {
    "type": "IAMUser",
    "principalId": "AIXDAYQEXAMPLEUMLYNGL",
    "arn": "arn:aws:iam::123456789012:user:intern",
    "accountId": "123456789012",
    "accessKeyId": "ASXIAGXEXAMPLEQULKNXV",
    "userName": "intern"
  },
  "eventTime": "2018-01-02T13:39:06Z",
  "eventSource": "sagemaker.amazonaws.com",
  "eventName": "CreateEndpoint",
  "awsRegion": "us-west-2",
  "sourceIPAddress": "127.0.0.1",
  "userAgent": "USER_AGENT",
  "requestParameters": {
    "endpointName": "ExampleEndpoint",
    "endpointConfigName": "ExampleEndpointConfig"
  },
  "responseElements": {
    "endpointArn": "arn:aws:sagemaker:us-west-2:123456789012:endpoint/exampleendpoint"
  },
  "requestID": "6b1b42b9-EXAMPLE",
  "eventID": "a6f85b21-EXAMPLE",
  "eventType": "AwsApiCall",
  "recipientAccountId": "444455556666"
}
```

The following example is a log entry for the CreateModel action, which creates one or more containers to host a previously trained model.

```json
{
  "eventVersion": "1.05",
  "userIdentity": {
    "type": "IAMUser",
    "principalId": "AIXDAYQEXAMPLEUMLYNGL",
    "arn": "arn:aws:iam::123456789012:user:intern",
    "accountId": "123456789012",
    "accessKeyId": "ASXIAGXEXAMPLEQULKNXV",
    "userName": "intern"
  },
  "eventTime": "2018-01-02T15:23:46Z",
  "eventSource": "sagemaker.amazonaws.com",
  "eventName": "CreateModel",
  "awsRegion": "us-west-2",
  "sourceIPAddress": "127.0.0.1",
  "userAgent": "USER_AGENT",
  "requestParameters": {
    "modelName": "ExampleModel",
    "convertToModelPackage": "true"
  },
  "responseElements": {
    "modelArn": "arn:aws:sagemaker:us-west-2:123456789012:model/examplemodel"
  },
  "requestID": "6b1b42b9-EXAMPLE",
  "eventID": "a6f85b21-EXAMPLE",
  "eventType": "AwsApiCall",
  "recipientAccountId": "444455556666"
}
```
Amazon SageMaker Developer Guide
Monitoring user resource access from Amazon SageMaker Studio

Monitoring user resource access from Amazon SageMaker Studio

With Amazon SageMaker Studio, you can monitor user resource access. To view resource access activity, you can configure AWS CloudTrail to monitor and record user activities by following the steps in Log Amazon SageMaker API Calls with AWS CloudTrail.

However, the AWS CloudTrail logs for resource access only list the Studio execution IAM role as the identifier. This level of logging is enough to audit user activity when each user profile has a distinct execution role. However, when a single execution IAM role is shared between several user profiles, you can't get information about the specific user that accessed the AWS resources.

You can get information about which specific user performed an action in an AWS CloudTrail log when using a shared execution role, using the `sourceIdentity` configuration to propagate the Studio user profile name. For more information about source identity, see Monitor and control actions taken with assumed roles.

Prerequisites

- Install and configure the AWS Command Line Interface following the steps in Installing or updating the latest version of the AWS CLI.
- Ensure that Studio users in your domain don't have a policy that allows them to update or modify the Studio domain.
- All execution roles must have the following trust policy permissions:
  - Any role that the Studio domain's execution role assumes must have the `sts:SetSourceIdentity` permission in the trust policy as follows.

```json
{
  "Version": "2012-10-17",
  "Statement": [
    {
      "Effect": "Allow",
      "Principal": {
        "Service": "sagemaker.amazonaws.com"
      },
      "Action": "sts:AssumeRoleWithWebIdentity"
    }
  ]
}
```
When you assume a role with another role, called role chaining, do the following:

- Permissions for sts:SetSourceIdentity are required in both the permissions policy of the principal that is assuming the role, and in the role trust policy of the target role. Otherwise, the assume role operation will fail.
- This role chaining can happen in Studio or any other downstream service, such as Amazon EMR. For more information about role chaining, see Roles terms and concepts.

Enable sourceIdentity

The ability to propagate the user profile name as the sourceIdentity in Studio is turned off by default.

To enable the ability to propagate the user profile name as the sourceIdentity, use the AWS CLI during domain creation and domain update. This feature is enabled at the domain level and not at the user profile level.

After you enable this configuration, administrators can view the user profile in the AWS CloudTrail log for the service accessed. The user profile is given as the sourceIdentity value in the userIdentity section. For more information about using AWS CloudTrail logs with SageMaker, see Log Amazon SageMaker API Calls with AWS CloudTrail.

You can use the following code to enable the propagation of the user profile name as the sourceIdentity during domain creation using the create-domain API.

```
create-domain
--domain-name <value>
--auth-mode <value>
--default-user-settings <value>
--subnet-ids <value>
--vpc-id <value>
[--tags <value>]
[--app-network-access-type <value>]
[--home-efs-file-system-kms-key-id <value>]
[--kms-key-id <value>]
[--app-security-group-management <value>]
[--domain-settings "ExecutionRoleIdentityConfig=USER_PROFILE_NAME"]
[--cli-input-json <value>]
[--generate-cli-skeleton <value>]
```

You can enable the propagation of the user profile name as the sourceIdentity during domain update using the update-domain API.

To update this configuration, all apps in the domain must be in the Stopped or Deleted state. For more information about how to stop and shut down apps, see Shut down and Update Studio Apps.

Use the following code to enable the propagation of the user profile name as the sourceIdentity.

```
update-domain
```
Turn off sourceIdentity

You can also turn off the propagation of the user profile name as the sourceIdentity using the AWS CLI. This occurs during domain update by passing the DISABLED value for the --role-session-context-config parameter as part of the update-domain API call.

**Note**
To update this configuration, all apps in the domain must be in the Stopped or Deleted state. For more information about how to stop and shut down apps, see Shut down and Update Studio Apps.

In the AWS CLI, use the following code to disable the propagation of the user profile name as the sourceIdentity.

```
update-domain
  --domain-id <value>
  [--default-user-settings <value>]
  [--domain-settings-for-update "ExecutionRoleIdentityConfig=DISABLED"]
  [--cli-input-json <value>]
  [--generate-cli-skeleton <value>]
```

Automating Amazon SageMaker with Amazon EventBridge

Amazon EventBridge monitors status change events in Amazon SageMaker. EventBridge enables you to automate SageMaker and respond automatically to events such as a training job status change or endpoint status change. Events from SageMaker are delivered to EventBridge in near real time. You can write simple rules to indicate which events are of interest to you, and what automated actions to take when an event matches a rule. For an example of how to create a rule, see Schedule a Pipeline with Amazon EventBridge (p. 3243).

Some examples of the actions that can be automatically triggered include the following:

- Invoking an AWS Lambda function
- Invoking Amazon EC2 Run Command
- Relaying the event to Amazon Kinesis Data Streams
- Activating an AWS Step Functions state machine
- Notifying an Amazon SNS topic or an AWS SMS queue

**SageMaker events monitored by EventBridge**

- Training job state change (p. 3682)
- Hyperparameter tuning job state change (p. 3683)
- Transform job state change (p. 3684)
- Endpoint state change (p. 3685)
- Feature group state change (p. 3686)
Training job state change

Indicates a change in the status of a SageMaker training job.

If the value of TrainingJobStatus is Failed, the event contains the FailureReason field, which provides a description of why the training job failed.
Hyperparameter tuning job state change

Indicates a change in the status of a SageMaker hyperparameter tuning job.

```json
{
    "version": "0",
    "id": "B4ee2571-85d4-695f-b930-0153b71dc42",
    "detail-type": "SageMaker HyperParameter Tuning Job State Change",
    "source": "aws.sagemaker",
    "account": "123456789012",
    "time": "2018-10-06T12:26:13Z",
    "region": "us-east-1",
    "resources": [
        "arn:aws:sagemaker:us-east-1:123456789012:tuningJob/x"
    ],
    "detail": {
        "HyperParameterTuningJobName": "016bffd3-6d71-4d3a-9710-0a332b2759fc",
        "HyperParameterTuningJobArn": "arn:aws:sagemaker:us-east-1:123456789012:tuningJob/x",
        "TrainingJobDefinition": {
            "StaticHyperParameters": {},
            "AlgorithmSpecification": {
                "TrainingImage": "trainingImageName",
                "TrainingInputMode": "inputModeFile",
                "MetricDefinitions": [
                    {
                        "Name": "metricName",
                        "Regex": "regex"
                    }
                ],
                "RoleArn": "roleArn",
                "InputDataConfig": [
                    {
                        "ChannelName": "channelName",
                        "DataSource": {
                            "S3DataSource": {
                                "S3DataType": "s3DataType",
                                "S3Uri": "s3Uri",
                                "S3DataDistributionType": "s3DistributionType"
                            }
                        },
                        "ContentType": "contentType",
```
Transform job state change

Indicates a change in the status of a SageMaker batch transform job.

If the value of TransformJobStatus is Failed, the event contains the FailureReason field, which provides a description of why the training job failed.
"TransformJobStatus": "another status... GO",
"FailureReason": "failed why 1",
"ModelName": "i am a beautiful model",
"MaxConcurrentTransforms": 5,
"MaxPayloadInMB": 10,
"BatchStrategy": "Strategizing...",
"Environment": {
  "environment1": "environment2"
},
"TransformInput": {
  "DataSource": {
    "S3DataSource": {
      "S3DataType": "s3DataType",
      "S3Uri": "s3Uri"
    }
  },
  "ContentType": "content type",
  "CompressionType": "compression type",
  "SplitType": "split type"
},
"TransformOutput": {
  "S3OutputPath": "s3Uri",
  "Accept": "accept",
  "AssembleWith": "assemblyType",
  "KmsKeyId": "kmsKeyId"
},
"TransformResources": {
  "InstanceType": "instanceType",
  "InstanceCount": 3
},
"CreationTime": "2018-10-06T12:26:13Z",
"TransformStartTime": "2018-10-06T12:26:13Z",
"TransformEndTime": "2018-10-06T12:26:13Z",
"Tags": {}
}

Endpoint state change

Indicates a change in the status of a SageMaker hosted real-time inference endpoint.

The following shows an event with an endpoint in the IN_SERVICE state.

```json
{
  "version": "0",
  "id": "d291b5a-b0ad-cace-a8e3-0f159d018e06",
  "detail-type": "SageMaker Endpoint State Change",
  "source": "aws.sagemaker",
  "account": "123456789012",
  "time": "1583831889050",
  "region": "us-west-2",
  "resources": [
  ],
  "detail": {
    "EndpointName": "MyEndpoint",
    "EndpointConfigName": "MyEndpointConfig",
    "ProductionVariants": [
      {
        "DesiredWeight": 1.0,
        "DesiredInstanceCount": 1.0
      }
    ]
  }
}
```
Feature group state change

Indicates a change either in the FeatureGroupStatus or the OfflineStoreStatus of a SageMaker feature group.

```json
{
  "version": "0",
  "id": "93201303-abdb-36a4-1b9b-4c1c3e3671c0",
  "detail-type": "SageMaker Feature Group State Change",
  "source": "aws.sagemaker",
  "account": "123456789012",
  "time": "2021-01-26T01:22:01Z",
  "region": "us-east-1",
  "resources": [
    "arn:aws:sagemaker:us-east-1:123456789012:feature-group/sample-feature-group"
  ],
  "detail": {
    "FeatureGroupName": "sample-feature-group",
    "RecordIdentifierFeatureName": "RecordIdentifier",
    "EventTimeFeatureName": "EventTime",
    "FeatureDefinitions": [
      {
        "FeatureName": "RecordIdentifier",
        "FeatureType": "Integral"
      },
      {
        "FeatureName": "EventTime",
        "FeatureType": "Fractional"
      }
    ],
    "CreationTime": 1611624059000,
    "OnlineStoreConfig": {
      "EnableOnlineStore": true
    },
    "OfflineStoreConfig": {
      "S3StorageConfig": {
        "S3Uri": "s3://offline/s3/uri"
      },
      "DisableGlueTableCreation": false,
      "DataCatalogConfig": {
        "TableName": "sample-feature-group-1611624059",
        "Catalog": "AwsDataCatalog",
        "Database": "sagemaker_featurestore"
      }
    },
    "RoleArn": "arn:aws:iam::123456789012:role/SageMakerRole",
    "FeatureGroupStatus": "Active",
    "Tags": {}
  }
}
```
Model package state change

Indicates a change in the status of a SageMaker model package.

```
{
    "version": "0",
    "id": "964e2571-85d4-695f-b930-0153b71dcb42",
    "detail-type": "SageMaker Model Package State Change",
    "source": "aws.sagemaker",
    "account": "123456789012",
    "time": "2021-02-24T17:00:14Z",
    "region": "us-east-2",
    "resources": [
    ],
    "source": ["aws.sagemaker"
],
    "detail": {
        "ModelPackageGroupName": "versionedmp-p-idy6c3elfiqj",
        "ModelPackageVersion": 2,
        "CreationTime": "2021-02-24T17:00:14Z",
        "InferenceSpecification": {
            "Containers": [
                {
                    "Image": "257758044811.dkr.ecr.us-east-2.amazonaws.com/sagemaker-xgboost:1.0-1-cpu-py3",
                    "ImageDigest": "sha256:4dc8a7e4a301b9a9e0a6b063f355393f6e623603361bd8b105f554d4f0c004",
                    "ModelDataUrl": "s3://sagemaker-project-p-idy6c3elfiqj/versionedmp-p-idy6c3elfiqj/AbaloneTrain/pipelines-4r83jejmhvorv-TrainAbaloneModel-xw869y8C4a/output/model.tar.gz"
                }
            ],
            "SupportedContentTypes": ["text/csv"
            ],
            "SupportedResponseMIMETypes": ["text/csv"
            ],
            "ModelPackageStatus": "Completed",
            "ModelPackageStatusDetails": {
                "ValidationStatuses": [],
                "ImageScanStatuses": []
            },
            "CertifyForMarketplace": false,
            "ModelApprovalStatus": "Rejected",
            "MetadataProperties": {
                "GeneratedBy": "arn:aws:sagemaker:us-east-2:123456789012:pipeline/versionedmp-p-idy6c3elfiqj/execution/4r83jejmhvorv"
            },
            "ModelMetrics": {
                "ModelQuality": {
                    "Statistics": {
                        "ContentType": "application/json",
                        "S3Uri": "s3://sagemaker-project-p-idy6c3elfiqj/versionedmp-p-idy6c3elfiqj/script-2021-02-24-10-55-15-413/output/evaluation/evaluation.json"
                    }
                }
            },
            "LastModifiedTime": "2021-02-24T17:00:14Z"
        }
    }
}
```
Pipeline execution state change

Indicates a change in the status of a SageMaker pipeline execution.

```json
{
  "version": "0",
  "id": "315c1398-40ff-a850-213b-158f7f3kd93ir",
  "detail-type": "SageMaker Model Building Pipeline Execution Status Change",
  "source": "aws.sagemaker",
  "account": "123456789012",
  "time": "2021-03-15T16:10:11Z",
  "region": "us-east-1",
  "resources": ["arn:aws:sagemaker:us-east-1:123456789012:pipeline/myPipeline-123",
    "arn:aws:sagemaker:us-east-1:123456789012:pipeline/myPipeline-123/execution/p4jn9xou8a8s"],
  "detail": {
    "pipelineExecutionDisplayName": "SomeDisplayName",
    "currentPipelineExecutionStatus": "Succeeded",
    "previousPipelineExecutionStatus": "Executing",
    "executionStartTime": "2021-03-15T16:10:11Z",
    "executionEndTime": "2021-03-15T16:10:10Z",
    "pipelineExecutionDescription": "SomeDescription",
    "pipelineArn": "arn:aws:sagemaker:us-east-1:123456789012:pipeline/myPipeline-123",
    "pipelineExecutionArn": "arn:aws:sagemaker:us-east-1:123456789012:pipeline/myPipeline-123/execution/p4jn9xou8a8s"
  }
}
```

Pipeline step state change

Indicates a change in the status of a SageMaker pipeline step.

If there is a cache hit, the event contains the cacheHitResult field.

If the value of currentStepStatus is Failed, the event contains the failureReason field, which provides a description of why the step failed.

```json
{
  "version": "0",
  "id": "ea37ccbb-5e2b-05e9-4073-1daazc940304",
  "detail-type": "SageMaker Model Building Pipeline Execution Step Status Change",
  "source": "aws.sagemaker",
  "account": "123456789012",
  "time": "2021-03-15T16:10:10Z",
  "region": "us-east-1",
  "resources": ["arn:aws:sagemaker:us-east-1:123456789012:pipeline/myPipeline-123",
    "arn:aws:sagemaker:us-east-1:123456789012:pipeline/myPipeline-123/execution/p4jn9xou8a8s"],
  "detail": {
    "metadata": {
      "processingJob": {
        "arn": "arn:aws:sagemaker:us-east-1:123456789012:processing-job/pipelines-p4jn9xou8a8s-myprocessingstep1-tmgxry49ug"
      }
    },
    "stepStartTime": "2021-03-15T16:03:14Z",
    "stepEndTime": "2021-03-15T16:10:09Z",
    "stepName": "myprocessingstep1",
    "pipelineExecutionArn": "arn:aws:sagemaker:us-east-1:123456789012:pipeline/myPipeline-123/execution/p4jn9xou8a8s"
  }
}
```
SageMaker image state change

Indicates a change in the status of a SageMaker image.

```
{
  "version": "0",
  "id": "cee033a3-17d8-49f8-865f-b9ebf485d9ee",
  "detail-type": "SageMaker Image State Change",
  "source": "aws.sagemaker",
  "account": "123456789012",
  "time": "2021-04-29T01:29:59Z",
  "region": "us-east-1",
  "resources": ["arn:aws:sagemaker:us-west-2:123456789012:image/cee033a3-17d8-49f8-865f-b9ebf485d9ee"]
}
```

SageMaker image version state change

Indicates a change in the status of a SageMaker image version.

```
{
  "version": "0",
  "id": "07fc4615-ebd7-15fc-1746-243411f09f04",
  "detail-type": "SageMaker Image Version State Change",
  "source": "aws.sagemaker",
  "account": "123456789012",
  "time": "2021-04-29T01:29:59Z",
  "region": "us-east-1",
  "resources": ["arn:aws:sagemaker:us-west-2:123456789012:image-version/07800032-2d29-48b7-8f82-5129225b2a85"]
}
```

For more information about the status values and their meanings for SageMaker jobs, endpoints, and pipelines, see the following links:

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Important
The following examples may not work for all endpoints. For a list of features that may exclude your endpoint, see the Exclusions (p. 2980) page.

Indicates a state change for an endpoint deployment. The following example shows an endpoint updating with a blue/green canary deployment.

```json
{
   "version": "0",
   "id": "0bd4a141-0a02-9d8a-f977-3924c3fb259c",
   "detail-type": "SageMaker Endpoint Deployment State Change",
   "source": "aws.sagemaker",
   "account": "123456789012",
   "time": "2021-10-25T01:52:12Z",
   "region": "us-west-2",
   "resources": [
   ],
   "detail": {
      "EndpointName": "sample-endpoint",
      "EndpointConfigName": "sample-endpoint-config-1",
      "ProductionVariants": [
         {
            "VariantName": "AllTraffic",
            "CurrentWeight": 1,
            "DesiredWeight": 1,
            "CurrentInstanceCount": 3,
            "DesiredInstanceCount": 3
         }
      ],
      "EndpointStatus": "UPDATING",
      "CreationTime": 1635195148181,
      "LastModifiedTime": 1635195148181,
      "Tags": {},
      "PendingDeploymentSummary": {
         "EndpointConfigName": "sample-endpoint-config-2",
         "StartTime": Timestamp,
         "ProductionVariants": [
            {
```
The following example indicates a state change for an endpoint deployment, which is being updated with new capacity on an existing endpoint configuration.

```
{
  "version": "0",
  "id": "0bd4a141-0a02-9d8a-f977-3924c3fb259c",
  "detail-type": "SageMaker Endpoint Deployment State Change",
  "source": "aws.sagemaker",
  "account": "123456789012",
  "time": "2021-10-25T01:52:12Z",
  "region": "us-west-2",
  "resources": [
  ],
  "detail": {
    "EndpointName": "sample-endpoint",
    "EndpointConfigName": "sample-endpoint-config-1",
    "ProductionVariants": [
      {
        "VariantName": "AllTraffic",
        "CurrentWeight": 1,
        "DesiredWeight": 1,
        "CurrentInstanceCount": 3,
        "DesiredInstanceCount": 6,
        "VariantStatus": [
          {
            "Status": "Updating",
            "StatusMessage": "Scaling out desired instance count to 6.",
            "StartTime": 1635195269181,
          }
        ]
      }
    ],
    "EndpointStatus": "UPDATING",
    "CreationTime": 1635195148181,
    "LastModifiedTime": 1635195148181,
    "Tags": {}
  }
}
```

The following secondary deployment statuses are also available for endpoints (found in the `VariantStatus` object.

- Creating: creating instances for the production variant.
Example message: "Launching X instance(s)."

- Deleting: terminating instances for the production variant.
  
  Example message: "Terminating X instance(s)."

- Updating: updating capacity for the production variant.
  
  Example messages: "Launching X instance(s).", "Scaling out desired instance count to X."

- ActivatingTraffic: turning on traffic for the production variant.
  
  Example message: "Activating traffic on canary capacity of X instance(s)."

- Baking: waiting period to monitor the CloudWatch alarms in the auto-rollback configuration.
  
  Example message: "Baking for X seconds (TerminationWaitInSeconds) with traffic enabled on full capacity of Y instance(s)."
API Reference Guide for Amazon SageMaker

Overview

Amazon SageMaker provides APIs, SDKs, and a command line interface that you can use to create and manage notebook instances and train and deploy models.

- Amazon SageMaker Python SDK (Recommended)
- Amazon SageMaker API Reference
- Amazon Augmented AI API Reference
- AWS Command Line Interface
- AWS SDK for .NET
- AWS SDK for C++
- AWS SDK for Go
- AWS SDK for Java
- AWS SDK for JavaScript
- AWS SDK for PHP
- AWS SDK for Python (Boto)
- AWS SDK for Ruby
- Amazon SageMaker Spark

You can also get code examples from the Amazon SageMaker example notebooks GitHub repository.

- Example notebooks

Programming Model for Amazon SageMaker

Making API calls directly from code is cumbersome, and requires you to write code to authenticate your requests. Amazon SageMaker provides the following alternatives:

- Use the SageMaker console–With the console, you don't write any code. You use the console UI to start model training or deploy a model. The console works well for simple jobs, where you use a built-in training algorithm and you don’t need to preprocess training data.

- Modify the example Jupyter notebooks–SageMaker provides several Jupyter notebooks that train and deploy models using specific algorithms and datasets. Start with a notebook that has a suitable algorithm and modify it to accommodate your data source and specific needs.

- Write model training and inference code from scratch–SageMaker provides multiple AWS SDK languages (listed in the overview) and the Amazon SageMaker Python SDK, a high-level Python library that you can use in your code to start model training jobs and deploy the resulting models.
• **The SageMaker Python SDK**—This Python library simplifies model training and deployment. In addition to authenticating your requests, the library abstracts platform specifics by providing simple methods and default parameters. For example:

  • To deploy your model, you call only the `deploy()` method. The method creates a SageMaker model artifact, an endpoint configuration, then deploys the model on an endpoint.

  • If you use a custom framework script for model training, you call the `fit()` method. The method creates a .gzip file of your script, uploads it to an Amazon S3 location, and then runs it for model training, and other tasks. For more information, see [Use Machine Learning Frameworks, Python, and R with Amazon SageMaker](p. 13).

• **The AWS SDKs** – The SDKs provide methods that correspond to the SageMaker API (see [Operations](p. 13)). Use the SDKs to programmatically start a model training job and host the model in SageMaker. SDK clients authenticate your requests by using your access keys, so you don’t need to write authentication code. They are available in multiple languages and platforms. For more information, see the preceeding list in the overview.

  In [Get Started with Amazon SageMaker](p. 33), you train and deploy a model using an algorithm provided by SageMaker. That exercise shows how to use both of these libraries. For more information, see [Get Started with Amazon SageMaker](p. 33).

• **Integrate SageMaker into your Apache Spark workflow**—SageMaker provides a library for calling its APIs from Apache Spark. With it, you can use SageMaker-based estimators in an Apache Spark pipeline. For more information, see [Use Apache Spark with Amazon SageMaker](p. 14).
## Document History for Amazon SageMaker

<table>
<thead>
<tr>
<th>Change</th>
<th>Description</th>
<th>Date</th>
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</thead>
</table>
| New features re:Invent 2021 (p. 3695) | The following new features were introduced at re:Invent 2021.  
- SageMaker Canvas  
- SageMaker Ground Truth Plus  
- SageMaker Inference Recommender  
- SageMaker Serverless Endpoints  
- SageMaker Studio Lab  
- SageMaker Studio Notebooks and Amazon EMR  
- SageMaker Training Compiler | December 1, 2021 |
| Autopilot time series data (p. 3695) | Amazon SageMaker Autopilot accepts time series as model inputs. For more information, see Amazon SageMaker Autopilot data and problem types. | October 25, 2021 |
| AWS managed policies (p. 3695) | Started tracking changes for SageMaker managed policies. | June 10, 2021 |
| New features re:Invent 2020 (p. 3695) | The following new features were introduced at re:Invent 2020.  
- Amazon SageMaker Model Building Pipelines  
- Automate MLOps with SageMaker Projects  
- SageMaker Edge Manager  
- SageMaker Clarify  
- SageMaker Data Wrangler  
- SageMaker Feature Store  
- SageMaker Studio JumpStart  
- Register and Deploy Models with Model Registry  
- SageMaker Distributed  
- Deep Profiling with SageMaker Debugger | December 1, 2020 |
<p>| Studio Notebooks (p. 3695) | SageMaker Studio Notebooks | April 28, 2020 |</p>
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<tr>
<th>New features re:Invent 2019 (p. 3695)</th>
<th>The following new features were introduced at re:Invent 2019.</th>
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<tbody>
<tr>
<td>• SageMaker Studio</td>
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<td>• SageMaker Studio Notebooks (preview)</td>
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<td>• SageMaker Experiments</td>
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<td>• SageMaker Autopilot</td>
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<td>• SageMaker Model Monitor</td>
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<td>New features re:Invent 2018 (p. 3695)</td>
<td>The following new features were introduced at re:Invent 2018.</td>
<td>November 28, 2018</td>
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<tr>
<td>• Amazon SageMaker Ground Truth</td>
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<td>• SageMaker Resources in AWS MarketPlace</td>
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<td>• Reinforcement Learning</td>
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<td>• Associate Git Repositories with SageMaker Notebook Instances</td>
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<td>• Semantic Segmentation Algorithm</td>
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<td>• Augmented Manifest Files in Training Jobs</td>
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<tr>
<td>Configuring notebook instances (p. 3695)</td>
<td>Use shell scripts to configure notebook instances when you create or start them. For more information, see Customize a Notebook Instance.</td>
<td>May 1, 2018</td>
</tr>
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<td>Application Auto Scaling support (p. 3695)</td>
<td>Amazon SageMaker now supports Application Auto Scaling for production variants. For information, see Automatically Scaling SageMaker Models</td>
<td>February 28, 2018</td>
</tr>
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<td>TensorFlow 1.5 and MXNet 1.0 support (p. 3695)</td>
<td>Amazon SageMaker Deep Learning containers now support TensorFlow 1.5 and Apache MXNet 1.0.</td>
<td>February 27, 2018</td>
</tr>
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<td>BlazingText algorithm (p. 3695)</td>
<td>Amazon SageMaker now supports the BlazingText algorithm.</td>
<td>January 18, 2018</td>
</tr>
<tr>
<td>Feature</td>
<td>Description</td>
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<tr>
<td>----------------------------------------------</td>
<td>-----------------------------------------------------------------------------</td>
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<tr>
<td>KMS encryption</td>
<td>Amazon SageMaker now supports KMS encryption for hosting instances and training model artifacts at rest.</td>
<td>January 17, 2018</td>
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<td>CloudTrail support</td>
<td>Amazon SageMaker now supports logging with AWS CloudTrail.</td>
<td>January 11, 2018</td>
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<td>DeepAR Forecasting algorithm</td>
<td>Amazon SageMaker now supports the DeepAR algorithm for time series forecasting.</td>
<td>January 8, 2018</td>
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AWS glossary

For the latest AWS terminology, see the AWS glossary in the AWS General Reference.