

ModelArts

Model Development

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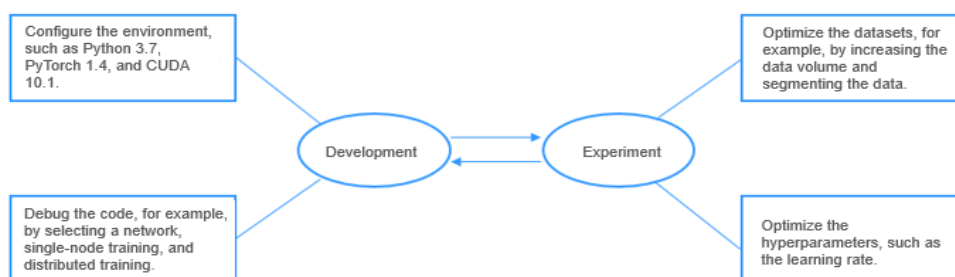
1 Introduction to Model Development

AI modeling involves two stages:

- Development: Prepare and configure the environment, and debug code for training based on deep learning. ModelArts DevEnviron is recommended for code debugging.
- Experiment: Optimize the datasets and hyperparameters, and obtain an ideal model through multiple rounds of experiments. The ModelArts training platform is recommended for training.

In the two stages, code is designed, developed and tested in repeated cycles. In the development stage, when the code becomes stable, the modeling process enters the experiment stage, during which hyperparameters are continuously optimized to iterate the model. In the experiment stage, when the training performance can be optimized, the modeling process returns to the development stage for optimizing code.

The following is part of the process for AI modeling.



ModelArts provides model training, which allows you to view training results and tune model parameters based on the training results. You can select resource pools with different instance flavors for model training.

The following guides you to train models on ModelArts:

- Upload the labeled data to OBS. For details, see [Preparing Data](#).
- Follow the instructions provided in [Preparing Algorithms](#) to use an algorithm for model training.

- Create a training job. You can perform this operation on the ModelArts console. For details, see [Creating a Training Job](#). For details about how to create models using custom algorithms, see [Using a Custom Algorithm to Build a Handwritten Digit Recognition Model](#).
- Follow the instructions provided in [Training Job Logs](#) to view training job logs and training resource usage.
- Follow the instructions provided in [Stopping, Rebuilding, or Searching for a Training Job](#) to stop or delete a training job.
- Follow the instructions provided in [Automatic Model Tuning \(AutoSearch\)](#) to automatically tune model hyperparameters.
- Troubleshoot if you encounter any problem during training. For details, see [Troubleshooting](#).

2 Preparing Data

ModelArts uses OBS to store data, and backs up and takes snapshots for models, achieving secure, reliable storage at low costs.

- [OBS](#)
- [Obtaining Training Data](#)

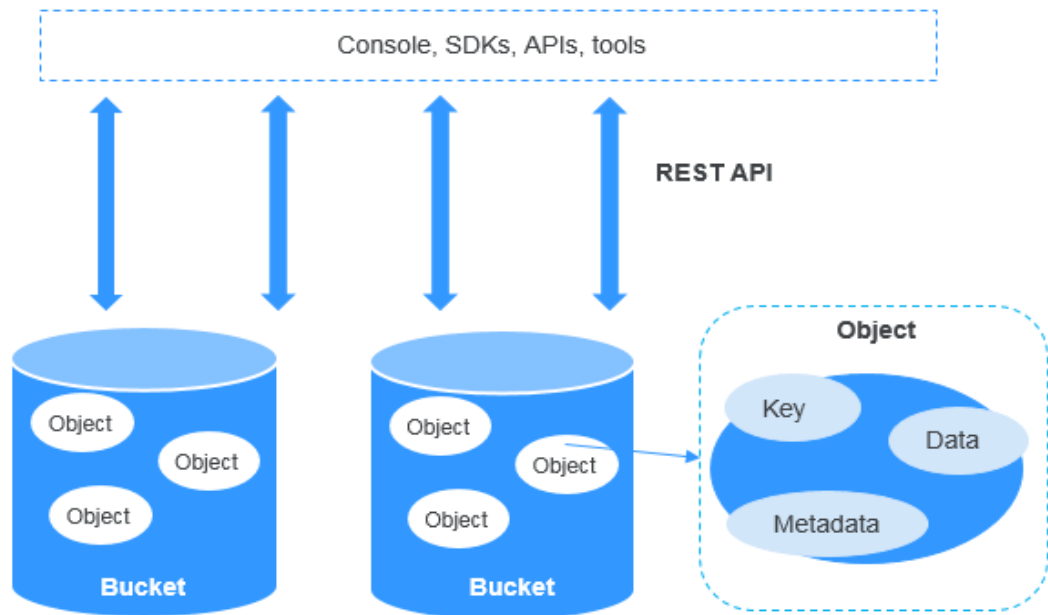
OBS

OBS provides stable, secure, and efficient cloud storage service that lets you store virtually any volume of unstructured data in any format. Bucket and objects are basic concepts in OBS. A bucket is a container for storing objects in OBS. Each bucket is specific to a region and has specific storage class and access permissions. A bucket is accessible through its domain name over the Internet. An object is the basic unit of data storage in OBS.

OBS is a data storage center for ModelArts. All the input data, output data, and cache data during AI development can be stored in OBS buckets for reading.

Before using ModelArts, [create an OBS bucket](#) and folders for storing data.

Figure 2-1 OBS



Obtaining Training Data

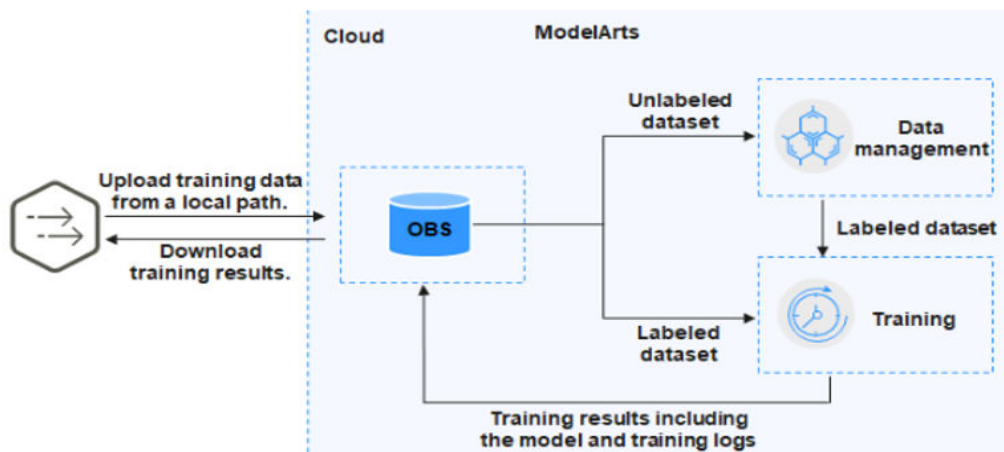
Use either of the following methods to obtain ModelArts training data:

- Datasets stored in OBS buckets
After labeling and preprocessing your dataset, upload it to an OBS bucket. When you create a training job, set **Input** to the path of the OBS bucket where the training data is stored.
- Datasets in data management
If your dataset has not labeled or requires preprocessing, import it to ModelArts data management for data preprocessing.

NOTE

ModelArts data management is being upgraded and is invisible to users who have not used data management. It is recommended that new users store their training data in OBS buckets.

Figure 2-2 Preparing data



3 Preparing Algorithms

3.1 Introduction to Algorithm Preparation

Machine learning explores general rules from limited volume of data and uses these rules to predict unknown data. To obtain more accurate prediction results, select a proper algorithm to train your model. ModelArts provides a large number of algorithm samples for different scenarios. This section describes algorithm sources and learning modes.

Algorithm Sources

You can use one of the following methods to build a ModelArts model:

- Using a preset image
To use a custom algorithm, use a framework built in ModelArts. ModelArts supports most mainstream AI engines. For details, see [Built-in Training Engines](#). These built-in engines pre-load some extra Python packages, such as NumPy. You can also use the `requirements.txt` file in the code directory to install dependency packages. For details about how to create a training job using a preset image, see [Using a Preset Image \(Custom Script\)](#).
- Using a custom image (For details about the new version of training, see [Using a Custom Image to Train a Model](#).)
The subscribed algorithms and built-in frameworks can be used in most training scenarios. In certain scenarios, ModelArts allows you to create custom images to train models. Custom images can be used to train models in ModelArts only after they are uploaded to the Software Repository for Container (SWR). Customizing an image requires a deep understanding of containers. Use this method only if the subscribed algorithms and custom scripts cannot meet your requirements.

Algorithm Learning Modes

ModelArts allows you to train models in different modes as required.

- Offline learning
Offline learning is the most fundamental mode for model training. In this mode, all data required for training must be provided at a time, and

optimizing the objective function stops when the training is complete. The advantage of this mode is that the trained models are stable, facilitating model verification and evaluation. However, it is time-consuming and low in storage space utilization.

- Incremental learning

Incremental learning is a continuous learning process. Compared with offline learning, it does not need to store all training data at a time, which alleviates the problem of limited storage resources. In addition, it saves a large amount of compute power and time, and reduces economic costs in retraining.

3.2 Using a Preset Image (Custom Script)

3.2.1 Overview

If the subscribed algorithms cannot meet your requirements or you want to migrate local algorithms to ModelArts for training, use the ModelArts preset images to create algorithms. This method is also called using a preset image.

This section describes how to use a preset image to create an algorithm.

- For details about ModelArts built-in engines and models, see [Built-in Training Engines](#).
- To migrate local algorithms to ModelArts, perform code adaptation. For details, see [Developing a Custom Script](#).
- For details about how to use a preset image to create an algorithm on the ModelArts console, see [Creating an Algorithm](#).

Built-in Training Engines

The following table lists the training engines and their versions supported by ModelArts.

 NOTE

Supported AI engines vary depending on regions.

Table 3-1 AI engines supported by training jobs of the new version

Runtime Environment	Supported Chip	System Architecture	System Version	AI Engine and Version	Supported CUDA or Ascend Version
TensorFlow	CPU/GPU	x86_64	Ubuntu18.04	tensorflow_2.1.0-cuda_10.1-py_3.7-ubuntu_18.04-x86_64	cuda10.1

Runtime Environment	Supported Chip	System Architecture	System Version	AI Engine and Version	Supported CUDA or Ascend Version
PyTorch	CPU/GPU	x86_64	Ubuntu18.04	pytorch_1.8.0-cuda_10.2-py_3.7-ubuntu_18.04-x86_64	cuda10.2
MPI	GPU	x86_64	Ubuntu18.04	mindspore_1.3.0-cuda_10.1-py_3.7-ubuntu_1804-x86_64	cuda_10.1
Horovod	GPU	x86_64	ubuntu_18.04	horovod_0.20.0-tensorflow_2.1.0-cuda_10.1-py_3.7-ubuntu_18.04-x86_64	cuda_10.1
				horovod_0.22.1-pytorch_1.8.0-cuda_10.2-py_3.7-ubuntu_18.04-x86_64	cuda_10.2

3.2.2 Developing a Custom Script

Before you use a preset image to create an algorithm, develop the algorithm code. This section describes how to modify local code for model training on ModelArts.

When creating an algorithm, set the code directory, boot file, input path, and output path. These settings enable the interaction between your codes and ModelArts.

- **Code directory**
Specify the code directory in the OBS bucket and upload training data such as training code, dependency installation packages, or pre-generated model to the directory. After you create the training job, ModelArts downloads the code directory and its subdirectories to the container.
Take OBS path **obs://obs-bucket/training-test/demo-code** as an example. The content in the OBS path will be automatically downloaded to **\$ {MA_JOB_DIR}/demo-code** in the training container, and **demo-code** (customizable) is the last-level directory of the OBS path.
Do not store training data in the code directory. When the training job starts, the data stored in the code directory will be downloaded to the backend. A large amount of training data may lead to a download failure. It is recommended that the size of the code directory does not exceed 50 MB.
- **Boot file**

The boot file in the code directory is used to start the training. Only Python boot files are supported.

- Input path

The training data must be uploaded to an OBS bucket or stored in the **dataset**. In the training code, **the input path** must be parsed. ModelArts automatically downloads the data in the input path to the local container directory for training. Ensure that you have the read permission to the OBS bucket. After the training job is started, ModelArts mounts a disk to the **/cache** directory. You can use this directory to store temporary files. For details about the size of the **/cache** directory, see [What Are Sizes of the /cache Directories for Different Resource Specifications in the Training Environment?](#)

- Output path

You are advised to set an empty directory as the training output path. In the training code, **the output path** must be parsed. ModelArts automatically uploads the training output to the output path. Ensure that you have the write and read permissions to the OBS bucket.

The following section describes how to develop training code in ModelArts.

(Optional) Introducing Dependencies

1. If your model references other dependencies, place the required file or installation package in **Code Directory** you set during algorithm creation.
 - For details about how to install the Python dependency package, see [How Do I Create a Training Job When a Dependency Package Is Referenced by the Model to Be Trained?](#)
 - For details about how to install a C++ dependency library, see [How Do I Install a Library That C++ Depends on?](#)
 - For details about how to load parameters to a pre-trained model, see [How Do I Load Some Well Trained Parameters During Job Training?](#)

Parsing Input and Output Paths

When a ModelArts model reads data stored in OBS or outputs data to a specified OBS path, perform the following operations to configure the input and output data:

1. Parse the input and output paths in the training code. The following method is recommended:

```
import argparse
# Create a parsing task.
parser = argparse.ArgumentParser(description='train mnist')

# Add parameters.
parser.add_argument('--data_url', type=str, default='./Data/mnist.npz', help='path where the dataset is saved')
parser.add_argument('--train_url', type=str, default='./Model', help='path where the model is saved')

# Parse the parameters.
args = parser.parse_args()
```

After the parameters are parsed, use **data_url** and **train_url** to replace the paths to the data source and the data output, respectively.

- When creating a training job, set the input and output paths.
Select the OBS path or dataset path as the training input, and the OBS path as the output.

Figure 3-1 Setting training input and output

Editing Training Code and Saving the Model

Training code and the code for saving the model are closely related to the AI engine you use. The following uses the TensorFlow framework as an example. Before using this case, you need to **download** the **mnist.npz** file and upload it to the OBS bucket. The training input is the OBS path where the **mnist.npz** file is stored.

```
import os
import argparse
import tensorflow as tf

parser = argparse.ArgumentParser(description='train mnist')
parser.add_argument('--data_url', type=str, default="./Data/mnist.npz", help='path where the dataset is saved')
parser.add_argument('--train_url', type=str, default="./Model", help='path where the model is saved')
args = parser.parse_args()

mnist = tf.keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data(args.data_url)
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)
])

loss_fn = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
model.compile(optimizer='adam',
              loss=loss_fn,
              metrics=['accuracy'])
model.fit(x_train, y_train, epochs=5)

model.save(os.path.join(args.train_url, 'model'))
```

Differences in Training Code Adaptation

In the old version, you are required to configure data input and output as follows:

```
# Parse CLI parameters.
import argparse
parser = argparse.ArgumentParser(description='MindSpore Lenet Example')
parser.add_argument('--data_url', type=str, default="/Data",
                    help='path where the dataset is saved')
parser.add_argument('--train_url', type=str, default="/Model", help='if is test, must provide\
                    path where the trained ckpt file')
args = parser.parse_args()
...
# Download data to your local container. In the code, local_data_path specifies the training input path.
mox.file.copy_parallel(args.data_url, local_data_path)
...
# Upload the local container data to the OBS path.
mox.file.copy_parallel(local_output_path, args.train_url)
```

3.2.3 Creating an Algorithm

Your locally developed algorithms or algorithms developed using other tools can be uploaded to ModelArts for unified management. Note the following when creating a custom algorithm:

1. [Prerequisites](#)
2. [Accessing the Algorithm Creation Page](#)
3. [Setting Basic Parameters](#)
4. [Setting the Boot Mode](#)
5. [Configuring Pipelines](#)
6. [Defining Hyperparameters](#)
7. [Supported Policies](#)
8. [Adding Training Constraints](#)
9. [Runtime Environment Preview](#)
10. [Follow-up Operations](#)

Prerequisites

- Data is available either by creating a dataset in ModelArts or by uploading the dataset used for training to the OBS directory.
- Your training script has been uploaded to the OBS directory. For details about how to develop a training script, see [Developing a Custom Script](#).
- At least one empty folder has been created in OBS for storing the training output.
- The account is not in arrears because resources are consumed when training jobs are running.
- The OBS directory you use and ModelArts are in the same region.

Accessing the Algorithm Creation Page

1. Log in to the ModelArts management console and click **Algorithm Management** in the left navigation pane.
2. On the **My Algorithms** page, click **Create**. The **Create Algorithm** page is displayed.

Setting Basic Parameters

Enter the basic information, including **Name** and **Description**.

Figure 3-2 Setting basic parameters

The screenshot shows a form with two input fields. The first field is labeled 'Name' with a red asterisk, containing the text 'algorithm-1a43'. The second field is labeled 'Description' and is empty. At the bottom right of the description field, there is a character count '0/256'.

Setting the Boot Mode

Select a preset image to create an algorithm.

Set **Image**, **Code Directory**, and **Boot File** based on the algorithm code. Ensure that the framework of the AI image you select is the same as the one you use for editing algorithm code. For example, if TensorFlow is used for editing algorithm code, select a TensorFlow image when you create an algorithm.

Table 3-2 Parameters

Parameter	Description
Boot Mode > Preset image	AI images supported by the new version of training are displayed by default. You can select Show Old Images to select the images supported by the old version. For details, see Overview .
Code Directory	<p>OBS path for storing the algorithm code. The files required for training, such as the training code, dependency installation packages, and pre-generated models, are uploaded to the code directory.</p> <p>Do not store training data in the code directory. When the training job starts, the data stored in the code directory will be downloaded to the backend. A large amount of training data may lead to a download failure.</p> <p>After you create the training job, ModelArts downloads the code directory and its subdirectories to the container.</p> <p>Take OBS path obs://obs-bucket/training-test/demo-code as an example. The content in the OBS path will be automatically downloaded to #{MA_JOB_DIR}/demo-code in the training container, and demo-code (customizable) is the last-level directory of the OBS path.</p> <p>NOTE</p> <ul style="list-style-type: none"> Any programming language is supported. The number of files (including files and folders) cannot exceed 1,000. The total size of files cannot exceed 5 GB.

Parameter	Description
Boot File	The file must be stored in the code directory and end with .py. ModelArts supports boot files edited only in Python. The boot file in the code directory is used to start a training job.

Figure 3-3 Using a custom script to create an algorithm

Configuring Pipelines

A preset image-based algorithm obtains data from an OBS bucket or dataset for model training. The training output is stored in an OBS bucket. The input and output parameters in your algorithm code must be parsed to enable data exchange between ModelArts and OBS. For details about how to develop code for training on ModelArts, see [Developing a Custom Script](#).

When you use a preset image to create an algorithm, configure the input and output pipelines.

- Input configurations

Table 3-3 Input configurations

Parameter	Description
Parameter Name	Set the name based on the data input parameter in your algorithm code. The code path parameter must be the same as the training input parameter parsed in your algorithm code. Otherwise, the algorithm code cannot obtain the input data. For example, If you use argparse in the algorithm code to parse data_url into the data input, set the data input parameter to data_url when creating the algorithm.
Description	Customizable description of the input parameter,
Obtained from	Source of the input parameter. You can select Hyperparameters (default) or Environment variables .

Parameter	Description
Constraints	<p>Whether data is obtained from a storage path or ModelArts dataset.</p> <p>If you select the ModelArts dataset as the data source, the following constraints are added:</p> <ul style="list-style-type: none"> • Labeling Type: For details, see Creating a Labeling Job. • Data Format, which can be Default, CarbonData, or both. Default indicates the manifest format. • Data Segmentation: available only for image classification, object detection, text classification, and sound classification datasets. Possible values are Segmented dataset, Dataset not segmented, and Unlimited. For details, see Publishing a Data Version.
Add	Multiple data input sources are allowed.

Figure 3-4 Input configurations

Input

Parameter Name Description

Obtained from Hyperparameters Environment variables

Constraints

- Output configurations

Table 3-4 Output configurations

Parameter	Description
Parameter Name	<p>Set the name based on the data output parameter in your algorithm code. The code path parameter must be the same as the training output parameter parsed in your algorithm code. Otherwise, the algorithm code cannot obtain the output path.</p> <p>For example, If you use argparse in the algorithm code to parse train_url into the data output, set the data output parameter to train_url when creating the algorithm.</p>
Description	Customizable description of the output parameter,
Obtained from	Source of the output parameter. You can select Hyperparameters (default) or Environment variables .
Add	Multiple data output paths are allowed.

Figure 3-5 Output configurations

Defining Hyperparameters

When you use a preset image to create an algorithm, ModelArts allows you to customize hyperparameters so you can view or modify them anytime. After the hyperparameters are defined, they are displayed in the startup command and transferred to your boot file as CLI parameters.

1. Import hyperparameters.

You can click **Add hyperparameter** to manually add hyperparameters.

Figure 3-6 Adding hyperparameters

2. Edit hyperparameters. For details, see [Table 3-5](#).

Table 3-5 Hyperparameters

Parameter	Description
Name	Hyperparameter name Enter 1 to 64 characters. Only letters, digits, hyphens (-), and underscores (_) are allowed.
Type	Type of the hyperparameter, which can be String , Integer , Float , or Boolean
Default	Default value of the hyperparameter, which is used for training jobs by default
Constraints	Click Restrained . Then, set the range of the default value or enumerated value in the dialog box displayed.
Required	Select Yes or No . <ul style="list-style-type: none"> • If you select No, you can delete the hyperparameter on the training job creation page when using this algorithm to create a training job. • If you select Yes, you cannot delete the hyperparameter on the training job creation page when using this algorithm to create a training job.

Parameter	Description
Description	Description of the hyperparameter Only letters, digits, spaces, hyphens (-), underscores (_), commas (,), and periods (.) are allowed.

Supported Policies

ModelArts supports auto search. Auto search automatically finds the optimal hyperparameters without any code modification. This improves model precision and convergence speed. For details about parameter settings, see [Parameters of hyperparameter search](#).

Only the `pytorch_1.8.0-cuda_10.2-py_3.7-ubuntu_18.04-x86_64` and `tensorflow_2.1.0-cuda_10.1-py_3.7-ubuntu_18.04-x86_64` images are available for auto search.

Adding Training Constraints

You can add training constraints of the algorithm based on your needs.

- **Resource Type:** Select the required resource types.
- **Multicard Training:** Choose whether to support multi-card training.
- **Distributed Training:** Choose whether to support distributed training.

Figure 3-7 Training constraints

Add Training Constraint Yes No

* Resource Type

* Multicard Training

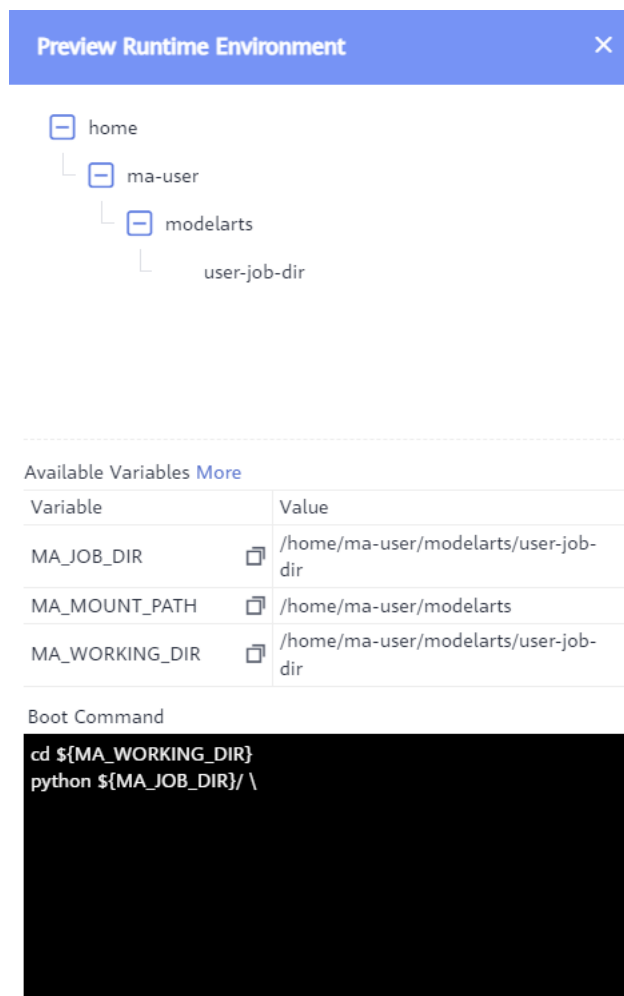
* Distributed Training

Runtime Environment Preview

Runtime Environment Preview 

When creating an algorithm, click the arrow on in the lower right corner of the page to know the path of the code directory, boot file, and input and output data in the training container.

Figure 3-8 Runtime environment preview



Follow-up Operations

After an algorithm is created, use it to create a training job. For details, see [Creating a Training Job](#).

3.3 Using Custom Images

The subscribed algorithms and preset images can be used in most training scenarios. In certain scenarios, ModelArts allows you to create custom images to train models.

Customizing an image requires a deep understanding of containers. Use this method only if the subscribed algorithms and preset images cannot meet your requirements. Custom images can be used to train models in ModelArts only after they are uploaded to the Software Repository for Container (SWR).

You can use custom images for training on ModelArts in either of the following ways:

- Using a preset image with customization

If you use a preset image to create a training job and you need to modify or add some software dependencies based on the preset image, you can customize the preset image. In this case, select a preset image and choose **Customize** from the framework version drop-down list box.

- Using a custom image
You can create an image based on the ModelArts image specifications, select your own image and configure the code directory (optional) and boot command to create a training job.

Using a Preset Image with Customization

The only difference between this method and creating a training job totally based on a preset image is that you must select an image. You can create a custom image based on a preset image.

Figure 3-9 Creating an algorithm using a preset image with customization

The screenshot shows the 'Boot Mode' configuration section. At the top, there are two tabs: 'Preset image' (highlighted in blue) and 'Custom image'. Below the tabs, there is a dropdown menu for selecting a preset image, and a 'Customize' button. Below this, there are three input fields: 'Image', 'Code Directory', and 'Boot File'. Each input field has a 'Select' button to its right. Red circles with numbers 1, 2, and 3 are overlaid on the 'Preset image' tab, the dropdown menu, and the 'Customize' button respectively.

The process of this method is the same as that of creating a training job based on a preset image. For example:

- The system automatically injects environment variables.
 - `PATH=${MA_HOME}/anaconda/bin:${PATH}`
 - `LD_LIBRARY_PATH=${MA_HOME}/anaconda/lib:${LD_LIBRARY_PATH}`
 - `PYTHONPATH=${MA_JOB_DIR}:${PYTHONPATH}`
- The selected boot file will be automatically started using Python commands. Ensure that the Python environment is correct. The PATH environment variable is automatically injected. Run the following commands to check the Python version for the training job:
 - `export MA_HOME=/home/ma-user; docker run --rm {image} ${MA_HOME}/anaconda/bin/python -V`
 - `docker run --rm {image} $(which python) -V`
- The system automatically adds hyperparameters associated with the preset image.

Using a Custom Image

Figure 3-10 Creating an algorithm using a custom image

The screenshot shows a configuration form for creating an algorithm. It includes the following elements:

- Boot Mode:** Two buttons, 'Preset image' and 'Custom image'. The 'Custom image' button is highlighted with a red border.
- Image:** A text input field followed by a 'Select' button.
- Code Directory:** A text input field followed by a 'Select' button.
- Boot Command:** A text area with a line number '1' on the left and a help icon (?) to its left.

For details about how to use custom images supported by the new-version training, see [Using a Custom Image to Create a CPU- or GPU-based Training Job](#).

If all used images are customized, do as follows to use a specified Conda environment to start training:

Training jobs do not run in a shell. Therefore, you are not allowed to run the **conda activate** command to activate a specified Conda environment. In this case, use other methods to start training.

For example, Conda in your custom image is installed in the **/home/ma-user/anaconda3** directory, the Conda environment is **python-3.7.10**, and the training script is stored in **/home/ma-user/modelarts/user-job-dir/code/train.py**. Use a specified Conda environment to start training in one of the following ways:

- Method 1: Configure the correct **DEFAULT_CONDA_ENV_NAME** and **ANACONDA_DIR** environment variables for the image.
Run the **python** command to start the training script. The following shows an example:

```
python /home/ma-user/modelarts/user-job-dir/code/train.py
```
- Method 2: Use the absolute path of Conda environment Python.
Run the **/home/ma-user/anaconda3/envs/python-3.7.10/bin/python** command to start the training script. The following shows an example:

```
/home/ma-user/anaconda3/envs/python-3.7.10/bin/python /home/ma-user/modelarts/user-job-dir/code/train.py
```
- Method 3: Configure the path environment variable.
Configure the bin directory of the specified Conda environment into the path environment variable. Run the **python** command to start the training script. The following shows an example:

```
export PATH=/home/ma-user/anaconda3/envs/python-3.7.10/bin:$PATH; python /home/ma-user/modelarts/user-job-dir/code/train.py
```
- Method 4: Run the **conda run -n** command.

Run the `/home/ma-user/anaconda3/bin/conda run -n python-3.7.10` command to execute the training. The following shows an example:
`/home/ma-user/anaconda3/bin/conda run -n python-3.7.10 python /home/ma-user/modelarts/user-job-dir/code/train.py`

 **NOTE**

If there is an error indicating that the .so file is unavailable in the `$ANACONDA_DIR/envs/$DEFAULT_CONDA_ENV_NAME/lib` directory, add the directory to `LD_LIBRARY_PATH` and place the following command before the preceding boot command:

```
export LD_LIBRARY_PATH=$ANACONDA_DIR/envs/$DEFAULT_CONDA_ENV_NAME/lib:$LD_LIBRARY_PATH;
```

For example, the example boot command used in method 1 is as follows:

```
export LD_LIBRARY_PATH=$ANACONDA_DIR/envs/$DEFAULT_CONDA_ENV_NAME/lib:$LD_LIBRARY_PATH; python /home/ma-user/modelarts/user-job-dir/code/train.py
```

3.4 Searching for an Algorithm

ModelArts allows you to quickly search for algorithms by performing the following operations.

Operation 1: Search for jobs by name, image, code directory, description, and creation time.

Operation 2: Click the refresh button in the upper right corner to refresh the algorithm list.

Operation 3: Configure the custom columns and other basic settings.

Figure 3-11 Searching for an algorithm

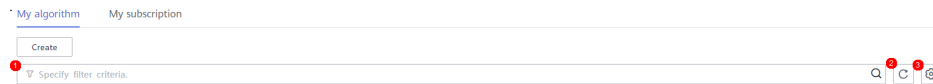
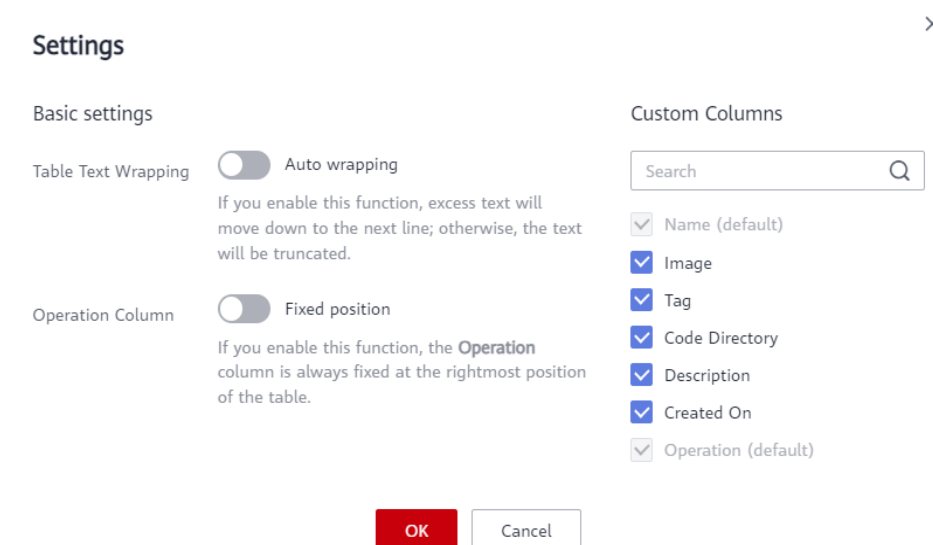


Figure 3-12 Configuring the custom columns and other basic settings



To sort algorithms in a column, click the arrow in the table header of the algorithm list.

Figure 3-13 Sorting



3.5 Deleting an Algorithm

Deleting Your Algorithm

Choose **Algorithm Management > My algorithm** and click **Delete** in the **Operation** column of the target algorithm. In the displayed dialog box, confirm the deletion.

3.6 Precautions for Migrating Training Data from the Old Version to the New Version

The differences between the new version and the old version lie in:

- [Differences in Training Job Creation](#)
- [Differences in Training Code Adaptation](#)
- [Differences in Built-in Training Engines](#)

Differences in Training Job Creation

In the old version, you can use custom algorithms, common frameworks, and custom images to create training jobs.

In the new version, you can use the custom algorithms to create training jobs.

In the new version, algorithms can be selected by category when you create a training job. This does not affect existing training jobs.

If you use custom algorithms or common frameworks to create training jobs in the old version, you can [use a custom script](#) to do so in the new version.

If you use custom images to create training jobs in the old version, you can [use a custom image](#) to do so in the new version.

Differences in Training Code Adaptation

In the old version, you are required to configure data input and output as follows:

```
# Parse CLI parameters.
import argparse
parser = argparse.ArgumentParser(description='MindSpore Lenet Example')
parser.add_argument('--data_url', type=str, default="/Data",
                    help='path where the dataset is saved')
parser.add_argument('--train_url', type=str, default="/Model", help='if is test, must provide\
                    path where the trained ckpt file')
args = parser.parse_args()
...
# Download data to your local container. In the code, local_data_path specifies the training input path.
```

```
mox.file.copy_parallel(args.data_url, local_data_path)
...
# Upload the local container data to the OBS path.
mox.file.copy_parallel(local_output_path, args.train_url)
```

In the new version, you only need to configure training input and output. In the code, **arg.data_url** and **arg.train_url** are used as local paths. For details, see [Developing a Custom Script](#).

```
# Parse CLI parameters.
import argparse
parser = argparse.ArgumentParser(description='MindSpore Lenet Example')
parser.add_argument('--data_url', type=str, default='./Data',
                    help='path where the dataset is saved')
parser.add_argument('--train_url', type=str, default='./Model', help='if is test, must provide\
                    path where the trained ckpt file')
args = parser.parse_args()
...
# The downloaded code does not need to be set. Use data_url and train_url for data training and output.
# Download data to your local container. In the code, local_data_path specifies the training input path.
#mox.file.copy_parallel(args.data_url, local_data_path)
...
# Upload the local container data to the OBS path.
#mox.file.copy_parallel(local_output_path, args.train_url)
```

Differences in Built-in Training Engines

- In the new version, MoXing 2.0.0 or later is installed by default for built-in training engines.
- In the new version, Python 3.7 or later is used for built-in training engines.
- In the new image, the default home directory has been changed from **/home/work** to **/home/ma-user**. Check whether the training code contains code of **/home/work**.
- Built-in training engines are different between the old and new versions. Commonly used built-in training engines have been upgraded in the new version.

To use a training engine in the old version, switch to the old version. [Table 3-6](#) lists the differences between the built-in training engines in the old and new versions.

Table 3-6 Differences between the built-in training engines in the old and new versions

Runtime Environment	Built-in Training Engine and Version	Old Version	New Version
TensorFlow	TensorFlow-1.8.0	√	x
	TensorFlow-1.13.1	√	Coming soon
	TensorFlow-2.1.0	√	√
MXNet	MXNet-1.2.1	√	x
Caffe	Caffe-1.0.0	√	x
Spark MLlib	Spark-2.3.2	√	x

Runtime Environment	Built-in Training Engine and Version	Old Version	New Version
Ray	Ray-0.7.4	√	x
XGBoost with scikit-learn	XGBoost-0.80-Sklearn-0.18.1	√	x
PyTorch	PyTorch-1.0.0	√	x
	PyTorch-1.3.0	√	x
	PyTorch-1.4.0	√	x
	PyTorch-1.8.0	x	√
MPI	MindSpore-1.3.0	x	√
Horovod	Horovod_0.20.0-TensorFlow_2.1.0	x	√
	horovod_0.22.1-pytorch_1.8.0	x	√
MindSpore-GPU	MindSpore-1.1.0	√	x
	MindSpore-1.2.0	√	x

4 Performing a Training

4.1 Creating a Training Job

ModelArts training management enables you to create training jobs, view training statuses, and manage job versions. Model training is an iterative optimization process. Through unified training management, you can flexibly select algorithms, data, and hyperparameters to obtain the optimal input configuration and model. After comparing metrics between training versions, you can determine the most satisfactory training job.

Prerequisites

- Data has been prepared. Specifically, you have created an available dataset in ModelArts, or you have uploaded the dataset used for training to the OBS directory.
- The algorithm used for training is available on the **Algorithm Management** page. The algorithm can be obtained by creating a custom script ([Using a Preset Image \(Custom Script\)](#)), or obtained by creating a custom image ([Using Custom Images](#)).
- At least one empty folder has been created in OBS for storing the training output. OBS buckets are not encrypted. ModelArts does not support encrypted OBS buckets. When creating an OBS bucket, do not enable bucket encryption.
- The account is not in arrears because resources are consumed when training jobs are running.
- The OBS directory you use and ModelArts are in the same region.
- Access authorization has been configured. For details, see [Configuring Access Authorization \(Global Configuration\)](#).

Creating a Training Job

1. Log in to the ModelArts management console.
2. In the navigation pane, choose **Training Management > Training Jobs**. The training job list is displayed.
3. Click **Create Training Job**. Then, configure parameters.

Table 4-1 Parameters of a training job

Parameter	Description
Name	<p>Name of a training job.</p> <p>The system automatically generates a name. You can rename it based on the following naming rules:</p> <ul style="list-style-type: none"> • The name contains 1 to 64 characters. • Letters, digits, hyphens (-), and underscores (_) are allowed.
Description	Description of a training job.

Table 4-2 Algorithm parameters of a training job

Parameter	Sub-Parameter	Description
Created By > Custom algorithms > Boot Mode	Preset images	<p>If Boot Mode is set to Preset images, select a preset engine and configure the code directory and boot file.</p> <ul style="list-style-type: none"> • Code Directory: code directory required for this training job. Upload code to the OBS bucket beforehand. The total size of files in the directory cannot exceed 5 GB, the number of files cannot exceed 1000, and the folder depth cannot exceed 32. • Boot File: Python boot script in the code directory. The boot file must be a .py file because ModelArts supports only boot files written in Python.

Parameter	Sub-Parameter	Description
Created By > Custom algorithms > Boot Mode	Preset images > Customization	<p>If Boot Mode is set to Preset images and the engine version to Customization, configure the image, code directory, and boot file.</p> <ul style="list-style-type: none"> ● Image: Select a container image path. <ul style="list-style-type: none"> – Private images or shared images: Click Select on the right to select an SWR image. Ensure that the image has been uploaded to SWR. – Public images: Enter the SWR image path in the format of <i>Organization name/Image name:Version name</i>. Do not contain the domain name (swr.<region>.xxx.com) in the path because the system will automatically add the domain name to the path. For example, if the SWR address of a public image is swr.<region>.xxx.com/test-image/tensorflow2_1_1:1.1.1, set this parameter to test-images/tensorflow2_1_1:1.1.1. ● User ID: User ID for running the container. The default value 1000 is recommended. This parameter is optional. If the UID needs to be specified, its value must be within the specified range. The UID ranges of different resource pools are as follows: <ul style="list-style-type: none"> – Public resource pool: 1000 to 65535 – Dedicated resource pool: 0 to 65535 ● Code Directory: code directory required for this training job. Upload code to the OBS bucket beforehand. The total size of files in the directory cannot exceed 5 GB, the number of files cannot exceed 1000, and the folder depth cannot exceed 32. ● Boot File: Python boot script in the code directory. The boot file must be a .py file because ModelArts supports only boot files written in Python.

Parameter	Sub-Parameter	Description
Created By > Custom algorithms > Boot Mode	Custom images	<p>If Boot Mode is set to Custom images, select an image and configure the code directory and boot command. For details, see Creating an Algorithm Using a Custom Image.</p> <ul style="list-style-type: none"> • Code Directory: code directory required for this training job. This parameter is optional. Take OBS path obs://obs-bucket/training-test/demo-code as an example. The content in the OBS path will be automatically downloaded to `\${MA_JOB_DIR}/demo-code in the training container, and demo-code (customizable) is the last-level directory of the OBS path. • Boot Command: boot command for the image. This parameter is mandatory. The boot command will be automatically executed after the code directory is downloaded. <ul style="list-style-type: none"> - If the training boot script is a .py file, train.py for example, the boot command can be python `\${MA_JOB_DIR}/demo-code/train.py. - If the training boot script is an .sh file, main.sh for example, the boot command can be bash `\${MA_JOB_DIR}/demo-code/main.sh. <p>Semicolons (;) and ampersands (&&) can be used to combine multiple boot commands. demo-code (customizable) in the boot command is the last-level directory of the OBS path.</p>
Created By > Custom algorithms	Local Code Directory	<p>You can specify the local directory of a training container. When a training starts, the system automatically downloads the code directory to this directory.</p> <p>The default local code directory is /home/ma-user/modelarts/user-job-dir. This parameter is optional.</p>
Created By > Custom algorithms	Work Directory	<p>Directory where the boot file in the training container is located. When a training starts, the system automatically runs the cd command change the work directory to the specified directory.</p>
Created By	My algorithms	<p>Select an algorithm or create an algorithm. For details, see Creating an Algorithm.</p>

Table 4-3 Parameters of training input and output

Parameter	Sub-Parameter	Description
Input	Name	<p>The recommended value is data_url. The training input must match the input configuration set in your selected algorithm. For details, see Table 3-3.</p> <p>You can select a dataset or data path for data input. When the training job is started, ModelArts automatically downloads the data in the input path to the container directory for training.</p>
	Dataset	<p>Select an available dataset and its version from the ModelArts Data Management module.</p> <p>Click Dataset and select the target dataset and its version in the dialog box displayed.</p> <p>NOTE If Dataset is unavailable, the training data of the selected algorithm cannot be from a dataset.</p>
	Data path	<p>Select the training data from your OBS bucket.</p> <p>Click Data path and select the OBS bucket and folder in the dialog box displayed.</p> <p>NOTE If Data path is unavailable, the training data of the selected algorithm cannot be from a data path.</p>
	Obtained from	<p>The following uses training input data_path as an example.</p> <p>If you select Hyperparameters, do as follows to obtain the training input:</p> <pre>import argparse parser = argparse.ArgumentParser() parser.add_argument('--data_path') args, unknown = parser.parse_known_args() data_path = args.data_path</pre> <p>If you select Environment variables, do as follows to obtain the training input:</p> <pre>import os data_path = os.getenv("data_path", "")</pre>
Output	Name	<p>The algorithm code reads the local path to the training output based on this parameter.</p> <p>The recommended value is train_url. The training output must match the output configuration set in your selected algorithm. For details, see Table 3-4.</p> <p>You can select an OBS path for data output. During training, ModelArts automatically uploads the training output to the OBS path.</p>

Parameter	Sub-Parameter	Description
	Data path	<p>This data path stores the training output. During and after the training, the system automatically synchronizes files from the local directory to the data path. Currently, only OBS paths can be set as the data path.</p> <p>Select the storage path of the training result (OBS path). To minimize errors, select an empty directory.</p>
	Obtained from	<p>The following uses the training output train_url as an example.</p> <p>Obtain the training output from hyperparameters by using the following code:</p> <pre>import argparse parser = argparse.ArgumentParser() parser.add_argument('--train_url') args, unknown = parser.parse_known_args() train_url = args.train_url</pre> <p>Obtain the training output from environment variables by using the following code:</p> <pre>import os train_url = os.getenv("train_url", "")</pre>
	Predownload	<p>If you set Predownload to Yes, the system automatically downloads the files in the training output data path to a local directory of the training container before the training job is started. Select Yes for resumable training and incremental training.</p>
Hyperparameters	None	<p>The value of this parameter varies according to the selected algorithm.</p> <p>If you have defined hyperparameters when creating an algorithm, all hyperparameters of the algorithm are displayed. Whether hyperparameters can be modified or deleted depends on how you configure the constraints when creating the algorithm. For details, see Defining Hyperparameters.</p>
Environment Variable	None	<p>Environment variables, which you can add as required. For details about the environment variables preset in the training container, see Viewing Environment Variables of a Training Container.</p>
Auto Restart	None	<p>Number of retries for a failed training job. If this parameter is enabled, a failed training job will be automatically re-delivered and run. On the training job details page, you can view the number of retries for a failed training job.</p> <ul style="list-style-type: none"> This function is disabled by default. If you enable this function, set the number of retries. The value ranges from 1 to 3 and cannot be changed.

 **NOTE**

The training input, training output, and hyperparameters vary according to the selected algorithm.

If the system displays a message for **Training Input**, indicating there is no input channel for the selected algorithm, you do not need to set data input on this page.

If the system displays a message for **Training Output**, indicating there is no output channel for the selected algorithm, you do not need to set data output on this page.

If the system displays a message for **Hyperparameters**, indicating the selected algorithm does not support custom hyperparameters, you do not need to set hyperparameters on this page.

4. Select an instance flavor. The value range of the training parameters is consistent with the constraints of existing algorithms.

Table 4-4 Resource parameters

Parameter	Description
Resource Pool	<p>Select resource pools for the job. Public and dedicated resource pools are available for you to select.</p> <p>If you select a dedicated resource pool, you can view details about the pool. If the number of available cards of this pool is insufficient, jobs may need to be queued. In this case, use another resource pool or reduce the number of cards required.</p> <p>NOTE Dedicated resource pools can be interconnected with your VPCs and subnets. If you want to change a VPC interconnected with your dedicated resource pool, you must select the VPC and subnet again. For details, see ModelArts Network.</p>
Resource Type	<p>Select CPU or GPU as needed. Set this parameter based on the resource type specified in your training code.</p>
Instance Flavor	<p>Select a resource flavor based on the resource type. If the type of resources to be used has been specified in your training code, only the options that comply with the constraints of the selected algorithm are available for you to choose. For example, if GPU is selected in the training code but you select CPU here, the training may fail.</p> <p>During training, ModelArts will mount NVME SSDs to the /cache directory. You can use this directory to store temporary files. The data disk size varies depending on the resource type. To prevent insufficient memory during training, click Check Input Size to check whether the disk size of selected instance flavor is sufficient for the input size.</p> <p>NOTICE The resource flavor GPU:n*nvidia-t4 (<i>n</i> indicates a specific number) does not support multi-process training.</p>

Parameter	Description
Compute Nodes	Set the number of compute nodes. The default value is 1 .
Job Priority	When using a new-version dedicated resource pool, you can set the priority of a training job. The value ranges from 1 to 3. The default priority is 1 , and the highest priority is 3 . By default, the job priority can be set to 1 or 2 . After the permission to set the highest job priority is configured, the priority can be set to 1 to 3 . You can change the priority of a pending job.
SFS Turbo	<p>When a dedicated resource pool is used for training, multiple SFS Turbo file systems can be mounted for one training job.</p> <ul style="list-style-type: none"> • File System: Select SFS Turbo. • Mount Path: SFS Turbo mounting path in the training container. • Storage Location: Specify the SFS Turbo storage location. If you have configured the folder control permission, select a storage location. If you have not configured the folder control permission, retain the default value <code>/</code> or customize a location. • Mounting Mode: Permission on the mounted SFS Turbo file system. This parameter is displayed as Read/Write or Read-only based on the permission of the SFS Turbo storage location. If you have not configured the folder control permission, this parameter is unavailable. <p>A file system can be mounted only once and to only one path. Each mount path must be unique. A maximum of 8 disks can be mounted to a training job.</p> <p>NOTE</p> <ul style="list-style-type: none"> • Before mounting an SFS Turbo file system to a training job, configure the VPC and subnet where SFS Turbo is deployed to be accessible in the dedicated resource pool. For details, see ModelArts Network. • The mounting path cannot be a <code>/</code> directory or a default mounting path, such as <code>/cache</code> and <code>/home/ma-user/modelarts</code>.
Persistent Log Saving	<p>If you select CPU or GPU flavors, Persistent Log Saving is available for you to set.</p> <p>This function is disabled by default. ModelArts automatically stores the logs for 30 days. You can download all logs on the job details page.</p> <p>After this function is enabled, select an empty OBS path for storing training logs. Ensure that you have read and write permissions to the selected OBS directory.</p>

Parameter	Description
Job Log Path	If you select Ascend resources, select an empty OBS path for storing training logs. Ensure that you have read and write permissions to the selected OBS directory.
Event Notification	<p>Whether to subscribe to event notifications. After this function is enabled, you will be notified of specific events, such as job status changes or suspected suspensions, via an SMS or email.</p> <p>If you enable this function, configure the following parameters as required:</p> <ul style="list-style-type: none"> • Topic: topic of event notifications. You can create a topic on the SMN console. • Event: type of the event to subscribe to. Options: JobStarted, JobCompleted, JobFailed, JobTerminated, and JobHanged. <p>NOTE</p> <ul style="list-style-type: none"> • After you create a topic on the SMN console, add a subscription to the topic, and confirm the subscription. Then, you will be notified of events. For details, see Adding a Subscription. • SMN charges you for the number of notification messages. For details, see Billing. • Currently, only training jobs using GPUs support JobHanged events.
Auto Stop	<p>This parameter is available when a paid resource is used.</p> <ul style="list-style-type: none"> • After this parameter is enabled and the auto stop time is set, a training job automatically stops at the specified time. • If this function is disabled, a training job will continue to run and charges will continue to be incurred. • The options are 1hour, 2hours, 4hours, 6hours, and Customization (1 hour to 720 hours).

5. (Optional) Configure advanced settings.

Table 4-5 Advanced settings

Parameter	Description
Tags	<p>ModelArts can work with Tag Management Service (TMS). When creating resource-consuming tasks in ModelArts, for example, training jobs, configure tags for these tasks so that ModelArts can use tags to manage resources by group.</p> <p>For details about how to use tags, see How Does ModelArts Use Tags to Manage Resources by Group?</p>

 **NOTE**

You can select a predefined TMS tag from the tag drop-down list or customize a tag. Predefined tags are available to all service resources that support tags. Customized tags are available only to the service resources of the user who has created the tags.

6. Click **Submit** to create the training job.

A training job generally runs for a period of time. To view the real-time status and basic information of a training job, switch to the training job list.

- In the training job list, **Status** of the newly created training job is **Pending**.
- When the status of a training job changes to **Completed**, the training job is complete, and the generated model is stored in the corresponding training output path.
- If the status is **Failed** or **Abnormal**, click the job name to go to the job details page and view logs for troubleshooting. For details, see [Training Job Details](#).

 **NOTE**

After a training job is created, it is started immediately. During the running, you will be charged based on your selected resources.

4.2 Viewing Training Job Details

1. Log in to the ModelArts management console.
2. In the navigation pane on the left, choose **Training Management > Training Jobs**.
3. In the training job list, click a job name to switch to the training job details page.
4. On the left of the training job details page, view basic job settings and algorithm parameters.

< | job-fd79

The screenshot displays the configuration details for a training job. The parameters are as follows:

- Job ID:** df08db2d-593c-426e-a6db
- Status:** Completed (indicated by a green checkmark)
- Created:** Nov 08, 2023 11:29:40 GMT+08:00
- Duration:** 00:10:19
- Retries:** 0
- Description:** -- (with an edit icon)
- Job Priority:** 1
- Algorithm Name:** --
- Preset image:** PyTorch | pytorch_1.8.0-cuda_10.2-py_3.7-ubuntu_18.04-x86_64
- Code Directory:** /.../number/mnist-code/ (with an Edit Code button)
- Boot File:** /.../number/mnist-code/train.py
- User ID:** 1102
- Local Code Directory:** /home/ma-user/modelarts/user-job-dir
- Work Directory:** /home/ma-user/modelarts/user-job-dir

– Basic job settings

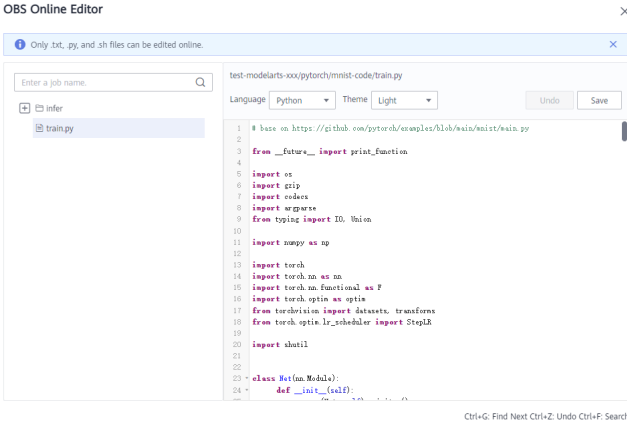
Table 4-6 Basic job settings

Parameter	Description
Job ID	Unique ID of a training job
Status	Training job status
Created	Time when the training job is created
Duration	Running duration of a training job

Parameter	Description
Retries	Number of times that a training job automatically restarts upon a fault. This parameter is available only when Auto Restart is enabled during training job creation.
Description	Description of a training job. You can click the edit icon to update the description of a training job.

- Algorithm parameters

Table 4-7 Algorithm parameters

Parameter	Description
Algorithm Name	Algorithm used in a training job You can click the algorithm name to go to the algorithm details page.
Preset images	Preset image used by a training job
Code Directory	<p>OBS path to the code directory of a training job You can click Edit Code on the right to edit the training script code in OBS Online Editor. OBS Online Editor is not available for a training job in the Pending, Creating, or Running status.</p>  <p>NOTE If you use the algorithm subscribed in AI Gallery to create a training job, then this parameter is not supported.</p>
Boot File	<p>Location where a boot file is stored.</p> <p>NOTE If you use the algorithm subscribed in AI Gallery to create a training job, then this parameter is not supported.</p>
User ID	ID of the user who runs the container.

Parameter	Description
Local Code Directory	Path to the training code in the training container
Work Directory	Path to the training startup file in the training container
Compute Nodes	Number of compute nodes
Dedicated resource pool	Dedicated resource pool information. This parameter is available only when a training job uses a dedicated resource pool.
Specifications	Training specifications used in a training job
Input - Input Path	OBS path where the input data is stored
Input - Parameter Name	Algorithm code parameter specified by the input path
Input - Obtained from	Method of obtaining the training job input.
Input - Local Path (Training Parameter Value)	Path for storing the input data in the ModelArts backend container. After the training is started, ModelArts downloads the data stored in OBS to the backend container.
Output - Output Path	OBS path where the output data is stored
Output - Parameter Name	Algorithm code parameter specified by the output path
Output - Obtained from	Method of obtaining the training job output.
Output - Local Path (Training Parameter Value)	Path for storing the output data in the ModelArts backend container
Hyperparameter	Hyperparameters used in a training job
Environment Variable	Environment variables for a training job

4.3 Training Job Logs

4.3.1 Introduction to Training Job Logs

Overview

Training logs record the runtime process and exception information of training jobs and provide useful details for fault location. The standard output and standard error information in your code are displayed in training logs. If you encounter an issue during the execution of a ModelArts training job, view logs first. In most scenarios, you can locate the issue based on the error information reported in logs.

Retention Period

Logs are classified into the following types based on the retention period:

- Real-time logs: generated during training job running and can be viewed on the ModelArts training job details page.
- Historical logs: After a training job is complete, you can view its historical logs on the ModelArts training job details page. ModelArts automatically stores the logs for 30 days.
- Permanent logs: dumped to your OBS bucket. When creating a training job, you can set an OBS dump path. You need to manually enable **Persistent Log Saving** for CPU- or GPU-based training jobs.

Figure 4-1 Enabling Persistent Log Saving



Real-time logs and historical logs have no difference in content. Real-time logs, historical logs, and permanent logs of CPU- or GPU-based training jobs are the same.

Related Chapters

- On the ModelArts training job details page, you can preview logs, download logs, and search for logs by keyword in the log pane. For details, see [Viewing Training Job Logs](#).
- ModelArts also enables you to quickly locate and rectify training faults. For details, see [Locating Faults by Analyzing Training Logs](#).

4.3.2 Common Logs

Common logs include the logs for **pip-requirement.txt**, training process, and ModelArts.

Log Type

Table 4-8 Log type

Type	Description
Training process log	Standard output of your training code
Installation logs for pip-requirement.txt	If pip-requirement.txt is defined in training code, PIP package installation logs are generated.
ModelArts logs	ModelArts logs are used by O&M personnel to locate service faults.

File Format

The format of a common log file is as follows. **task id** is the node ID of a training job.

Unified log format: modelarts-job-[job id]-[task id].log

Example: log/modelarts-job-95f661bd-1527-41b8-971c-eca55e513254-worker-0.log

- Single-node training jobs generate a log file, and **task id** defaults to **worker-0**.
- Distributed training generates multiple node log files, which are distinguished by **task id**, such as **worker-0** and **worker-1**.

Common logs include the logs for **pip-requirement.txt**, training process, and ModelArts.

ModelArts Logs

ModelArts logs can be filtered in the common log file **modelarts-job-[job id]-[task id].log** using the following keywords: **[ModelArts Service Log]** or **Platform=ModelArts-Service**.

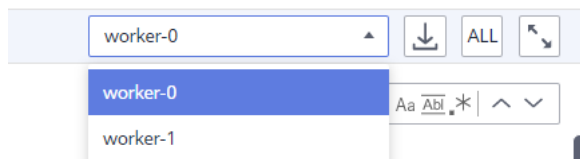
- Type 1: **[ModelArts Service Log] xxx**
[ModelArts Service Log][init] download code_url: s3://dgg-test-user/snt9-test-cases/mindspore/lenet/
- Type 2: **time="xxx" level="xxx" msg="xxx" file="xxx" Command=xxx**
Component=xxx Platform=xxx
time="2021-07-26T19:24:11+08:00" level=info msg="start the periodic upload task, upload period = 5 seconds " file="upload.go:46" Command=obs/upload Component=ma-training-toolkit Platform=ModelArts-Service

4.3.3 Viewing Training Job Logs

On the training job details page, you can preview logs, download logs, search for logs by keyword, and filter system logs in the log pane.

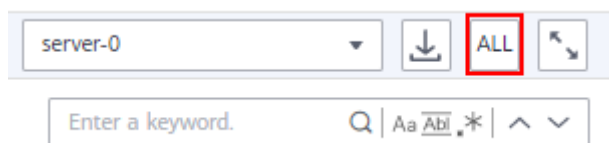
- Previewing logs
You can preview logs of each compute node, if multiple compute nodes are used, in the training log pane by choosing the target node from the drop-down list on the right.

Figure 4-2 Viewing logs of different compute nodes



If a log file is oversized, the system displays only the latest logs in the log pane. To view all logs, click the link in the upper part of the log pane, which will direct you to a new page.

Figure 4-3 Viewing all logs

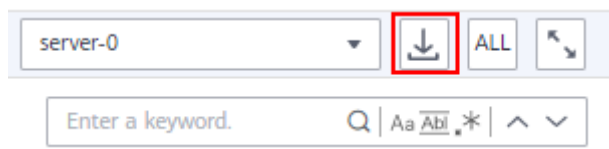


NOTE

- If the total size of all logs exceeds 500 MB, the log page may be frozen. In this case, download the logs to view them locally.
- A log preview link can be accessed by anyone within one hour after it is generated. You can share the link with others.
Ensure that no privacy information is contained in the logs. Otherwise, information leakage may occur.

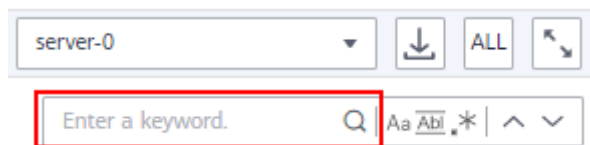
- **Downloading logs**
Training logs are retained for only 30 days. To permanently store logs, click the download icon in the upper right corner of the log pane. You can download the logs of multiple compute nodes in a batch. You can also enable **Persistent Log Saving** and set a log path when you create a training job. In this way, the logs will be automatically stored in the specified OBS path.
If a training job is created on an Ascend compute node, certain system logs cannot be downloaded in the training log pane. To obtain these logs, go to the **Job Log Path** you set when you created the training job.

Figure 4-4 Downloading logs



- **Searching for logs by keyword**
In the upper right corner of the log pane, enter a keyword in the search box to search for logs, as shown in [Figure 4-5](#).

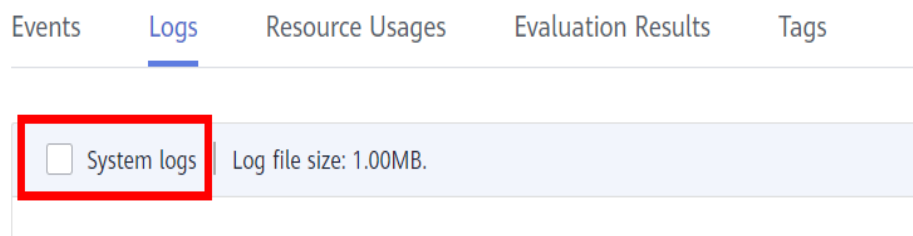
Figure 4-5 Searching for logs by keyword



The system will highlight the keyword and redirect you between search results. Only the logs loaded in the log pane can be searched for. If the logs are not fully displayed (see the message displayed on the page), obtain all the logs by downloading them or clicking the full log link and then search for the logs. On the page redirected by the full log link, press **Ctrl+F** to search for logs.

- Filtering system logs

Figure 4-6 System logs



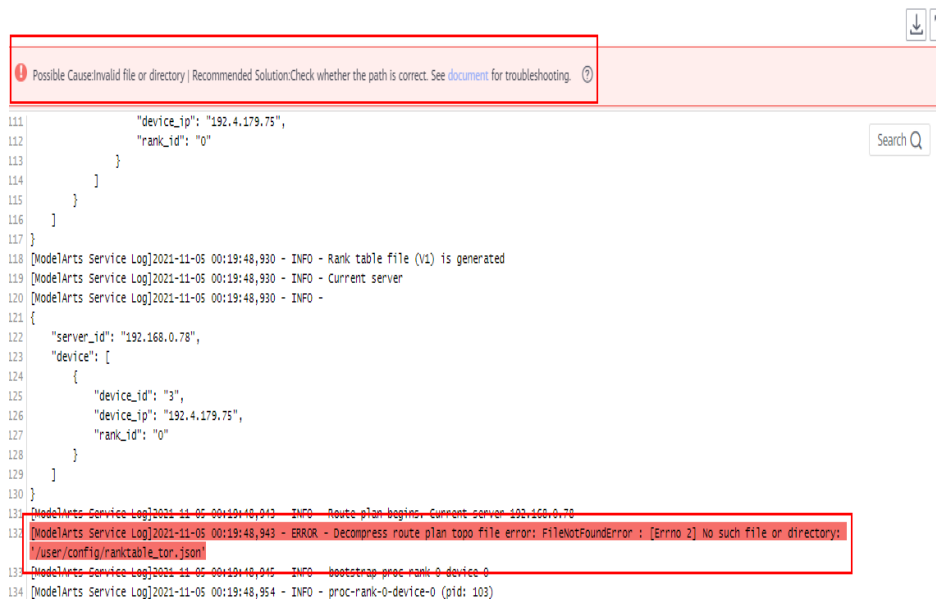
If **System logs** is selected, system logs and user logs are displayed. If **System logs** is deselected, only user logs are displayed.

4.3.4 Locating Faults by Analyzing Training Logs

If you encounter an issue during the execution of a ModelArts training job, view logs first. In most scenarios, you can locate the issue based on the error information reported in logs.

If a training job fails, ModelArts automatically identifies the failure cause and displays a message on the log page. The message consists of possible causes, recommended solutions, and error logs (marked in red).

Figure 4-7 Identifying training faults



ModelArts provides possible causes (for reference only) and solutions for some common training faults. Not all faults can be identified. For a distributed job, only the analysis result of the current node is displayed. To obtain the failure cause of a training job, check the analysis results of all nodes used by the training job.

To rectify common training faults, perform the following steps:

1. Rectify the fault based on the analysis and suggestions provided on the log page.
 - Solution 1: A troubleshooting document is provided for you to follow.
 - Solution 2: Rebuild the training job and run it again.
2. If the fault persists, analyze the error information in the logs to locate and rectify the fault.
3. If the provided solutions cannot rectify your fault, you can submit a service ticket for technical support.

4.4 Viewing Training Job Events

Any key event of a training job will be recorded at the backend after the training job is displayed for you. You can check events on the training job details page.

This helps you better understand the running process of a training job and locate faults more accurately when a task exception occurs. The following job events are supported:

- Training job created.
- Training job failures:
- Preparations timed out. The possible cause is that the cross-region algorithm synchronization or creating shared storage timed out.
- The training job is queuing and awaiting resource allocation.

- Failed to be queued.
- The training job starts to run.
- Training job executed.
- Failed to run the training job.
- The training job is preempted.
- The system detects that your training job may be suspended. Go to the job details page to view the cause and handle the issue.
- The training job has been restarted.
- The training job has been manually stopped.
- The training job has been stopped. (Maximum running duration: 1 hour)
- The training job has been stopped. (Maximum running duration: 3 hours)
- The training job has been manually deleted.
- Billing information synchronized.
- [worker-0] The training environment is being pre-checked.
- [worker-0] [Duration: second] Pre-check completed.
- [worker-0] [Duration: second] Pre-check failed. Error: xxx
- [worker-0] [Duration: second] Pre-check failed. Error: xxx
- [worker-0] The training code is being downloaded.
- [worker-0] [Duration: second] Training code downloaded.
- [worker-0] [Duration: second] Failed to download the training code. Failure cause:
- [worker-0] The training input is being downloaded.
- [worker-0] [Duration: second] Training input (parameter: xxx) downloaded.
- [worker-0] [Duration: second] Failed to download the training input (parameter: xxx). Failure cause:
- [worker-0] Python dependency packages are being installed. Import the following files:
- [worker-0] [Duration: second] Python dependency packages installed. Import the following files:
- [worker-0] The training job starts to run.
- [worker-0] Training job executed.
- [worker-0] The training input is being uploaded.
- [worker-0] [Duration: second] Training output (parameter: xxx) uploaded.

During the training process, key events can be manually or automatically refreshed.

Procedure

1. In the navigation pane of the ModelArts management console, choose **Training Management > Training Jobs**. In the training job list, click a job name.
2. Click **Events** to view events.

Figure 4-8 Events

Event Type	Event Message	Occurred
Normal	Job completed.	2022/11/15 10:50:50 GMT+08:00
Normal	[Task: worker-0] Uploading (periodically) training outputs and logs finished. Exit code 0.	2022/11/15 10:50:48 GMT+08:00
Normal	[Task: worker-0] Training finished. Exit code 0.	2022/11/15 10:50:46 GMT+08:00
Normal	[Task: worker-0] training started.	2022/11/15 10:47:13 GMT+08:00
Normal	Job is running.	2022/11/15 10:47:10 GMT+08:00
Normal	[Task: worker-0] Uploading (periodically) training outputs and logs started.	2022/11/15 10:47:08 GMT+08:00
Normal	[Task: worker-0] Environment Initialized. Exit code 0.	2022/11/15 10:47:06 GMT+08:00
Normal	[Task: worker-0] Download training input({'name': 'data_url', 'local_dir': '/home/ma-user/modelarts/inputs/data_url_0', 'access...})	2022/11/15 10:47:05 GMT+08:00
Normal	[Task: worker-0] Download training code finished. Time used 1s.	2022/11/15 10:47:04 GMT+08:00
Normal	[Task: worker-0] Pre-training checks finished. Time used 1s.	2022/11/15 10:47:02 GMT+08:00

4.5 Viewing the Resource Usage of a Training Job

Operations

You can view the resource usage of a compute node in the **Resource Usages** window. The data of at most the last three days can be displayed. When the resource usage window is opened, the data is loading and refreshed periodically.

Operation 1: If a training job uses multiple compute nodes, choose a node from the drop-down list box to view its metrics.

Operation 2: Click **cpuUsage**, **gpuMemUsage**, **gpuUtil**, **memUsage**, **npuMemUsage**, or **npuUtil** to show or hide the usage chart of the parameter.

Operation 3: Hover the cursor on the graph to view the usage at the specific time.

Figure 4-9 Resource Usages

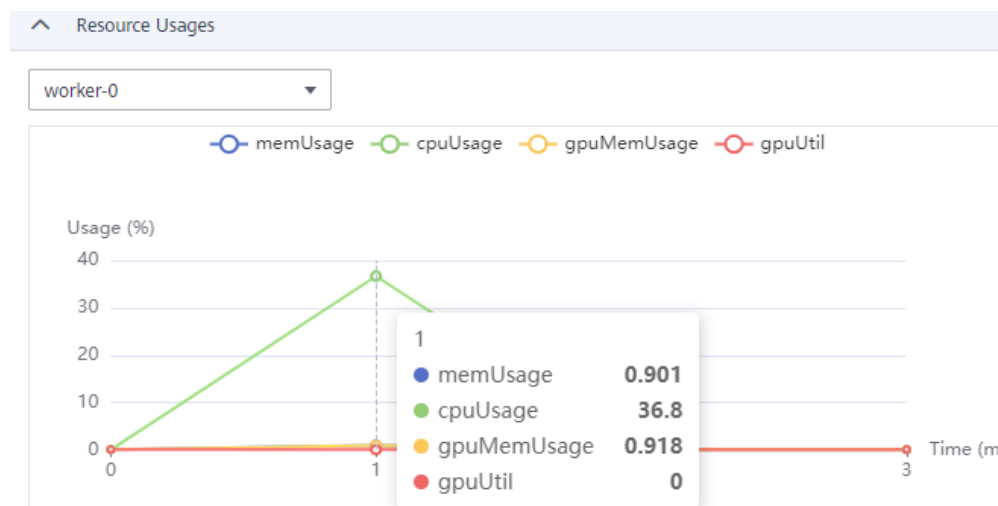


Table 4-9 Parameters

Parameter	Description
cpuUsage	CPU usage

Parameter	Description
gpuMemUsage	GPU memory usage
gpuUtil	GPU usage
memUsage	Memory usage
npuMemUsage	NPU memory usage
npuUtil	NPU usage

Alarms of Job Resource Usage

You can view the job resource usage on the training job list page. If the average GPU/NPU usage of a job is lower than 50%, an alarm is displayed in the training job list.

Figure 4-10 Job resource usage in the job list



The job resource usage here involves only GPU and NPU resources. The method of calculating the average GPU/NPU usage of a job is: Summarize the usage of each GPU/NPU accelerator card at each time point of the job and calculate the average value. If a job uses multiple compute nodes, summarize the usage of all compute nodes and then obtain the average usage of a single job.

Improving Job Resource Utilization

- Increasing the value of **batch_size** increases GPU and NPU usage. You must decide the batch size that will not cause a memory overflow.
- If the time for reading data in a batch is longer than the time for GPUs or NPUs to calculate data in a batch, GPU or NPU usage may fluctuate. In this case, optimize the performance of data reading and data augmentation. For example, read data in parallel or use tools such as NVIDIA Data Loading Library (DALI) to improve the data augmentation speed.
- If a model is large and frequently saved, GPU or NPU usage is affected. In this case, do not save models frequently. Similarly, make sure that other non-GPU/NPU operations, such as log printing and training metric saving, do not affect the training process for too much time.

4.6 Evaluation Results

After a training job has been executed, ModelArts evaluates your model and provides optimization diagnosis and suggestions.

- When you use a built-in algorithm to create a training job, you can view the evaluation result without any configurations. The system automatically provides optimization suggestions based on your model metrics. Read the suggestions and guidance on the page carefully to further optimize your model.
- For a training job created by writing a training script or using a custom image, you need to add the evaluation code to the training code so that you can view the evaluation result and diagnosis suggestions after the training job is complete.

NOTE

- Only validation sets of the image type are supported.
- You can add the evaluation code only when the training scripts of the following frequently-used frameworks are used:
 - TF-1.13.1-python3.6
 - TF-2.1.0-python3.6
 - PyTorch-1.4.0-python3.6

This section describes how to use the evaluation code in a training job. To adapt and modify the training code, three steps are involved, [Adding the Output Path](#), [Copying the Dataset to the Local Host](#), and [Mapping the Dataset Path to OBS](#).

Adding the Output Path

The code for adding the output path is simple. That is, add a path for storing the evaluation result file to the code, which is called **train_url**, that is, the training output path on the console. Add **train_url** to the analysis function and use **save_path** to obtain **train_url**. The sample code is as follows:

```
FLAGS = tf.app.flags.FLAGS
tf.app.flags.DEFINE_string('model_url', '', 'path to saved model')
tf.app.flags.DEFINE_string('data_url', '', 'path to output files')
tf.app.flags.DEFINE_string('train_url', '', 'path to output files')
tf.app.flags.DEFINE_string('adv_param_json',
                           '{"attack_method": "FGSM", "eps": 40}',
                           'params for adversarial attacks')
FLAGS(sys.argv, known_only=True)

...

# analyse
res = analyse(
    task_type=task_type,
    pred_list=pred_list,
    label_list=label_list,
    name_list=file_name_list,
    label_map_dict=label_dict,
    save_path=FLAGS.train_url)
```

Copying the Dataset to the Local Host

Copying a dataset to the local host is to prevent the OBS connection from being interrupted due to long-time access. Therefore, copy the dataset to the local host before performing operations.

There are two methods for copying datasets. The recommended method is to use the OBS path.

- OBS path (recommended)
Call the `copy_parallel` API of MoXing to copy the corresponding OBS path.
- Dataset in ModelArts data management (manifest file format)
Call the `copy_manifest` API of MoXing to copy the file to the local host and obtain the path of the new manifest file. Then, use SDK to parse the new manifest file.

NOTE

ModelArts data management is being upgraded and is invisible to users who have not used data management. It is recommended that new users store their training data in OBS buckets.

```
if data_path.startswith('obs://'):
    if 'manifest' in data_path:
        new_manifest_path, _ = mox.file.copy_manifest(data_path, '/cache/data/')
        data_path = new_manifest_path
    else:
        mox.file.copy_parallel(data_path, '/cache/data/')
        data_path = '/cache/data/'
print('----- download dataset success -----')
```

Mapping the Dataset Path to OBS

The actual path of the image file, that is, the OBS path, needs to be entered in the JSON body. Therefore, after analysis and evaluation are performed on the local host, the original local dataset path needs to be mapped to the OBS path, and the new list needs to be sent to the analysis API.

If the OBS path is used as the input of `data_url`, you only need to replace the string of the local path.

```
if FLAGS.data_url.startswith('obs://'):
    for idx, item in enumerate(file_name_list):
        file_name_list[idx] = item.replace(data_path, FLAGS.data_url)
```

If the manifest file is used, the original manifest file needs to be parsed again to obtain the list and then the list is sent to the analysis API.

```
if or FLAGS.data_url.startswith('obs://'):
    if 'manifest' in FLAGS.data_url:
        file_name_list = []
        manifest, _ = get_sample_list(
            manifest_path=FLAGS.data_url, task_type='image_classification')
        for item in manifest:
            if len(item[1]) != 0:
                file_name_list.append(item[0])
```

An example code for image classification that can be used to create training jobs is as follows:

```
import json
import logging
```

```

import os
import sys
import tempfile

import h5py
import numpy as np
from PIL import Image

import moxing as mox
import tensorflow as tf
from deep_moxing.framework.manifest_api.manifest_api import get_sample_list
from deep_moxing.model_analysis.api import analyse, tmp_save
from deep_moxing.model_analysis.common.constant import TMP_FILE_NAME

logging.basicConfig(level=logging.DEBUG)

FLAGS = tf.app.flags.FLAGS
tf.app.flags.DEFINE_string('model_url', '', 'path to saved model')
tf.app.flags.DEFINE_string('data_url', '', 'path to output files')
tf.app.flags.DEFINE_string('train_url', '', 'path to output files')
tf.app.flags.DEFINE_string('adv_param_json',
                           '{"attack_method":"FGSM","eps":40}',
                           'params for adversarial attacks')
FLAGS(sys.argv, known_only=True)

def _preprocess(data_path):
    img = Image.open(data_path)
    img = img.convert('RGB')
    img = np.asarray(img, dtype=np.float32)
    img = img[np.newaxis, :, :, :]
    return img

def softmax(x):
    x = np.array(x)
    orig_shape = x.shape
    if len(x.shape) > 1:
        # Matrix
        x = np.apply_along_axis(lambda x: np.exp(x - np.max(x)), 1, x)
        denominator = np.apply_along_axis(lambda x: 1.0 / np.sum(x), 1, x)
        if len(denominator.shape) == 1:
            denominator = denominator.reshape((denominator.shape[0], 1))
        x = x * denominator
    else:
        # Vector
        x_max = np.max(x)
        x = x - x_max
        numerator = np.exp(x)
        denominator = 1.0 / np.sum(numerator)
        x = numerator.dot(denominator)
    assert x.shape == orig_shape
    return x

def get_dataset(data_path, label_map_dict):
    label_list = []
    img_name_list = []
    if 'manifest' in data_path:
        manifest, _ = get_sample_list(
            manifest_path=data_path, task_type='image_classification')
        for item in manifest:
            if len(item[1]) != 0:
                label_list.append(label_map_dict.get(item[1][0]))
                img_name_list.append(item[0])
            else:
                continue
    else:
        label_name_list = os.listdir(data_path)

```

```

label_dict = {}
for idx, item in enumerate(label_name_list):
    label_dict[str(idx)] = item
    sub_img_list = os.listdir(os.path.join(data_path, item))
    img_name_list += [
        os.path.join(data_path, item, img_name) for img_name in sub_img_list
    ]
    label_list += [label_map_dict.get(item)] * len(sub_img_list)
return img_name_list, label_list

def deal_ckpt_and_data_with_obs():
    pb_dir = FLAGS.model_url
    data_path = FLAGS.data_url

    if pb_dir.startswith('obs://'):
        mox.file.copy_parallel(pb_dir, '/cache/ckpt/')
        pb_dir = '/cache/ckpt'
        print('----- download success -----')
    if data_path.startswith('obs://'):
        if '.manifest' in data_path:
            new_manifest_path, _ = mox.file.copy_manifest(data_path, '/cache/data/')
            data_path = new_manifest_path
        else:
            mox.file.copy_parallel(data_path, '/cache/data/')
            data_path = '/cache/data/'
        print('----- download dataset success -----')
    assert os.path.isdir(pb_dir), 'Error, pb_dir must be a directory'
    return pb_dir, data_path

def evaluation():
    pb_dir, data_path = deal_ckpt_and_data_with_obs()
    index_file = os.path.join(pb_dir, 'index')
    try:
        label_file = h5py.File(index_file, 'r')
        label_array = label_file['labels_list'][:].tolist()
        label_array = [item.decode('utf-8') for item in label_array]
    except Exception as e:
        logging.warning(e)
        logging.warning('index file is not a h5 file, try json.')
        with open(index_file, 'r') as load_f:
            label_file = json.load(load_f)
            label_array = label_file['labels_list'][:].
    label_map_dict = {}
    label_dict = {}
    for idx, item in enumerate(label_array):
        label_map_dict[item] = idx
        label_dict[idx] = item
    print(label_map_dict)
    print(label_dict)

    data_file_list, label_list = get_dataset(data_path, label_map_dict)

    assert len(label_list) > 0, 'missing valid data'
    assert None not in label_list, 'dataset and model not match'

    pred_list = []
    file_name_list = []
    img_list = []

    for img_path in data_file_list:
        img = _preprocess(img_path)
        img_list.append(img)
        file_name_list.append(img_path)

    config = tf.ConfigProto()
    config.gpu_options.allow_growth = True
    config.gpu_options.visible_device_list = '0'

```

```

with tf.Session(graph=tf.Graph(), config=config) as sess:
    meta_graph_def = tf.saved_model.loader.load(
        sess, [tf.saved_model.tag_constants.SERVING], pb_dir)
    signature = meta_graph_def.signature_def
    signature_key = 'predict_object'
    input_key = 'images'
    output_key = 'logits'
    x_tensor_name = signature[signature_key].inputs[input_key].name
    y_tensor_name = signature[signature_key].outputs[output_key].name
    x = sess.graph.get_tensor_by_name(x_tensor_name)
    y = sess.graph.get_tensor_by_name(y_tensor_name)
    for img in img_list:
        pred_output = sess.run([y], {x: img})
        pred_output = softmax(pred_output[0])
        pred_list.append(pred_output[0].tolist())

label_dict = json.dumps(label_dict)
task_type = 'image_classification'

if FLAGS.data_url.startswith('obs://'):
    if 'manifest' in FLAGS.data_url:
        file_name_list = []
        manifest, _ = get_sample_list(
            manifest_path=FLAGS.data_url, task_type='image_classification')
        for item in manifest:
            if len(item[1]) != 0:
                file_name_list.append(item[0])
        for idx, item in enumerate(file_name_list):
            file_name_list[idx] = item.replace(data_path, FLAGS.data_url)
# analyse
res = analyse(
    task_type=task_type,
    pred_list=pred_list,
    label_list=label_list,
    name_list=file_name_list,
    label_map_dict=label_dict,
    save_path=FLAGS.train_url)

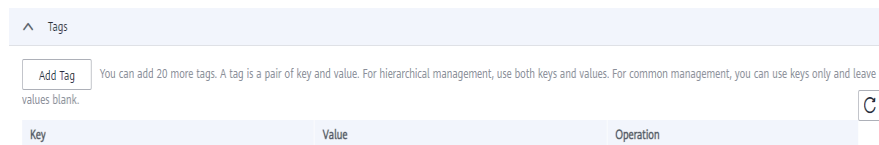
if __name__ == "__main__":
    evaluation()

```

4.7 Viewing Training Tags

View tags of a training job. Tags can be added, modified, and deleted. For details about how to use tags, see [How Does ModelArts Use Tags to Manage Resources by Group?](#)

Figure 4-11 Tags



4.8 Viewing Environment Variables of a Training Container

What Is an Environment Variable

This section describes environment variables preset in a training container. The environment variables include:

- Path environment variables
- Environment variables of a distributed training job
- Nvidia Collective multi-GPU Communication Library (NCCL) environment variables
- OBS environment variables
- Environment variables of the PIP source
- Environment variables of the API Gateway address
- Environment variables of job metadata

Configuring Environment Variables

When you create a training job, you can add environment variables or modify environment variables preset in the training container.

Figure 4-12 Setting environment variables



Environment Variables Preset in a Training Container

The following tables list environment variables preset in a training container, including [Table 4-10](#), [Table 4-11](#), [Table 4-12](#), [Table 4-13](#), [Table 4-14](#), [Table 4-15](#), and [Table 4-16](#).

The environment variable values are examples.

Table 4-10 Path environment variables

Variable	Description	Example
PATH	Executable file paths	PATH=/usr/local/nvidia/bin:/usr/local/cuda/bin:/usr/local/sbin:/usr/local/bin:/usr/sbin:/usr/bin:/sbin:/bin

Variable	Description	Example
LD_LIBRARY_PATH	Dynamic load library paths	LD_LIBRARY_PATH=/usr/local/seccomponent/lib:/usr/local/cuda/lib64:/usr/local/cuda/compat:/root/miniconda3/lib:/usr/local/nvidia/lib:/usr/local/nvidia/lib64
LIBRARY_PATH	Static library paths	LIBRARY_PATH=/usr/local/cuda/lib64/stubs
MA_HOME	Main directory of a training job	MA_HOME=/home/ma-user
MA_JOB_DIR	Parent directory of the training algorithm folder	MA_JOB_DIR=/home/ma-user/modelarts/user-job-dir
MA_MOUNT_PATH	Path mounted to a ModelArts training container, which is used to temporarily store training algorithms, algorithm input, algorithm output, and logs	MA_MOUNT_PATH=/home/ma-user/modelarts
MA_LOG_DIR	Training log directory	MA_LOG_DIR=/home/ma-user/modelarts/log
MA_SCRIPT_INTERPRETER	Training script interpreter	MA_SCRIPT_INTERPRETER=
WORKSPACE	Training algorithm directory	WORKSPACE=/home/ma-user/modelarts/user-job-dir/code

Table 4-11 Environment variables of a distributed training job

Variable	Description	Example
MA_CURRENT_IP	IP address of a job container.	MA_CURRENT_IP=192.168.23.38
MA_NUM_GPUS	Number of accelerator cards in a job container.	MA_NUM_GPUS=8

Variable	Description	Example
MA_TASK_NAME	Name of a job container, for example: <ul style="list-style-type: none"> • worker in MindSpore and PyTorch. • learner or worker in reinforcement learning engines. • ps or worker in TensorFlow. 	MA_TASK_NAME=worker
MA_NUM_HOSTS	Compute nodes required for a training job.	MA_NUM_HOSTS=4
VC_TASK_INDEX	Sequence number of a job container for multi-node training. The value of the first container is 0.	VC_TASK_INDEX=0
VC_WORKER_NUM	Compute nodes required for a training job.	VC_WORKER_NUM=4
VC_WORKER_HOSTS	Domain name of each node for multi-node training. Use commas (,) to separate the domain names in sequence. You can obtain the IP address through domain name resolution.	VC_WORKER_HOSTS=modelarts-job-a0978141-1712-4f9b-8a83-000000000000-worker-0.modelarts-job-a0978141-1712-4f9b-8a83-000000000000,modelarts-job-a0978141-1712-4f9b-8a83-000000000000-worker-1.ob-a0978141-1712-4f9b-8a83-000000000000,modelarts-job-a0978141-1712-4f9b-8a83-000000000000-worker-2.modelarts-job-a0978141-1712-4f9b-8a83-000000000000,ob-a0978141-1712-4f9b-8a83-000000000000-worker-3.modelarts-job-a0978141-1712-4f9b-8a83-000000000000

Table 4-12 NCCL environment variables

Variable	Description	Example
NCCL_VERSION	NCCL version	NCCL_VERSION=2.7.8

Variable	Description	Example
NCCL_DEBUG	NCCL log level	NCCL_DEBUG=INFO
NCCL_IB_HCA	InfiniBand NIC to use for communication	NCCL_IB_HCA=^mlx5_bond_0
NCCL_SOCKET_IFNAME	IP interface to use for communication	NCCL_SOCKET_IFNAME=bond0, eth0

Table 4-13 OBS environment variables

Variable	Description	Example
S3_ENDPOINT	OBS endpoint	-
S3_VERIFY_SSL	Whether to use SSL to access OBS	S3_VERIFY_SSL=0
S3_USE_HTTPS	Whether to use HTTPS to access OBS	S3_USE_HTTPS=1

Table 4-14 Environment variables of the PIP source and API Gateway address

Variable	Description	Example
MA_PIP_HOST	Domain name of the PIP source	MA_PIP_HOST=repo.myhuaweicloud.com
MA_PIP_URL	Address of the PIP source	MA_PIP_URL=http://repo.myhuaweicloud.com/repository/pypi/simple/
MA_APIGW_ENDPOINT	ModelArts API Gateway address	MA_APIGW_ENDPOINT=https://modelarts.region.cn-east-3.myhuaweicloud.com

Table 4-15 Environment variables of job metadata

Variable	Description	Example
MA_CURRENT_INSTANCE_NAME	Name of the current node for multi-node training	MA_CURRENT_INSTANCE_NAME=modelarts-job-a0978141-1712-4f9b-8a83-0000000000-worker-1

Table 4-16 Precheck environment variables

Variable	Description	Example
MA_SKIP_IMAGE_DETECT	Whether to enable ModelArts precheck. The default value is 1 , which indicates that the pre-check is enabled; the value 0 indicates that the pre-check is disabled. It is a good practice to enable precheck to detect node and driver faults before they affect services.	1

4.9 Stopping, Rebuilding, or Searching for a Training Job

Saving As an Algorithm

To modify the algorithm of a training job, click **Save As Algorithm** in the upper right corner of the training job details page.

On the **Algorithms** page, the algorithm parameters for the last training job are automatically set. You can modify the settings.

 **NOTE**

This function is not supported for algorithms subscribed in AI Gallery.

Stopping a Training Job

In the training job list, click **Stop** in the **Operation** column of a training job that is in creating, pending, or running state to stop the job.

After a training job is stopped, its billing stops on ModelArts.

A training job in completed, failed, terminated, or abnormal state cannot be stopped.

Rebuilding a Training Job

If you are not satisfied with a created training job, click **Rebuild** in the **Operation** column to rebuild it. The page for creating a training job is displayed. On this page, the parameter settings for the previous training job are automatically retained. You only need to modify certain parameter settings.

Searching for a Training Job

If you log in to ModelArts using an IAM account, all training jobs under this account are displayed in the training job list. To quickly search for a training job, use the following methods:

Method 1: Click **Only my jobs**. Then, only jobs created under the current IAM user account are displayed in the training job list.

Method 2: Search for jobs by name, ID, job type, status, creation time, algorithm, and resource pool.

Method 3: Click the refresh button in the upper right corner of the job list to refresh it.

Method 4: Configure the custom columns and other basic settings.

Figure 4-13 Searching for a training job

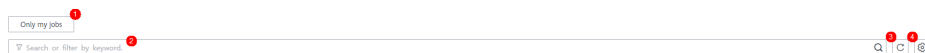
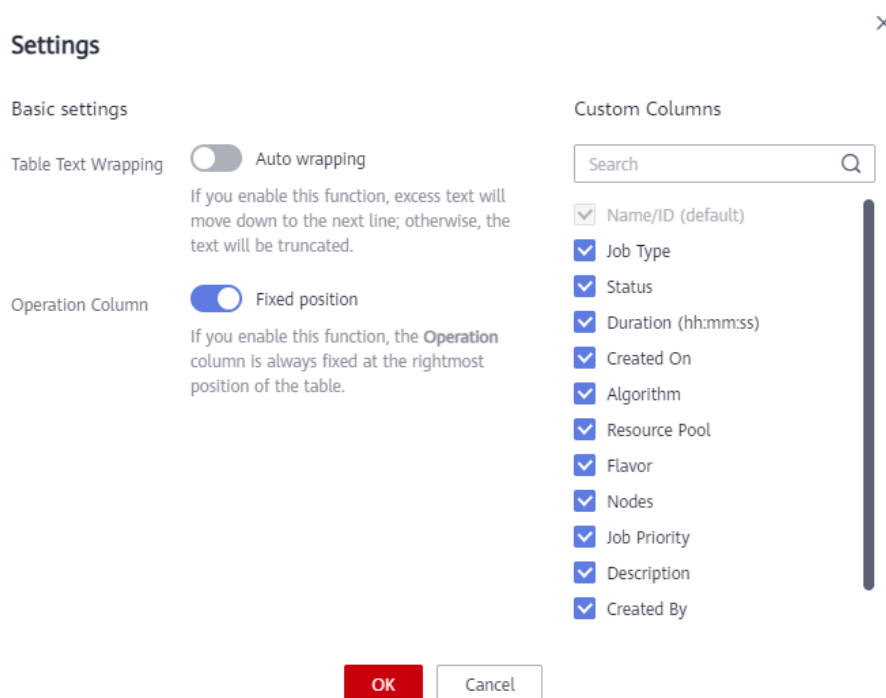


Figure 4-14 Configuring the custom columns and other basic settings



4.10 CloudShell

4.10.1 Logging In to a Training Container Using Cloud Shell

Application Scenario

You can use Cloud Shell provided by the ModelArts console to log in to a running training container.

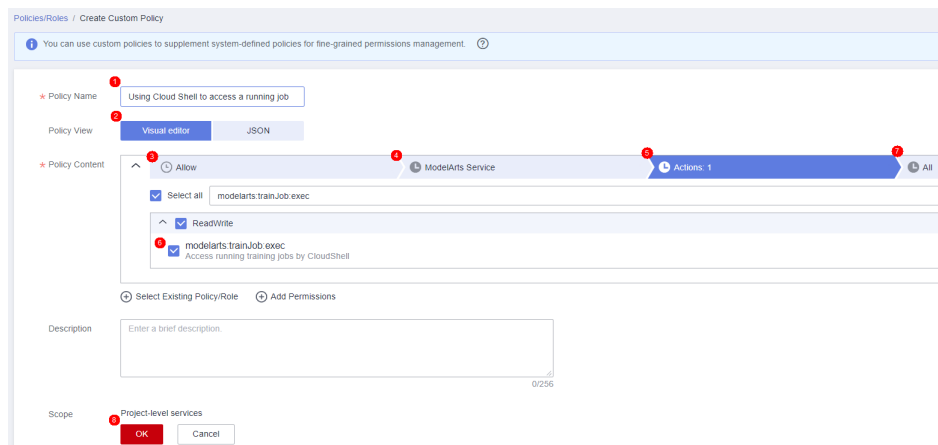
Constraints

You can use Cloud Shell to log in to a running training container using a dedicated resource pool.

Preparation: Assigning the Cloud Shell Permission to an IAM User

1. Log in to the Huawei Cloud management console as a tenant user, hover the cursor over your username in the upper right corner, and choose **Identity and Access Management** from the drop-down list to switch to the IAM management console.
2. On the IAM console, choose **Permissions > Policies/Roles** from the navigation pane, click **Create Custom Policy** in the upper right corner, and configure the following parameters.
 - **Policy Name:** Enter a custom policy name, for example, **Using Cloud Shell to access a running job**.
 - **Policy View:** Select **Visual editor**.
 - **Policy Content:** Select **Allow**, **ModelArts Service**, **modelarts:trainJob:exec**, and default resources.

Figure 4-15 Creating a custom policy



3. In the navigation pane, choose **User Groups**. Then, click **Authorize** in the **Operation** column of the target user group. On the **Authorize User Group** page, select the custom policies created in 2, and click **Next**. Then, select the scope and click **OK**.

After the configuration, all users in the user group have the permission to use Cloud Shell to log in to a running training container.

If no user group is available, create a user group, add users using the user group management function, and configure authorization. If the target user is

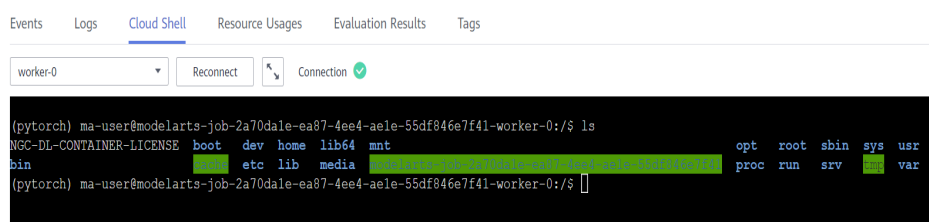
not in a user group, you can add the user to a user group through the user group management function.

Using Cloud Shell

1. Configure parameters based on [Preparation: Assigning the Cloud Shell Permission to an IAM User](#).
2. On the ModelArts console, choose **Training Management > Training Jobs**. Go to the details page of the target training job and log in to the training container on the Cloud Shell tab.

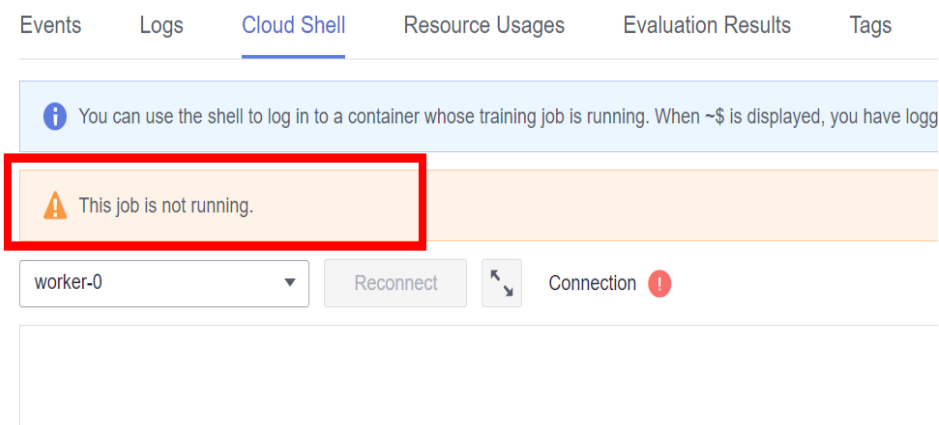
Verify that the login is successful, as shown in the following figure.

Figure 4-16 Cloud Shell



If the job is not running or the permission is insufficient, CloudShell cannot be used. Locate the fault as prompted.

Figure 4-17 Error message




4.11 Releasing Training Job Resources

Release resources of a training job when not in use to avoid unnecessary charges.

- On the **Training Jobs** page, click **Delete** in the **Operation** column. In the displayed dialog box, click **OK** to delete the training job.
- Go to OBS and delete the OBS bucket and files used by the training job.

After the resources are released, check the resource usage on the **Dashboard** page.

Figure 4-18 Checking the resource usage

Usage Details 

Text Classification - ExeML		Image Classification - ExeML		Training Jobs-Beta New - Trai...		AI Application Management		Real-Time Services - Service ...	
Running	Projects	Running	Projects	Running	Projects	AI App...	AI Versions	Running	Services
0	1	0	1	0	23	20	20	0	1

5 Advanced Training Operations

5.1 Automatic Recovery from a Training Fault

5.1.1 Training Fault Tolerance Check

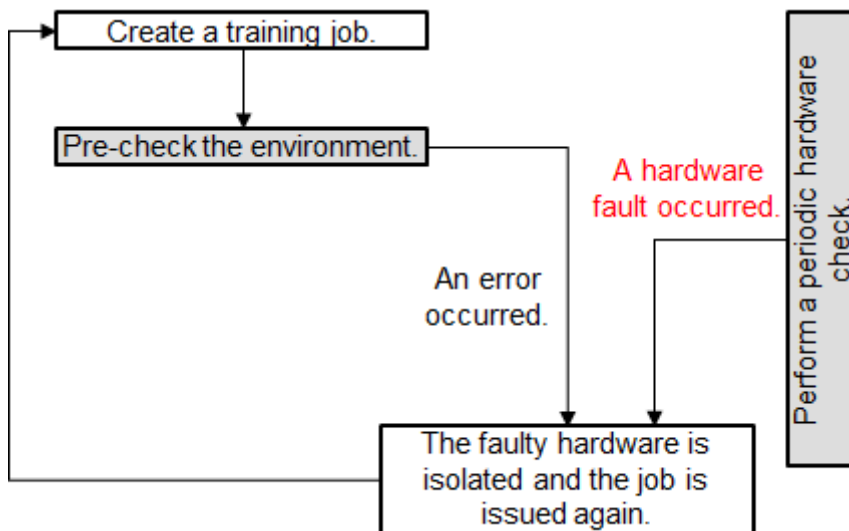
During model training, a training failure may occur due to a hardware fault. For hardware faults, ModelArts provides fault tolerance check to isolate faulty nodes to improve user experience in training.

The fault tolerance check involves environment pre-check and periodic hardware check. If any fault is detected during either of the checks, ModelArts automatically isolates the faulty hardware and issues the training job again. In distributed training, the fault tolerance check will be performed on all compute nodes used by the training job.

The following shows four failure scenarios, among which the failure in scenario 4 is not caused by a hardware fault. You can enable fault tolerance in the other three scenarios to automatically resume the training job.

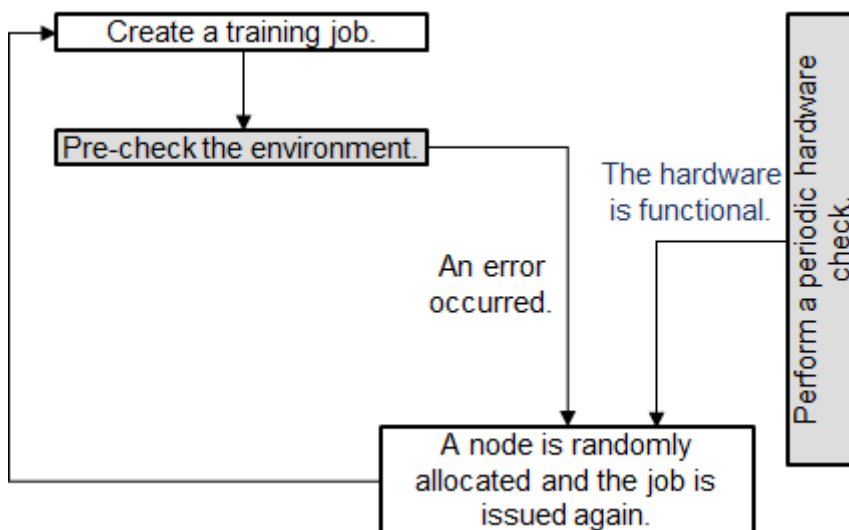
- Scenario 1: The environment pre-check fails, and the hardware is faulty. Then, ModelArts automatically isolates all faulty nodes and issues the training job again.

Figure 5-1 Pre-check failure and hardware fault



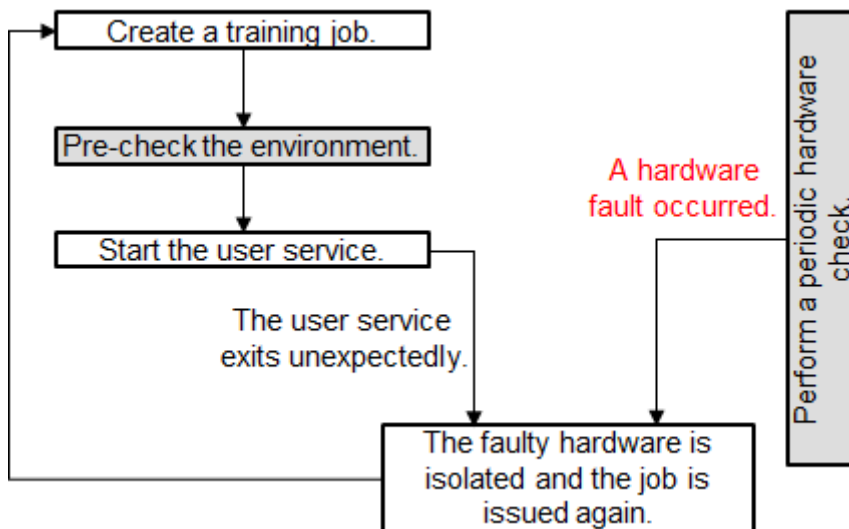
- Scenario 2: The environment pre-check fails but the hardware is functional. Then, ModelArts automatically isolates all faulty nodes and issues the training job again.

Figure 5-2 Pre-check failure but functional hardware



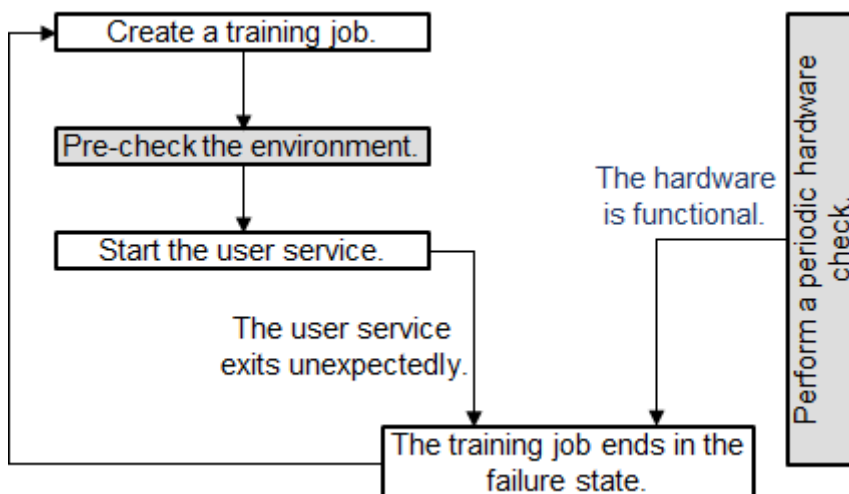
- Scenario 3: The environment pre-check is successful and the user service starts. A hardware fault occurs and the user service exits unexpectedly. Then, ModelArts automatically isolates all faulty nodes and issues the training job again.

Figure 5-3 Service failure and hardware fault



- Scenario 4: The environment pre-check is successful and the user service starts. The hardware is functional. A fault occurs in the user service, the training job ends in the failure state.

Figure 5-4 Service failure and functional hardware



After the faulty node is isolated, ModelArts creates a training job on new compute nodes. If the resources provided by the resource pool are limited, the re-issued training job will be queued with the highest priority. If the waiting time exceeds 30 minutes, the training job will automatically exit. This indicates that the resources are so limited that the training job cannot start. In this case, buy a dedicated resource pool to obtain dedicated resources.

If you use a dedicated resource pool to create a training job, the faulty nodes identified during the fault tolerance check will be removed. The system automatically adds healthy compute nodes to the dedicated resource pool. (This function is coming soon.)

More details of a fault tolerance check:

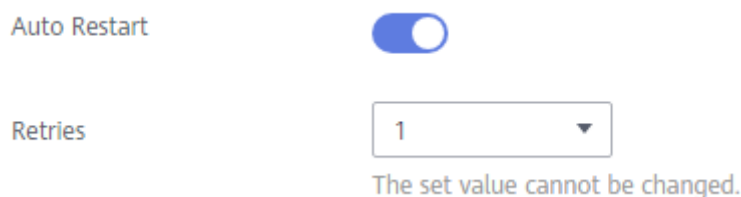
1. [Enabling Fault Tolerance Check](#)
2. [Check Items and Conditions](#)
3. [Effect of a Fault Tolerance Check](#)
4. After the environment pre-check is successful, any hardware fault will interrupt the user service. Add the reload ckpt code logic to the training so that the pre-trained model saved before the training is interrupted can be obtained. For details, see [Resumable Training and Incremental Training](#).

Enabling Fault Tolerance Check

To enable fault tolerance check, enable auto restart when creating a training job.

- Configure fault tolerance check on the ModelArts management console:
Enable **Auto Restart** on the ModelArts management console. **Auto Restart** is disabled by default, indicating that the job will not be re-issued and the environment pre-check will not be enabled. After **Auto Restart** is enabled, the number of restart retries ranges from 1 to 3.

Figure 5-5 Auto Restart



- Configure fault tolerance check using an API:
Enable auto restart upon a fault using an API. When creating a training job, configure the **fault-tolerance/job-retry-num** field in **annotations** of the **metadata** field.
If the **fault-tolerance/job-retry-num** field is added, auto restart is enabled. The value can be an integer ranging from **1** to **3**, specifying the maximum number of times that a job can be re-issued. If this hyperparameter is not specified, the default value **0** is used, indicating that the job will not be re-issued and the environment pre-check will not be enabled.

```
{
  "kind": "job",
  "metadata": {
    "annotations": {
      "fault-tolerance/job-retry-num": "3"
    }
  }
}
```

Check Items and Conditions

Check Item	Item (Log Keyword)	Execution Condition	Requirements for a Check
Domain name detection	dns	None	The domain names of the volcano containers in the .host file in /etc/volcano are successfully resolved.
Disk size - Container root directory	disk-size root	None	The directory is greater than 32 GB.
Disk size - /dev/shm	disk-size shm	None	The directory is greater than 1 GB.
Disk size - /cache	disk-size cache	None	The directory is greater than 32 GB.
ulimit check	ulimit	An IB network is used.	<ul style="list-style-type: none"> • Maximum locked memory > 16000 • Open files > 1000000 • Stack size > 8000 • Maximum user processes > 1000000
GPU check	gpu-check	GPU and the v2 training engine are used (not available in CN-North Beijing 4).	GPUs are detected.

Effect of a Fault Tolerance Check

- If the fault tolerance check is passed, the logs of the check items will be recorded, indicating that the check items are successful. You can search for the keyword **item** in the log file. A fault tolerance check minimizes reported runtime faults.

```
[ModelArts Service Log][task] Detect
[ModelArts Service Log][INFO][detect] code: 0, message: ok, item: dns
[ModelArts Service Log][INFO][detect] code: 0, message: ok, item: disk-size root
[ModelArts Service Log][INFO][detect] code: 0, message: ok, item: disk-size shm
[ModelArts Service Log][INFO][detect] code: 0, message: ok, item: disk-size cache
[ModelArts Service Log][init] download code_url: s3://test-qianjiajun/tolerance_test/
```

- If a fault tolerance check fails, check failure logs will be recorded. You can search for the keyword **item** in the log file to view the failure information.

```
[Modelarts Service Log][init] running
[Modelarts Service Log][init] ip of the pod: 172.16.0.160
[Modelarts Service Log][INFO]detect item: dns; json:{"code": 0, "message": "ok"}
[Modelarts Service Log][INFO][task][detect] code: 0, message: ok, item: dns
[Modelarts Service Log][INFO]detect item: disk-size root; json:{"code": 13, "message": "the disk space of the path
\"/^\" is 4892852224, which is less than 34359738368"}
[Modelarts Service Log][ERROR][task][detect] code: 13, message: the disk space of the path "/" is 4892852224, which is
less than 34359738368, item: disk-size root
[Modelarts Service Log][init] exiting..
[Modelarts Service Log][init] wait python processes exit...
```

If the number of job restarts does not reach the specified time, the job will be automatically issued again. You can search for keywords **error,exiting** to obtain the logs recording a restarted job that ends with a failure.

Using reload ckpt to Resume an Interrupted Training

With fault tolerance enabled, if a training job is restarted due to a hardware fault, you can obtain the pre-trained model in the code to restore the training to the state before the restart. To do so, add reload ckpt to the code. For details, see [Resumable Training and Incremental Training](#).

5.2 Resumable Training and Incremental Training

Overview

Resumable training indicates that an interrupted training job can be automatically resumed from the checkpoint where the previous training was interrupted. This method is applicable to model training that takes a long time.

Incremental training is a method in which input data is continuously used to extend the existing model's knowledge to further train the model.

Checkpoints are used to resume model training or incrementally train a model.

During model training, training results (including but not limited to epochs, model weights, optimizer status, and scheduler status) are continuously saved. In this way, an interrupted training job can be automatically resumed from the checkpoint where the previous training was interrupted.

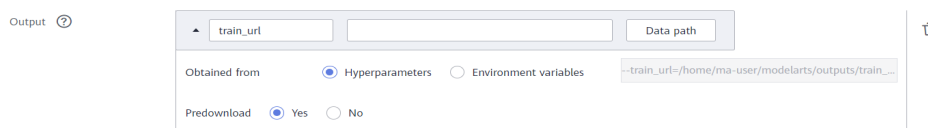
To resume a training job, load a checkpoint and use the checkpoint information to initialize the training status. To do so, add reload ckpt to the code.

Resumable Training and Incremental Training in ModelArts

To resume model training or incrementally train a model in ModelArts, configure **Training Output**.

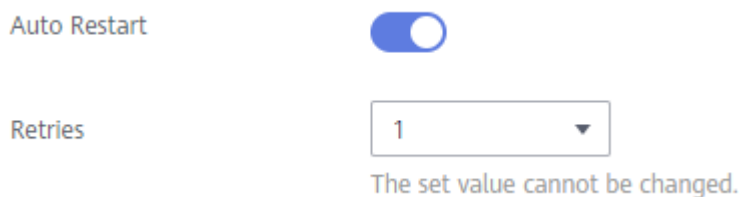
When creating a training job, configure the data path to the training output, save checkpoints in this data path, and set **Predownload** to **Yes**. If you set **Predownload** to **Yes**, the system automatically downloads the **checkpoint** file in the training output data path to a local directory of the training container before the training job is started.

Figure 5-6 Configuring training output



Enable fault tolerance check (auto restart) for resumable training. On the training job creation page, enable **Auto Restart**. If the environment pre-check fails, the hardware is not functional, or the training job fails, ModelArts will automatically issue the training job again.

Figure 5-7 Auto Restart



reload ckpt for PyTorch

1. Use either of the following methods to save a PyTorch model.

- Save model parameters only.

```
state_dict = model.state_dict()
torch.save(state_dict, path)
```

- Save the entire model (not recommended).

```
torch.save(model, path)
```

2. Save the data generated during model training.

The data includes the network weight, optimizer weight, and epoch, which will be used to resume the interrupted training.

```
checkpoint = {
    "net": model.state_dict(),
    "optimizer": optimizer.state_dict(),
    "epoch": epoch
}
if not os.path.isdir('model_save_dir'):
    os.makedirs('model_save_dir')
torch.save(checkpoint, 'model_save_dir/ckpt_{}.pth'.format(str(epoch)))
```

3. Execute the code.

```
import os
import argparse
parser.add_argument("--train_url", type=str)
args = parser.parse_known_args()
# train_url is set to /home/ma-user/modelarts/outputs/train_url_0.
train_url = args.train_url

# Check whether there is a model file in the output path. If there is no file, the model will be trained
from the beginning by default. If there is a model file, the CKPT file with the maximum epoch value
will be loaded as the pre-trained model.
if os.listdir(train_url):
    print('> load last ckpt and continue training!!')
    last_ckpt = sorted([file for file in os.listdir(train_url) if file.endswith(".pth")])[-1]
    local_ckpt_file = os.path.join(train_url, last_ckpt)
    print('last_ckpt:', last_ckpt)
    # Load the checkpoint.
```

```
checkpoint = torch.load(local_ckpt_file)
# Load the parameters that can be learned by the model.
model.load_state_dict(checkpoint['net'])
# Load optimizer parameters.
optimizer.load_state_dict(checkpoint['optimizer'])
# Obtain the saved epoch. The model will continue to be trained based on the epoch value.
start_epoch = checkpoint['epoch']
start = datetime.now()
total_step = len(train_loader)
for epoch in range(start_epoch + 1, args.epochs):
    for i, (images, labels) in enumerate(train_loader):
        images = images.cuda(non_blocking=True)
        labels = labels.cuda(non_blocking=True)
        # Forward pass
        outputs = model(images)
        loss = criterion(outputs, labels)
        # Backward and optimize
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()
    ...

# Save the network weight, optimizer weight, and epoch during model training.
checkpoint = {
    "net": model.state_dict(),
    "optimizer": optimizer.state_dict(),
    "epoch": epoch
}
if not os.path.isdir(train_url):
    os.makedirs(train_url)
torch.save(checkpoint, os.path.join(train_url, 'ckpt_best_{}.pth'.format(epoch)))
```

5.3 Detecting Training Job Suspension

Overview

A training job may be suspended due to unknown reasons. If the suspension cannot be detected promptly, resources cannot be released, leading to a waste. To minimize resource cost and improve user experience, ModelArts provides suspension detection for training jobs. With this function, suspension can be automatically detected and displayed on the log details page. You can also enable notification so that you can be promptly notified of job suspension.

Detection Rules

Determine whether a job is suspended based on the monitored job process status and resource usage. A process is started to periodically monitor the changes of the two metrics.

- Job process status: If the process I/O of a training job changes, the next detection period starts. If the process I/O of the job remains unchanged in multiple detection periods, the resource usage detection starts.
- Resource usage: If the process I/O remains unchanged, the system collects the GPU usage within a certain period of time and determines whether the resource usage changes based on the variance and median of the GPU usage within the period. If the GPU usage is not changed, the job is suspended.

Constraints

Suspension can be detected only for training jobs that run on GPUs.

Procedure

Suspension detection is automatically performed during job running. No additional configuration is required. After detecting that a job is suspended, the system displays a message on the training job details page, indicating that the job may be suspended. If you want to be notified of suspension (by SMS or email), enable event notification on the job creation page.

Cases

Common cases and solutions to training job suspension are as follows:

[Data Replication Suspension](#)

[Suspension Before Training](#)

[Suspension During Training](#)

[Suspension in the Last Training Epoch](#)

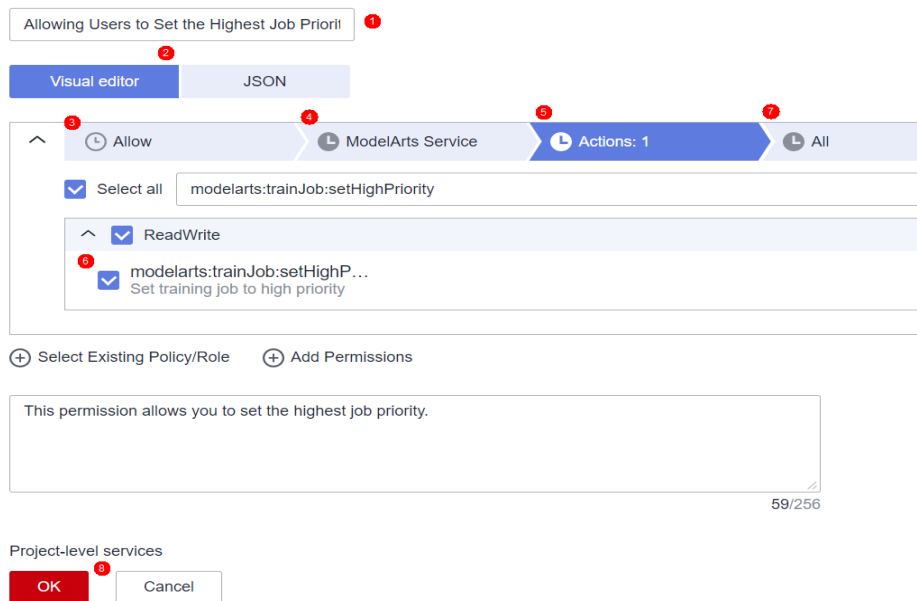
5.4 Permission to Set the Highest Job Priority

You can configure the priority when you create a training job using a new-version dedicated resource pool. You can change the priority of a pending job. The value ranges from 1 to 3. The default priority is **1**, and the highest priority is **3**. By default, the job priority can be set to **1** or **2**. After the permission to set the highest job priority is configured, the priority can be set to **1** to **3**.

Assigning the Permission to Set the Highest Job Priority to an IAM User

1. Log in to the Huawei Cloud management console as a tenant user, hover the cursor over your username in the upper right corner, and choose **Identity and Access Management** from the drop-down list to switch to the IAM management console.
2. On the IAM console, choose **Permissions > Policies/Roles** from the navigation pane, click **Create Custom Policy** in the upper right corner, and configure the following parameters.
 - **Policy Name:** Enter a custom policy name, for example, **Allowing Users to Set the Highest Job Priority**.
 - **Policy View:** Select **Visual editor**.
 - **Policy Content:** Select **Allow, ModelArts Service, modelarts:trainJob:setHighPriority**, and default resources.

Figure 5-8 Creating a custom policy



3. In the navigation pane, choose **User Groups**. Then, click **Authorize** in the **Operation** column of the target user group. On the **Authorize User Group** page, select the custom policies created in 2, and click **Next**. Then, select the scope and click **OK**.

After the configuration, all users in the user group have the permission to use Cloud Shell to log in to a running training container.

If no user group is available, create a user group, add users using the user group management function, and configure authorization. If the target user is not in a user group, you can add the user to a user group through the user group management function.

6 Visualized Model Training

6.1 Introduction to Training Job Visualization

ModelArts notebook of the new version supports TensorBoard and MindInsight for visualizing training jobs. In the development environment, use small datasets to train and debug algorithms, during which you can check algorithm convergence and detect issues to facilitate debugging.

You can create visualization jobs of TensorBoard and MindInsight types on ModelArts.

Both TensorBoard and MindInsight effectively display the change trend of a training job and the data used in the training.

- **TensorBoard**
TensorBoard effectively displays the computational graph of TensorFlow in the running process, the trend of all metrics in time, and the data used in the training. For more details about TensorBoard, see [TensorBoard official website](#).
TensorBoard visualization training jobs support only CPU and GPU flavors based on TensorFlow 2.1, and PyTorch 1.4 and 1.8 images. Select images and flavors based on the site requirements.
- **MindInsight**
MindInsight visualizes information such as scalars, images, computational graphs, and model hyperparameters during training. It also provides functions such as training dashboard, model lineage, data lineage, and performance debugging, helping you train and debug models efficiently. MindInsight supports MindSpore training jobs. For more information about MindInsight, see [MindSpore official website](#).
The following shows the images and flavors supported by MindInsight visualization training jobs, and select images and flavors based on the site requirements.
 - MindSpore 1.2.0 (CPU or GPU)

You can use the summary file generated during model training to create a visualization job in Notebook of DevEnviron.

- For details about how to create a MindInsight visualization job in a development environment, see [MindInsight Visualization Jobs](#).
- For details about how to create a TensorBoard visualization job in a development environment, see [TensorBoard Visualization Jobs](#).

6.2 MindInsight Visualization Jobs

ModelArts notebook of the new version supports MindInsight visualization jobs. In a development environment, use a small dataset to train and debug an algorithm. This is used to check algorithm convergence and detect training issues, facilitating debugging.

MindInsight visualizes information such as scalars, images, computational graphs, and model hyperparameters during training. It also provides functions such as training dashboard, model lineage, data lineage, and performance debugging, helping you train and debug models efficiently. MindInsight supports MindSpore training jobs. For more information about MindInsight, see [MindSpore official website](#).

MindSpore allows you to save data into the summary log file and obtain the data on the MindInsight GUI.

Prerequisites

When using MindSpore to edit a training script, add the code for collecting the summary record to the script to ensure that the summary file is generated in the training result.

For details, see [Collecting Summary Record](#).

Note

- To run a MindInsight training job in a development environment, start MindInsight and then the training process.
- Only one-card single-node training is supported.
- A running visualization job is not billed separately. When the target notebook instance is stopped, the billing stops.
- If the summary file is stored in OBS, OBS storage will be billed separately. After a job is complete, stop the notebook instance and clear OBS data to stop billing.

Creating a MindInsight Visualization Job in a Development Environment

[Step 1 Create a Development Environment and Access It Online](#)

[Step 2 Upload the Summary Data](#)

[Step 3 Start MindInsight](#)

[Step 4 View Visualized Data on the Training Dashboard](#)

Step 1 Create a Development Environment and Access It Online

Log in to ModelArts management console, choose **DevEnviron** > **Notebook**, and create a development environment instance for the MindSpore engine. After the

instance is created, click **Open** in the **Operation** column of the instance to access it online.

The images and resource types supported by MindInsight visualization training jobs are as follows:

- MindSpore 1.2.0 (CPU or GPU)
- MindSpore 1.5.x or later (Ascend)

Step 2 Upload the Summary Data

Summary data is required for MindInsight visualization in a development environment.

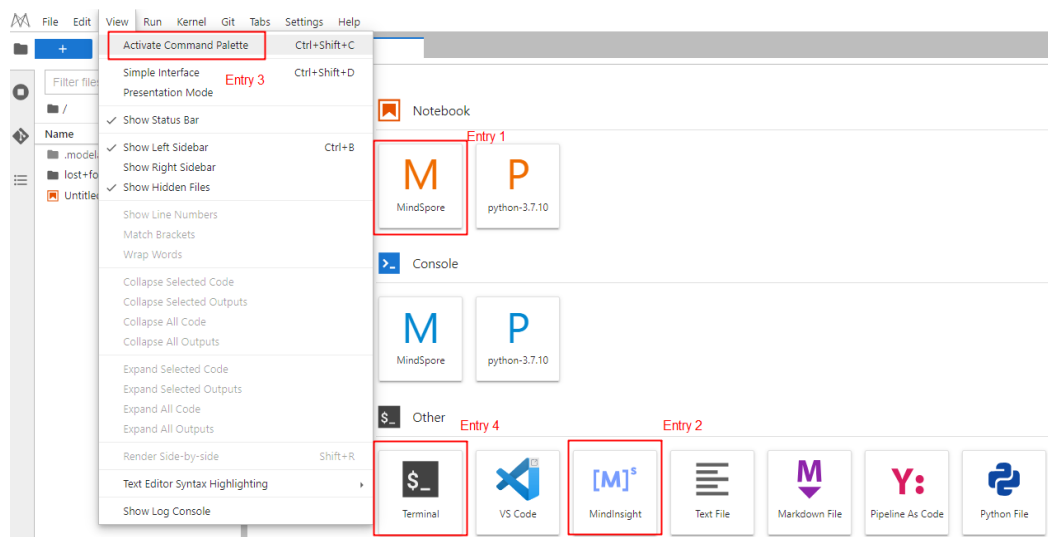
Upload the summary data to the `/home/ma-user/work/` directory in a development environment or store it in an OBS parallel file system.

- For details about how to upload the summary data to `/home/ma-user/work/`, see [Uploading Files to JupyterLab](#).
- To store the summary data in an OBS parallel file system that is mounted to a notebook instance, upload the summary file generated during model training to the OBS parallel file system and ensure that the OBS parallel file system and ModelArts are in the same region. When MindInsight is started in a notebook instance, the notebook instance automatically reads the summary data from the mounted OBS parallel file system.

Step 3 Start MindInsight

Choose a way you like to start MindInsight in JupyterLab.

Figure 6-1 Starting MindInsight in JupyterLab



Method 1

M

1. Click [MindSpore](#) to go to the JupyterLab development environment. An IPYNB file will be automatically created.
2. Enter the following command in the dialog box:

```
%reload_ext mindinsight
%mindinsight --port {PORT} --summary-base-dir {SUMMARY_BASE_DIR}
```

Parameters:

- **port {PORT}**: web service port for visualization, which defaults to **8080**. If the default port **8080** has been used, specify a port ranging from 1 to 65535.
- **summary-base-dir {SUMMARY_BASE_DIR}**: data storage path in the development environment
 - Local path to the development environment: **./work/xxx** (relative path) or **/home/ma-user/work/xxx** (absolute path)
 - Path to the OBS parallel file system bucket: **obs://xxx/**

For example:

If the summary data is stored in **/home/ma-user/work/** of a development environment, run the following command:

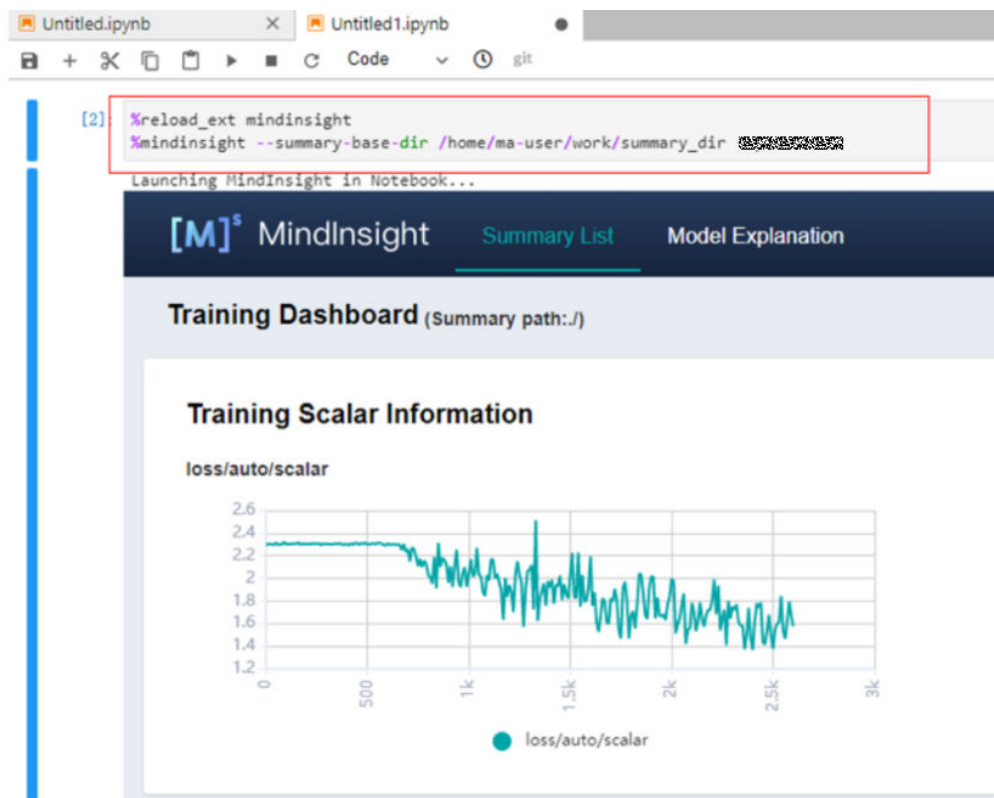
```
%mindinsight --summary-base-dir /home/ma-user/work/xxx
```

Or

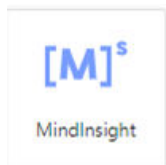
If the summary data is stored in an OBS parallel file system, run the following command. Then, the development environment will automatically mount the storage path to the OBS parallel file system and read data from the path.

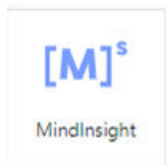
```
%mindinsight --summary-base-dir obs://xxx/
```

Figure 6-2 MindInsight page (1)



Method 2

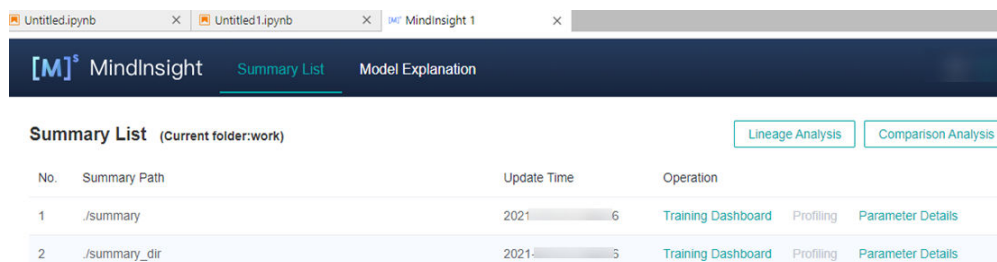


Click  to go to the MindInsight page.

Data is read from **/home/ma-user/work/** by default.

If there are two projects or more, select the target project to view its logs.

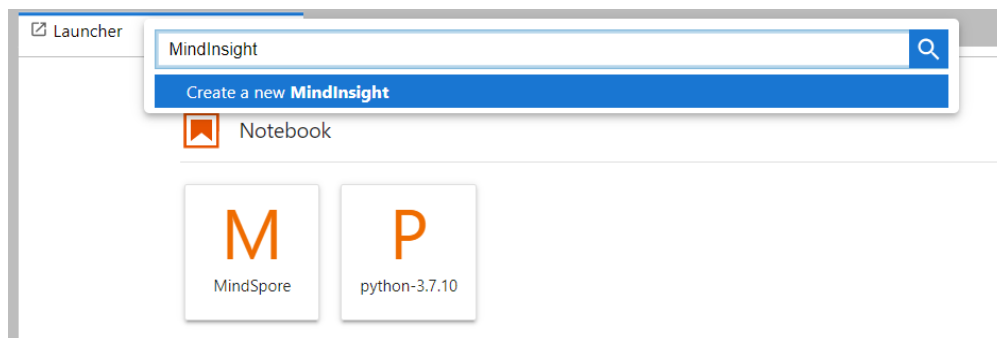
Figure 6-3 MindInsight page (2)



Method 3

1. Choose **View > Activate Command Palette**, enter **MindInsight** in the search box, and click **Create a new MindInsight**.

Figure 6-4 Create a new MindInsight



2. Enter the path to the summary data or the storage path to the OBS parallel file system, and click **CREATE**.
 - Local path to the development environment: **./summary** (relative path) or **/home/ma-user/work/summary** (absolute path)
 - Path to the OBS parallel file system: **obs://xxx/**

Figure 6-5 Path to the summary data

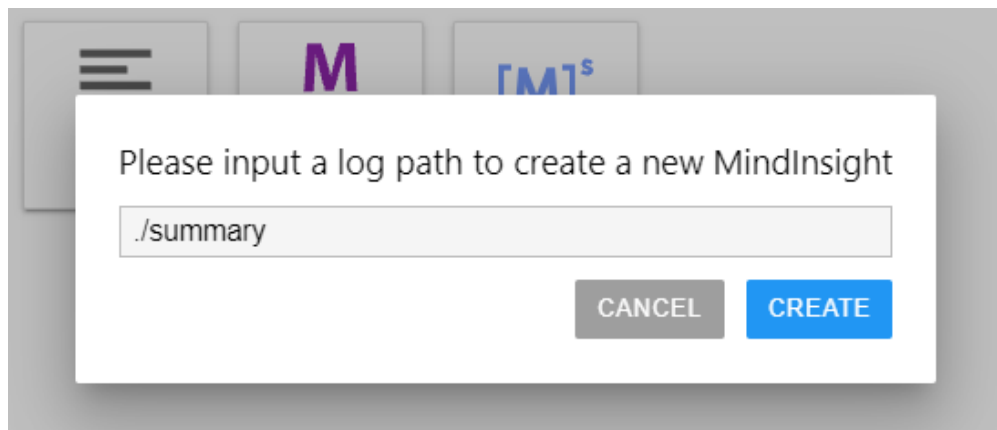
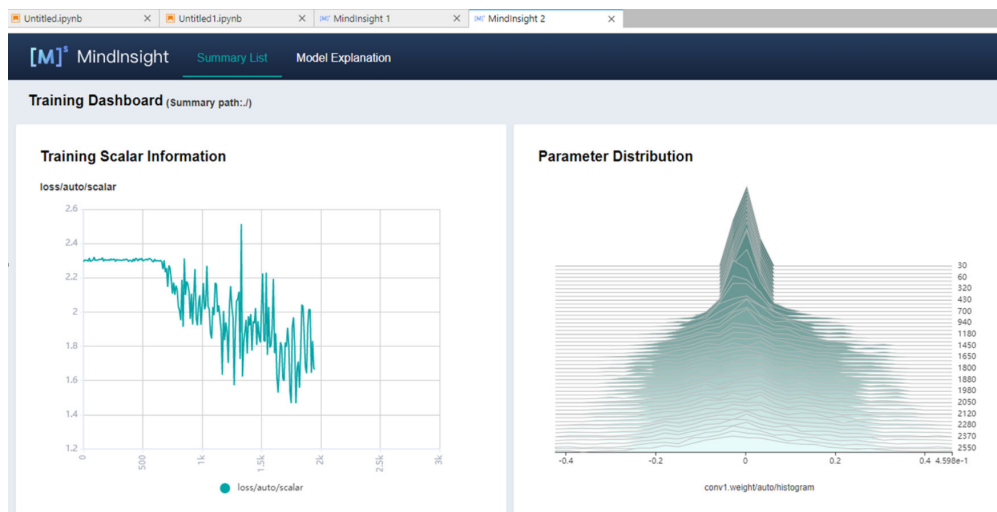


Figure 6-6 MindInsight page (3)



 NOTE

A maximum of 10 MindInsight instances can be started using method 2 or 3.

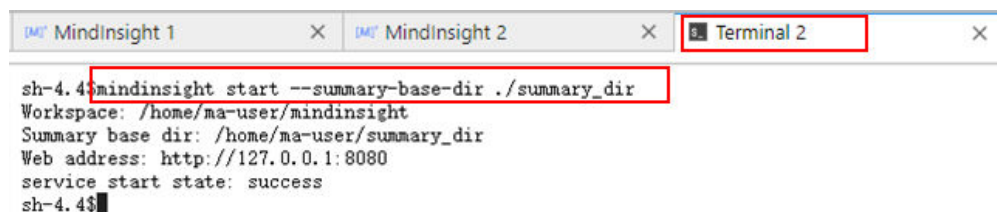
Method 4



Click **Terminal** and run the following command (the UI will not be displayed):

```
mindinsight start --summary-base-dir ./summary_dir
```

Figure 6-7 Opening MindInsight through Terminal



Step 4 View Visualized Data on the Training Dashboard

The training dashboard is important for MindInsight visualization. It allows visualization for scalars, parameter distribution, computational graphs, dataset graphs, images, and tensors.

For more information, see [Viewing Training Dashboard](#) on the MindSpore official website.

Related Operations

To stop a MindInsight instance, use one of the following methods:

- Method 1: Enter the following command in the `.ipynb` file window of JupyterLab. in which the port number is configured in [Start MindInsight](#) (8080 by default):

```
!mindinsight stop --port 8080
```


- Method 2: Click . The MindInsight instance management page is displayed, which shows all started MindInsight instances. Click **SHUT DOWN** next to the target instance to stop it.

Figure 6-8 Stopping an instance




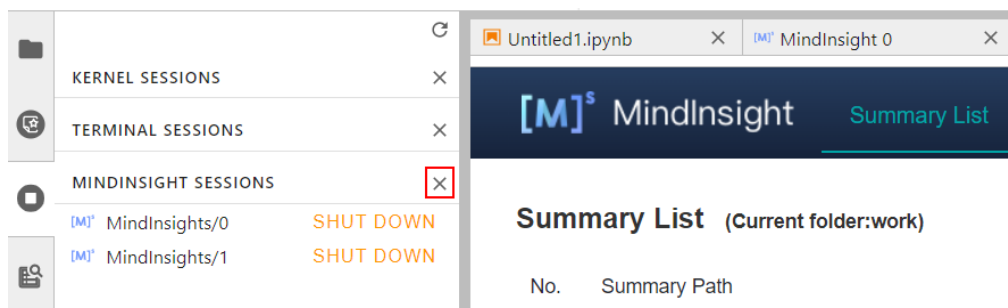
- Method 3: Click  in the following figure to close all started MindInsight instances.

Figure 6-9 Stopping all started MindInsight instances



- Method 4 (not recommended): Close the MindInsight window on JupyterLab. In this way, only the visualization window is closed, but the instance is still running on the backend.

6.3 TensorBoard Visualization Jobs

ModelArts supports TensorBoard for visualizing training jobs. TensorBoard is a visualization tool package of TensorFlow. It provides visualization functions and tools required for machine learning experiments.

TensorBoard effectively displays the computational graph of TensorFlow in the running process, the trend of all metrics in time, and the data used in the training.

Prerequisites

When you write a training script, add the code for collecting the summary record to the script to ensure that the summary file is generated in the training result.

For details about how to add the code for collecting the summary record to a TensorFlow-powered training script, see [TensorFlow official website](#).

Note

- A running visualization job is not billed separately. When the target notebook instance is stopped, the billing stops.
- If the summary file is stored in OBS, you will be charged for the storage. After a job is complete, stop the notebook instance and clear OBS data to stop billing.

Process of Creating a TensorBoard Visualization Job in a Development Environment

[Step 1 Create a Development Environment and Access It Online](#)

[Step 2 Upload the Summary Data](#)

[Step 3 Start TensorBoard](#)

[Step 4 View Visualized Data on the Training Dashboard](#)

Step 1 Create a Development Environment and Access It Online

On the ModelArts management console, choose **DevEnviron > Notebook**, and create an instance using a TensorFlow or PyTorch image. After the instance is created, click **Open** in the **Operation** column of the instance to access it online.

Only CPU and GPU flavors with TensorFlow2.1, PyTorch1.4, or PyTorch1.8 and later images can support TensorBoard visualization for training jobs. Select images and flavors based on the site requirements.

Step 2 Upload the Summary Data

Summary data is required for using TensorBoard visualization functions in DevEnviron.

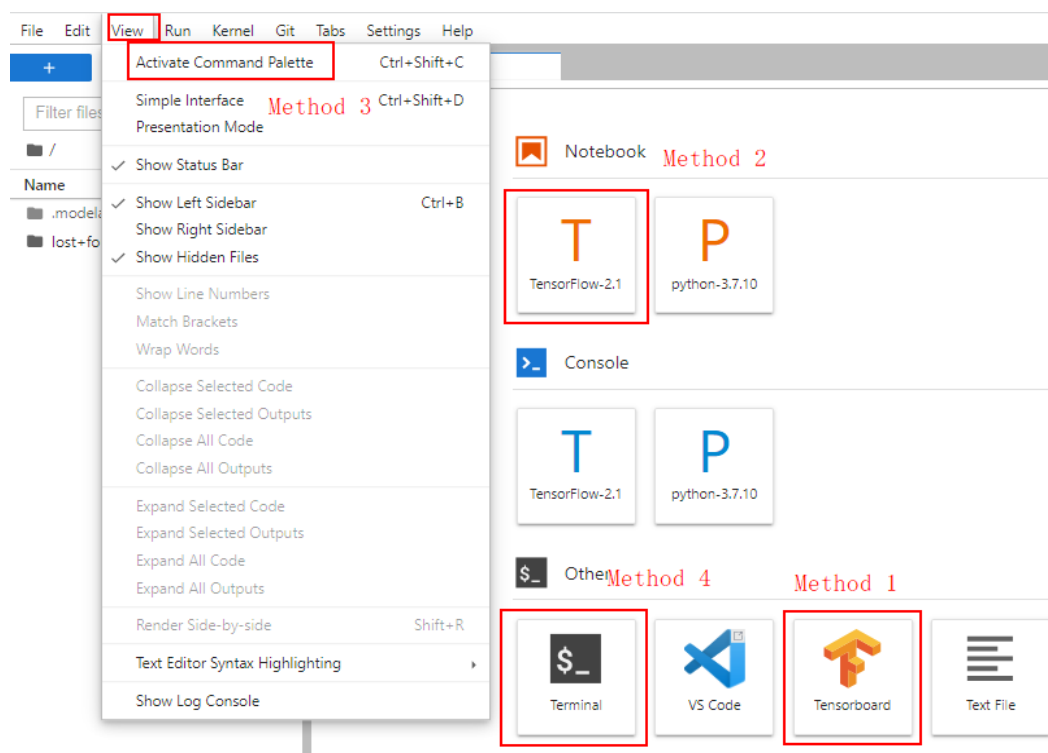
You can upload the summary data to the `/home/ma-user/work/` directory in the development environment or store it in the OBS parallel file system.

- For details about how to upload the summary data to the notebook path / **home/ma-user/work/**, see [Uploading Files to JupyterLab](#).
- To store the summary data in an OBS parallel file system that is mounted to a notebook instance, upload the summary file generated during model training to the OBS parallel file system and ensure that the OBS parallel file system and ModelArts are in the same region. When TensorBoard is started in a notebook instance, the notebook instance automatically mounts the OBS parallel file system directory and reads the summary data.

Step 3 Start TensorBoard

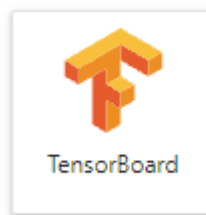
There are multiple methods to open TensorBoard in JupyterLab in the development environment. Select one based on your habits.

Figure 6-10 Starting TensorBoard in JupyterLab



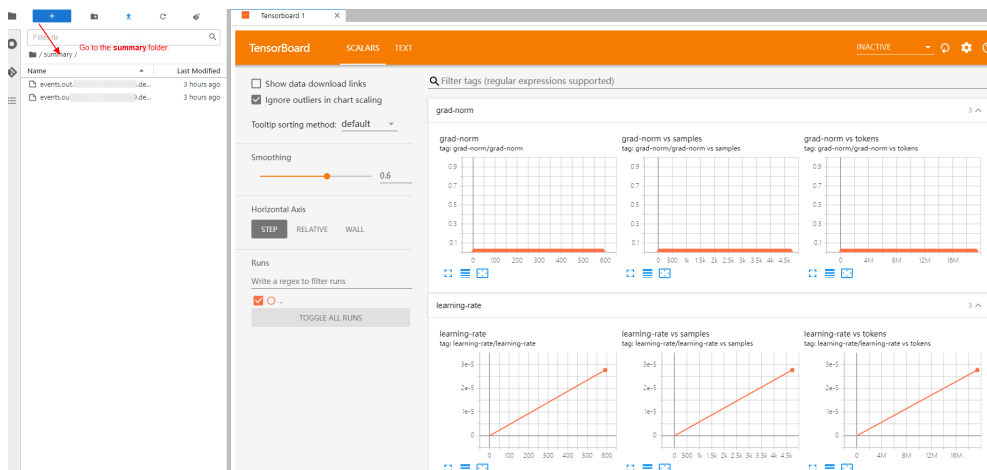
Method 1 (recommended):

1. Open JupyterLab, in the navigation pane on the left, create the **summary** folder, and upload data to **/home/ma-user/work/summary**. The folder name must be **summary**.



2. Go to the **summary** folder and click **TensorBoard** page. See [Figure 6-11](#). to go to the

Figure 6-11 TensorBoard page (1)




Method 2

NOTICE

You can upgrade TensorBoard to any version except 2.4.0. After the upgrade, the new version of TensorBoard is used only in method 2. For other methods, use TensorBoard 2.1.1.



1. Click  to go to the JupyterLab development environment. The .ipynb file is automatically created.
2. Enter the following command in the dialog box:

```
%reload_ext ma_tensorboard
%ma_tensorboard --port {PORT} --logdir {BASE_DIR}
```

Parameters:

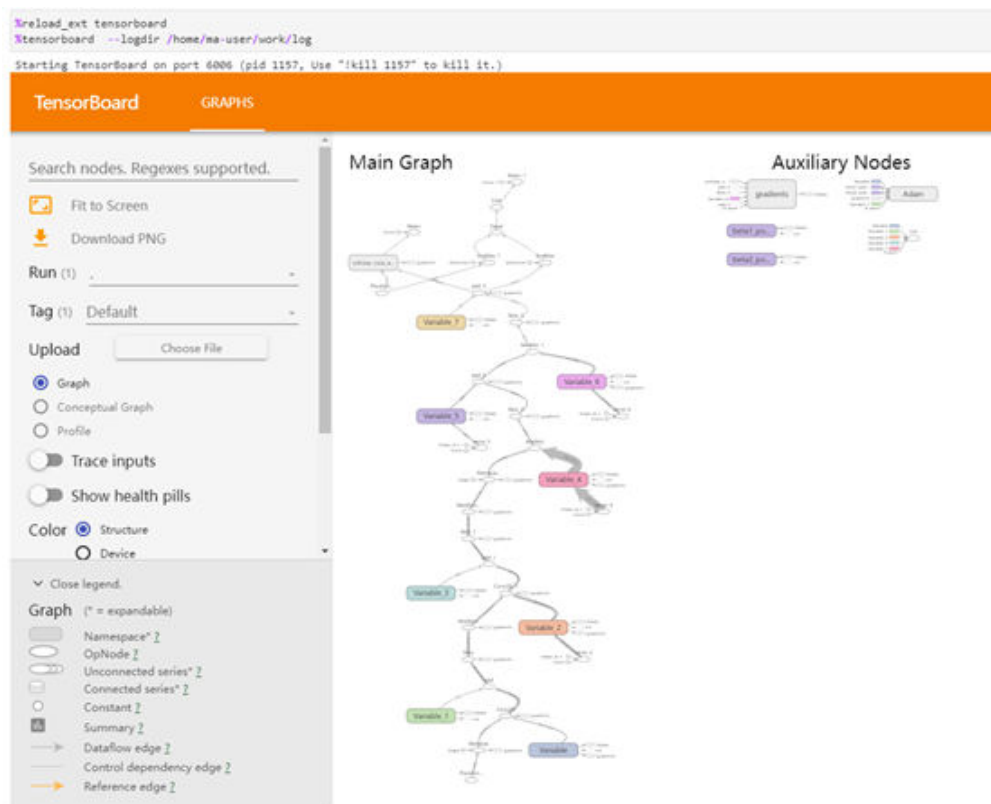
- **port {PORT}**: web service port for visualization, which defaults to **8080**. If the default port **8080** has been used, specify a port ranging from 1 to 65535.
- **logdir {BASE_DIR}**: data storage path in the development environment
 - Local path of the development environment: **./work/xxx** (relative path) or **/home/ma-user/work/xxx** (absolute path)
 - Path of the OBS parallel file system: **obs://xxx/**

Example:

```
# If the summary data is stored in /home/ma-user/work/ of the development environment, run the
following command:
%ma_tensorboard --port {PORT} --logdir /home/ma-user/work/xxx
or
# If the summary data is stored in the OBS parallel file system, run the following command and the
development environment automatically mounts the storage path of the OBS parallel file system and
```

```
reads data.
%ma_tensorboard --port {PORT} --logdir obs://xxx/
```

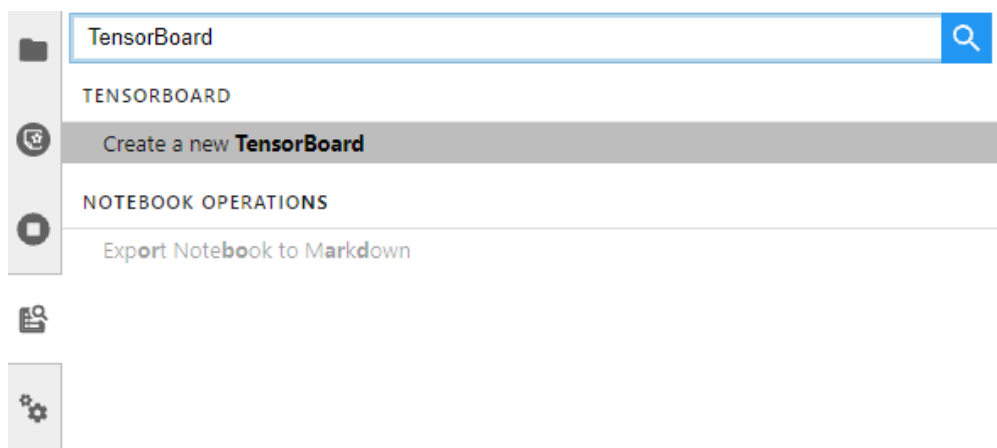
Figure 6-12 TensorBoard page (2)



Method 3

1. Choose **View > Activate Command Palette**, enter **TensorBoard** in the search box, and click **Create a new TensorBoard**.

Figure 6-13 Create a new TensorBoard



2. Enter the path of the summary data you want to view or the storage path of the OBS parallel file system.

- Local path of the development environment: **./summary** (relative path) or **/home/ma-user/work/summary** (absolute path)
- Path of the OBS parallel file system bucket: **obs://xxx/**

Figure 6-14 Entering the summary data path

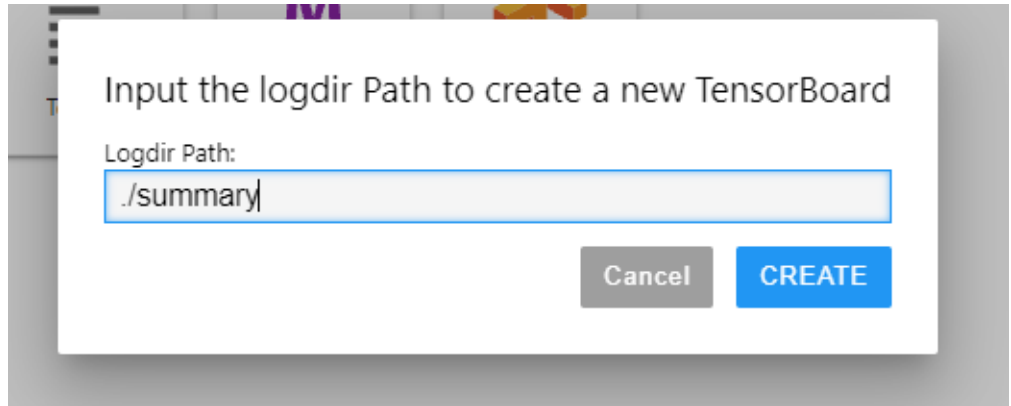
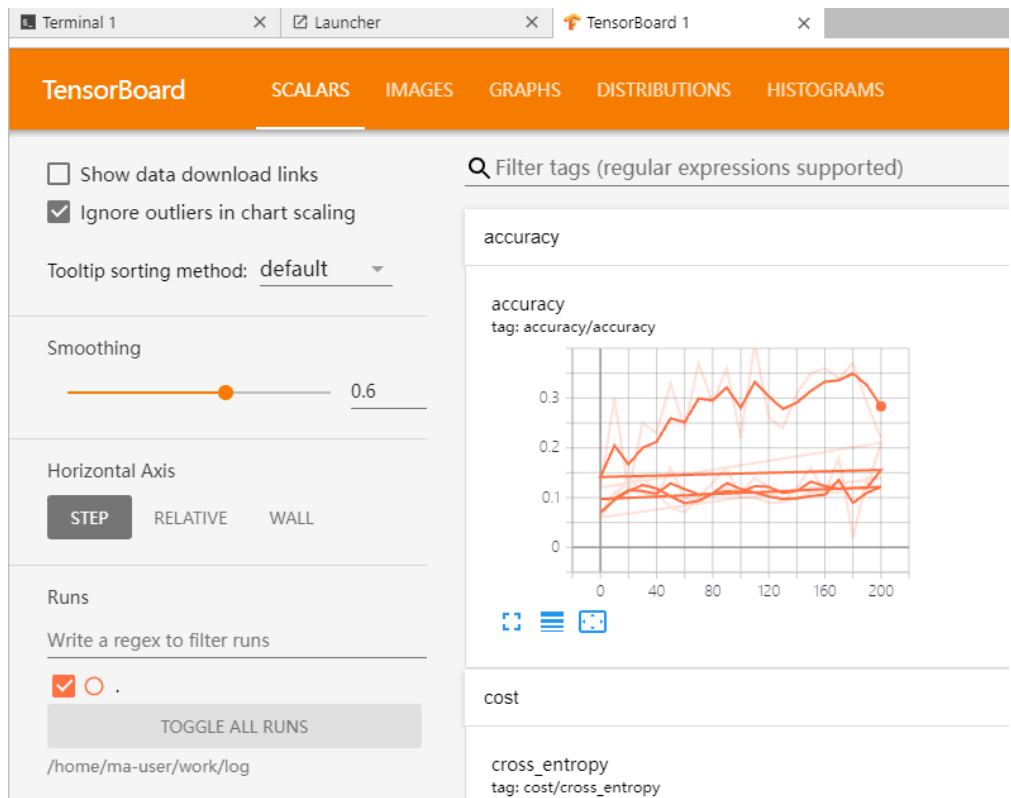


Figure 6-15 TensorBoard page (3)



Method 4



Click **Terminal** and run the following command. The UI will not be displayed.

```
tensorboard --logdir ./log
```

Figure 6-16 Opening TensorBoard through Terminal

```
sh-4.4$pwd
/home/as-user
sh-4.4$tensorboard --logdir ./log
2021-10-18 20:34:53.584976: I tensorflow/stream_executor/platform/default/dso_loader.cc:44] Successfully opened dynamic library libnvinfer.so.6
2021-10-18 20:34:53.589272: I tensorflow/stream_executor/platform/default/dso_loader.cc:44] Successfully opened dynamic library libnvinfer_plugin.so.6
Serving TensorBoard on localhost; to expose to the network, use a proxy or pass --bind_all
TensorBoard 2.1.1 at http://localhost:6006/ (Press CTRL+C to quit)
```

Step 4 View Visualized Data on the Training Dashboard

For TensorBoard visualization, you need the training dashboard. It lets you visualize scalars, images, and computational graphs.

For more functions, see [Get started with TensorBoard](#).

Related Operations

To stop a TensorBoard instance, use any of the following methods:


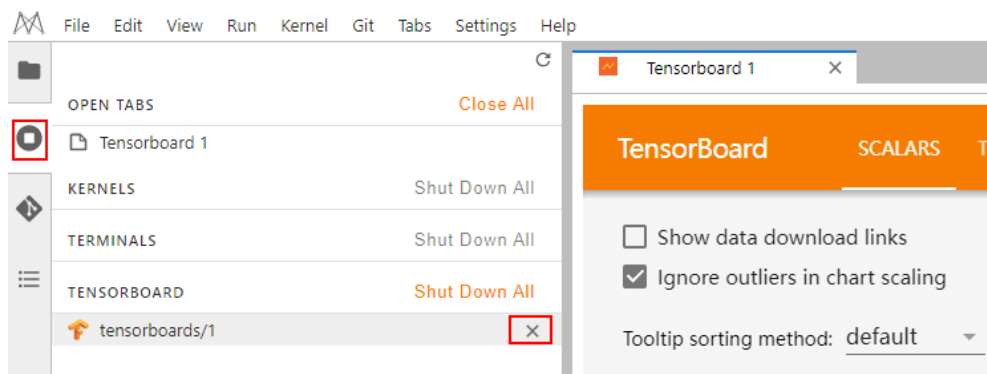
- Method 1: Click . The TensorBoard instance management page is displayed, which shows all started TensorBoard instances. Click **SHUT DOWN** next to an instance.

Figure 6-17 Clicking SHUT DOWN to stop an instance



- Method 2: Enter the following command in the .ipynb file window in JupyterLab (Obtain PID on the startup screen or using the command **ps -ef | grep tensorboard**):
!kill PID


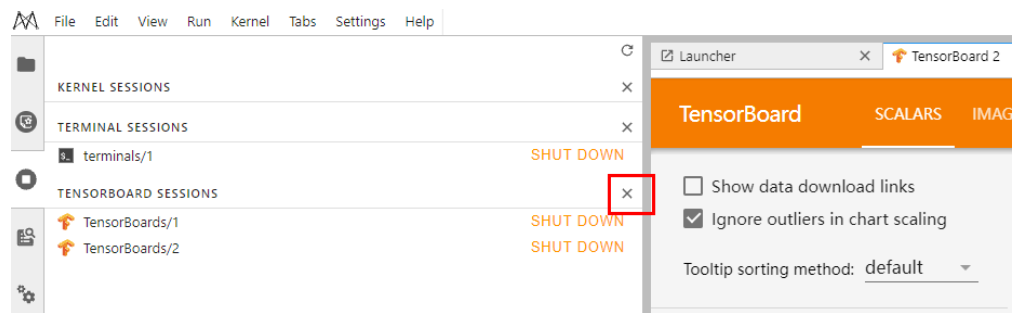
- Method 3: Click  as shown in the following figure to stop all started TensorBoard instances.

Figure 6-18 Stopping all started TensorBoard instances



- (Not recommended) Method 4: Close the TensorBoard window in JupyterLab. This method closes only the window, but the instance is still running on the backend.

7 Distributed Training

7.1 Distributed Training

ModelArts provides the following capabilities:

- Extensive built-in images, meeting your requirements
- Custom development environments set up using built-in images
- Extensive tutorials, helping you quickly understand distributed training
- Distributed training debugging in development tools such as PyCharm, VS Code, and JupyterLab

Constraints

- The development environment refers to provided by ModelArts, excluding the old-version Notebook.
- If the instance flavors are changed, you can only perform single-node debugging. You cannot perform distributed debugging or submit remote training jobs.
- Only the PyTorch and MindSpore AI frameworks can be used for multi-node distributed debugging. If you want to use MindSpore, each node must be equipped with eight cards.
- The OBS paths in the debugging code should be replaced with your OBS paths.
- PyTorch is used to write debugging code in this document. The process is the same for different AI frameworks. You only need to modify some parameters.

Related Chapters

- [Single-Node Multi-Card Training Using DataParallel](#): describes single-node multi-card training using DataParallel, and corresponding code modifications.
- [Multi-Node Multi-Card Training Using DistributedDataParallel](#) : describes multi-node multi-card training using DistributedDataParallel, and corresponding code modifications.
- [Distributed Debugging Adaptation and Code Example](#): describes the procedure and code example of distributed debugging adaptation.

- **Sample Code of Distributed Training:** provides a complete code sample of distributed parallel training for the classification task of ResNet18 on the CIFAR-10 dataset.
- **Debugging a Training Job:** describes how to use the SDK to debug a single-node or multi-node training job on the ModelArts development environment.

7.2 Single-Node Multi-Card Training Using DataParallel

This section describes how to perform single-node multi-card parallel training based on the PyTorch engine.

For details about the distributed training using the MindSpore engine, see [the MindSpore official website](#).

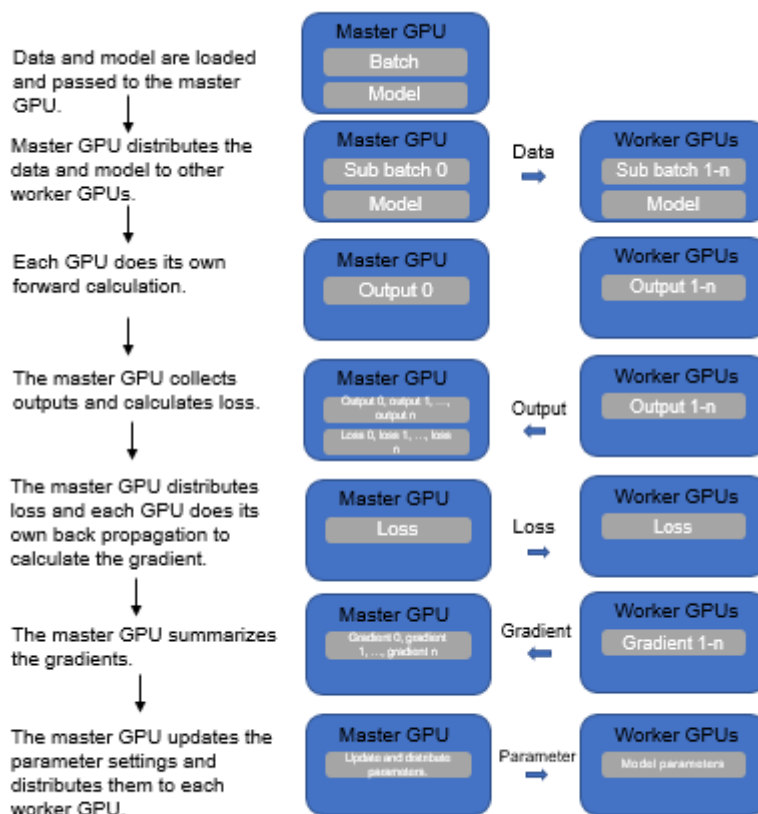
Training Process

The process of single-node multi-card parallel training is as follows:

1. A model is copied to multiple GPUs.
2. Data of each batch is distributed evenly to each worker GPU.
3. Each GPU does its own forward propagation and an output is obtained.
4. The master GPU with device ID 0 collects the output of each GPU and calculates the loss.
5. The master GPU distributes the loss to each worker GPU. Each GPU does its own backward propagation and calculates the gradient.
6. The master GPU collects gradients, updates parameter settings, and distributes the settings to each worker GPU.

The detailed flowchart is as follows.

Figure 7-1 Single-node multi-card parallel training



Advantages and Disadvantages

- Straightforward coding: Only one line of code needs to be modified.
- Bottlenecks in communication: The master GPU is used to update and distribute parameter settings, which causes high communication costs.
- Unbalanced GPU loading: The master GPU is used to summarize outputs, calculate loss, and update weights. Therefore, the GPU memory and usage are higher than those of other GPUs.

Code Modifications

Model distribution: `DataParallel(model)`

The code is slightly changed and the following is a simple example:

```
import torch
class Net(torch.nn.Module):
    pass

model = Net().cuda()

### DataParallel Begin ###
model = torch.nn.DataParallel(Net().cuda())
### DataParallel End ###
```

7.3 Multi-Node Multi-Card Training Using DistributedDataParallel

This section describes how to perform multi-node multi-card parallel training based on the PyTorch engine.

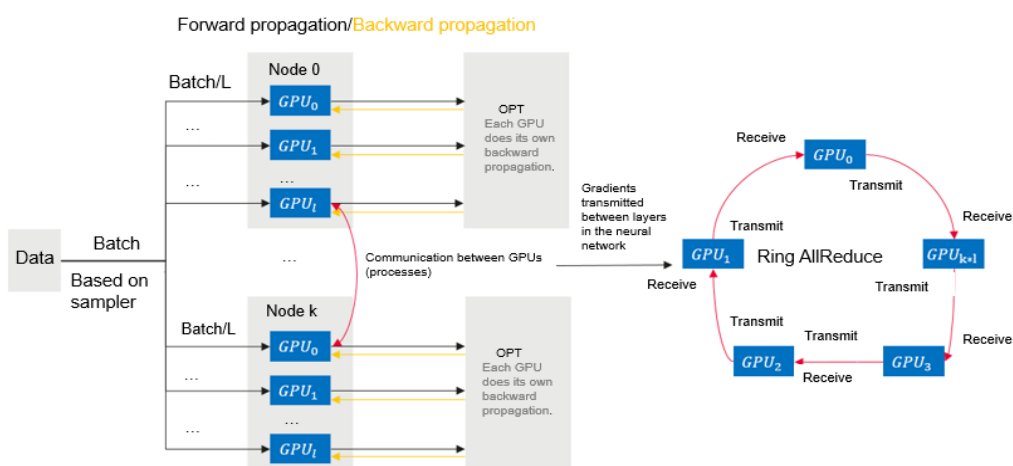
Training Process

Compared with DataParallel, DistributedDataParallel can start multiple processes for computing, greatly improving compute resource usage. Based on **torch.distributed**, DistributedDataParallel has obvious advantages over DataParallel in the distributed computing case. The process is as follows:

1. Initializes the process group.
2. Creates a distributed parallel model. Each process has the same model and parameters.
3. Creates a distributed sampler for data distribution to enable each process to load a unique subset of the original dataset in a mini batch.
4. Parameters are organized into buckets based on their shapes or sizes, which are generally determined by each layer of the network that requires parameter update in a neural network model.
5. Each process does its own forward propagation and computes its gradient.
6. After all parameter gradients at a bucket are obtained, communication is performed for gradient averaging.
7. Each GPU updates model parameters.

The detailed flowchart is as follows.

Figure 7-2 Multi-node multi-card parallel training



Advantages

- Fast communication

- Balanced load
- Fast running speed

Code Modifications

- Multi-process startup
- New variables such as rank ID and world_size are used along with the TCP protocol.
- Sampler for data distribution to avoid duplicate data between different processes
- Model distribution: DistributedDataParallel(model)
- Model saved in GPU 0

```
import torch
class Net(torch.nn.Module):
    pass

model = Net().cuda()

### DataParallel Begin ###
model = torch.nn.DataParallel(Net().cuda())
### DataParallel End ###
```

Related Operations

- For details about distributed debugging adaptation and code example, see [Distributed Debugging Adaptation and Code Example](#).
- This document also provides a complete code sample of distributed parallel training for the classification task of ResNet18 on the cifar10 dataset. For details, see [Sample Code of Distributed Training](#).

7.4 Distributed Debugging Adaptation and Code Example

In DistributedDataParallel, each process loads a subset of the original dataset in a batch, and finally the gradients of all processes are averaged as the final gradient. Due to a large number of samples, a calculated gradient is more reliable, and a learning rate can be increased.

This section describes the code of single-node training and distributed parallel training for the classification job of ResNet18 on the CIFAR-10 dataset. Directly execute the code to perform multi-node distributed training with CPUs or GPUs; comment out the distributed training settings in the code to perform single-node single-card training.

The training code contains three input parameters: basic training parameters, distributed parameters, and data parameters. The distributed parameters are automatically input by the platform. **custom_data** indicates whether to use custom data for training. If this parameter is set to **true**, torch-based random data is used for training and validation.

Dataset

CIFAR-10 dataset

In notebook instances, torchvision of the default version cannot be used to obtain datasets. Therefore, the sample code provides three training data loading methods.

Click **CIFAR-10 python version** on the [download page](#) to download the CIFAR-10 dataset.

- Download the CIFAR-10 dataset using torchvision.
- Download the CIFAR-10 dataset based on the URL and decompress the dataset in a specified directory. The sizes of the training set and test set are (50000, 3, 32, 32) and (10000, 3, 32, 32), respectively.
- Use Torch to obtain a random dataset similar to CIFAR-10. The sizes of the training set and test set are (5000, 3, 32, 32) and (1000, 3, 32, 32), respectively. The labels are still of 10 types. Set **custom_data** to **true**, and the training task can be directly executed without loading data.

Training Code

In the following code, those commented with `### Settings for distributed training` and `... ###` are code modifications for multi-node distributed training.

Do not modify the sample code. After the data path is changed to your path, multi-node distributed training can be executed on ModelArts.

After the distributed code modifications are commented out, the single-node single-card training can be executed. For details about the complete code, see [Sample Code of Distributed Training](#).

- **Importing dependency packages**

```
import datetime
import inspect
import os
import pickle
import random

import argparse
import numpy as np
import torch
import torch.distributed as dist
from torch import nn, optim
from torch.utils.data import TensorDataset, DataLoader
from torch.utils.data.distributed import DistributedSampler
from sklearn.metrics import accuracy_score
```

- **Defining the method and random number for loading data** (The code for loading data is not described here due to its large amount.)

```
def setup_seed(seed):
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
    np.random.seed(seed)
    random.seed(seed)
    torch.backends.cudnn.deterministic = True

def get_data(path):
    pass
```

- **Defining a network structure**

```
class Block(nn.Module):

    def __init__(self, in_channels, out_channels, stride=1):
        super().__init__()
        self.residual_function = nn.Sequential(
            nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=stride, padding=1, bias=False),
```

```

        nn.BatchNorm2d(out_channels),
        nn.ReLU(inplace=True),
        nn.Conv2d(out_channels, out_channels, kernel_size=3, padding=1, bias=False),
        nn.BatchNorm2d(out_channels)
    )

    self.shortcut = nn.Sequential()
    if stride != 1 or in_channels != out_channels:
        self.shortcut = nn.Sequential(
            nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=stride, bias=False),
            nn.BatchNorm2d(out_channels)
        )

    def forward(self, x):
        out = self.residual_function(x) + self.shortcut(x)
        return nn.ReLU(inplace=True)(out)

class ResNet(nn.Module):

    def __init__(self, block, num_classes=10):
        super().__init__()
        self.conv1 = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=3, padding=1, bias=False),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True))
        self.conv2 = self.make_layer(block, 64, 64, 2, 1)
        self.conv3 = self.make_layer(block, 64, 128, 2, 2)
        self.conv4 = self.make_layer(block, 128, 256, 2, 2)
        self.conv5 = self.make_layer(block, 256, 512, 2, 2)
        self.avg_pool = nn.AdaptiveAvgPool2d((1, 1))
        self.dense_layer = nn.Linear(512, num_classes)

    def make_layer(self, block, in_channels, out_channels, num_blocks, stride):
        strides = [stride] + [1] * (num_blocks - 1)
        layers = []
        for stride in strides:
            layers.append(block(in_channels, out_channels, stride))
            in_channels = out_channels
        return nn.Sequential(*layers)

    def forward(self, x):
        out = self.conv1(x)
        out = self.conv2(out)
        out = self.conv3(out)
        out = self.conv4(out)
        out = self.conv5(out)
        out = self.avg_pool(out)
        out = out.view(out.size(0), -1)
        out = self.dense_layer(out)
        return out

```

- **Training and validation**

```

def main():
    file_dir = os.path.dirname(inspect.getframeinfo(inspect.currentframe()).filename)

    seed = datetime.datetime.now().year
    setup_seed(seed)

    parser = argparse.ArgumentParser(description='Pytorch distribute training',
                                    formatter_class=argparse.ArgumentDefaultsHelpFormatter)
    parser.add_argument('--enable_gpu', default='true')
    parser.add_argument('--lr', default='0.01', help='learning rate')
    parser.add_argument('--epochs', default='100', help='training iteration')

    parser.add_argument('--init_method', default=None, help='tcp_port')
    parser.add_argument('--rank', type=int, default=0, help='index of current task')
    parser.add_argument('--world_size', type=int, default=1, help='total number of tasks')

    parser.add_argument('--custom_data', default='false')

```

```

parser.add_argument('--data_url', type=str, default=os.path.join(file_dir, 'input_dir'))
parser.add_argument('--output_dir', type=str, default=os.path.join(file_dir, 'output_dir'))
args, unknown = parser.parse_known_args()

args.enable_gpu = args.enable_gpu == 'true'
args.custom_data = args.custom_data == 'true'
args.lr = float(args.lr)
args.epochs = int(args.epochs)

if args.custom_data:
    print('[warning] you are training on custom random dataset, '
          'validation accuracy may range from 0.4 to 0.6.')

### Settings for distributed training. Initialize DistributedDataParallel process. The init_method,
rank, and world_size parameters are automatically input by the platform. ###
dist.init_process_group(init_method=args.init_method, backend="nccl", world_size=args.world_size,
rank=args.rank)
### Settings for distributed training. Initialize DistributedDataParallel process. The init_method,
rank, and world_size parameters are automatically input by the platform. ###

tr_set, val_set = get_data(args.data_url, custom_data=args.custom_data)

batch_per_gpu = 128
gpus_per_node = torch.cuda.device_count() if args.enable_gpu else 1
batch = batch_per_gpu * gpus_per_node

tr_loader = DataLoader(tr_set, batch_size=batch, shuffle=False)

### Settings for distributed training. Create a sampler for data distribution to ensure that different
processes load different data. ###
tr_sampler = DistributedSampler(tr_set, num_replicas=args.world_size, rank=args.rank)
tr_loader = DataLoader(tr_set, batch_size=batch, sampler=tr_sampler, shuffle=False, drop_last=True)
### Settings for distributed training. Create a sampler for data distribution to ensure that different
processes load different data. ###

val_loader = DataLoader(val_set, batch_size=batch, shuffle=False)

lr = args.lr * gpus_per_node
max_epoch = args.epochs
model = ResNet(Block).cuda() if args.enable_gpu else ResNet(Block)

### Settings for distributed training. Build a DistributedDataParallel model. ###
model = nn.parallel.DistributedDataParallel(model)
### Settings for distributed training. Build a DistributedDataParallel model. ###

optimizer = optim.Adam(model.parameters(), lr=lr)
loss_func = torch.nn.CrossEntropyLoss()

os.makedirs(args.output_dir, exist_ok=True)

for epoch in range(1, max_epoch + 1):
    model.train()
    train_loss = 0

### Settings for distributed training. DistributedDataParallel sampler. Random numbers are set for
the DistributedDataParallel sampler based on the current epoch number to avoid loading duplicate
data. ###
tr_sampler.set_epoch(epoch)
### Settings for distributed training. DistributedDataParallel sampler. Random numbers are set for
the DistributedDataParallel sampler based on the current epoch number to avoid loading duplicate
data. ###

for step, (tr_x, tr_y) in enumerate(tr_loader):
    if args.enable_gpu:
        tr_x, tr_y = tr_x.cuda(), tr_y.cuda()
    out = model(tr_x)
    loss = loss_func(out, tr_y)
    optimizer.zero_grad()
    loss.backward()

```

```

optimizer.step()
train_loss += loss.item()
print('train | epoch: %d | loss: %.4f' % (epoch, train_loss / len(tr_loader)))

val_loss = 0
pred_record = []
real_record = []
model.eval()
with torch.no_grad():
    for step, (val_x, val_y) in enumerate(val_loader):
        if args.enable_gpu:
            val_x, val_y = val_x.cuda(), val_y.cuda()
        out = model(val_x)
        pred_record += list(np.argmax(out.cpu().numpy(), axis=1))
        real_record += list(val_y.cpu().numpy())
        val_loss += loss_func(out, val_y).item()
val_accu = accuracy_score(real_record, pred_record)
print('val | epoch: %d | loss: %.4f | accuracy: %.4f' % (epoch, val_loss / len(val_loader), val_accu),
'\n')

if args.rank == 0:
    # save ckpt every epoch
    torch.save(model.state_dict(), os.path.join(args.output_dir, f'epoch_{epoch}.pth'))

if __name__ == '__main__':
    main()

```

- **Result comparison**

100-epoch **cifar-10** dataset training is completed using two resource types respectively: single-node single-card and two-node 16-card. The training duration and test set accuracy are as follows.

Table 7-1 Training result comparison

Resource Type	Single-Node Single-Card	Two-Node 16-Card
Duration	60 minutes	20 minutes
Accuracy	80+	80+

7.5 Sample Code of Distributed Training

The following provides a complete code sample of distributed parallel training for the classification task of ResNet18 on the CIFAR-10 dataset.

The content of the training boot file **main.py** is as follows (if you need to execute a single-node and single-card training job, delete the code for distributed reconstruction):

```

import datetime
import inspect
import os
import pickle
import random
import logging

import argparse
import numpy as np

```



```
from sklearn.metrics import accuracy_score
import torch
from torch import nn, optim
import torch.distributed as dist
from torch.utils.data import TensorDataset, DataLoader
from torch.utils.data.distributed import DistributedSampler

file_dir = os.path.dirname(inspect.getframeinfo(inspect.currentframe()).filename)

def load_pickle_data(path):
    with open(path, 'rb') as file:
        data = pickle.load(file, encoding='bytes')
    return data

def _load_data(file_path):
    raw_data = load_pickle_data(file_path)
    labels = raw_data[b'labels']
    data = raw_data[b'data']
    filenames = raw_data[b'filenames']

    data = data.reshape(10000, 3, 32, 32) / 255
    return data, labels, filenames

def load_cifar_data(root_path):
    train_root_path = os.path.join(root_path, 'cifar-10-batches-py/data_batch_')
    train_data_record = []
    train_labels = []
    train_filenames = []
    for i in range(1, 6):
        train_file_path = train_root_path + str(i)
        data, labels, filenames = _load_data(train_file_path)
        train_data_record.append(data)
        train_labels += labels
        train_filenames += filenames
    train_data = np.concatenate(train_data_record, axis=0)
    train_labels = np.array(train_labels)

    val_file_path = os.path.join(root_path, 'cifar-10-batches-py/test_batch')
    val_data, val_labels, val_filenames = _load_data(val_file_path)
    val_labels = np.array(val_labels)

    tr_data = torch.from_numpy(train_data).float()
    tr_labels = torch.from_numpy(train_labels).long()
    val_data = torch.from_numpy(val_data).float()
    val_labels = torch.from_numpy(val_labels).long()
    return tr_data, tr_labels, val_data, val_labels

def get_data(root_path, custom_data=False):
    if custom_data:
        train_samples, test_samples, img_size = 5000, 1000, 32
        tr_label = [1] * int(train_samples / 2) + [0] * int(train_samples / 2)
        val_label = [1] * int(test_samples / 2) + [0] * int(test_samples / 2)
        random.seed(2021)
        random.shuffle(tr_label)
        random.shuffle(val_label)
        tr_data, tr_labels = torch.randn((train_samples, 3, img_size, img_size)).float(),
        torch.tensor(tr_label).long()
        val_data, val_labels = torch.randn((test_samples, 3, img_size, img_size)).float(),
```

```
torch.tensor(
    val_label).long()
tr_set = TensorDataset(tr_data, tr_labels)
val_set = TensorDataset(val_data, val_labels)
return tr_set, val_set
elif os.path.exists(os.path.join(root_path, 'cifar-10-batches-py')):
    tr_data, tr_labels, val_data, val_labels = load_cifar_data(root_path)
    tr_set = TensorDataset(tr_data, tr_labels)
    val_set = TensorDataset(val_data, val_labels)
    return tr_set, val_set
else:
    try:
        import torchvision
        from torchvision import transforms
        tr_set = torchvision.datasets.CIFAR10(root='./data', train=True,
            download=True, transform=transforms)
        val_set = torchvision.datasets.CIFAR10(root='./data', train=False,
            download=True, transform=transforms)

        return tr_set, val_set
    except Exception as e:
        raise Exception(
            f"{e}, you can download and unzip cifar-10 dataset manually, "
            "the data url is http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz")

class Block(nn.Module):

    def __init__(self, in_channels, out_channels, stride=1):
        super().__init__()
        self.residual_function = nn.Sequential(
            nn.Conv2d(in_channels, out_channels, kernel_size=3, stride=stride, padding=1,
bias=False),
            nn.BatchNorm2d(out_channels),
            nn.ReLU(inplace=True),
            nn.Conv2d(out_channels, out_channels, kernel_size=3, padding=1, bias=False),
            nn.BatchNorm2d(out_channels)
        )

        self.shortcut = nn.Sequential()
        if stride != 1 or in_channels != out_channels:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(out_channels)
            )

    def forward(self, x):
        out = self.residual_function(x) + self.shortcut(x)
        return nn.ReLU(inplace=True)(out)

class ResNet(nn.Module):

    def __init__(self, block, num_classes=10):
        super().__init__()
        self.conv1 = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=3, padding=1, bias=False),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True))
        self.conv2 = self.make_layer(block, 64, 64, 2, 1)
        self.conv3 = self.make_layer(block, 64, 128, 2, 2)
        self.conv4 = self.make_layer(block, 128, 256, 2, 2)
        self.conv5 = self.make_layer(block, 256, 512, 2, 2)
```

```
self.avg_pool = nn.AdaptiveAvgPool2d((1, 1))
self.dense_layer = nn.Linear(512, num_classes)

def make_layer(self, block, in_channels, out_channels, num_blocks, stride):
    strides = [stride] + [1] * (num_blocks - 1)
    layers = []
    for stride in strides:
        layers.append(block(in_channels, out_channels, stride))
        in_channels = out_channels
    return nn.Sequential(*layers)

def forward(self, x):
    out = self.conv1(x)
    out = self.conv2(out)
    out = self.conv3(out)
    out = self.conv4(out)
    out = self.conv5(out)
    out = self.avg_pool(out)
    out = out.view(out.size(0), -1)
    out = self.dense_layer(out)
    return out

def setup_seed(seed):
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
    np.random.seed(seed)
    random.seed(seed)
    torch.backends.cudnn.deterministic = True

def obs_transfer(src_path, dst_path):
    import moxing as mox
    mox.file.copy_parallel(src_path, dst_path)
    logging.info(f"end copy data from {src_path} to {dst_path}")

def main():
    seed = datetime.datetime.now().year
    setup_seed(seed)

    parser = argparse.ArgumentParser(description='Pytorch distribute training',
                                     formatter_class=argparse.ArgumentDefaultsHelpFormatter)
    parser.add_argument('--enable_gpu', default='true')
    parser.add_argument('--lr', default='0.01', help='learning rate')
    parser.add_argument('--epochs', default='100', help='training iteration')

    parser.add_argument('--init_method', default=None, help='tcp_port')
    parser.add_argument('--rank', type=int, default=0, help='index of current task')
    parser.add_argument('--world_size', type=int, default=1, help='total number of tasks')

    parser.add_argument('--custom_data', default='false')
    parser.add_argument('--data_url', type=str, default=os.path.join(file_dir, 'input_dir'))
    parser.add_argument('--output_dir', type=str, default=os.path.join(file_dir, 'output_dir'))
    args, unknown = parser.parse_known_args()

    args.enable_gpu = args.enable_gpu == 'true'
    args.custom_data = args.custom_data == 'true'
    args.lr = float(args.lr)
    args.epochs = int(args.epochs)

    if args.custom_data:
```

```

        logging.warning('you are training on custom random dataset, '
            'validation accuracy may range from 0.4 to 0.6.')

### Settings for distributed training. Initialize DistributedDataParallel process. The
init_method, rank, and world_size parameters are automatically input by the platform. ###
    dist.init_process_group(init_method=args.init_method, backend="nccl",
        world_size=args.world_size, rank=args.rank)
### Settings for distributed training. Initialize DistributedDataParallel process. The
init_method, rank, and world_size parameters are automatically input by the platform. ###

    tr_set, val_set = get_data(args.data_url, custom_data=args.custom_data)

    batch_per_gpu = 128
    gpus_per_node = torch.cuda.device_count() if args.enable_gpu else 1
    batch = batch_per_gpu * gpus_per_node

    tr_loader = DataLoader(tr_set, batch_size=batch, shuffle=False)

### Settings for distributed training. Create a sampler for data distribution to ensure that
different processes load different data. ###
    tr_sampler = DistributedSampler(tr_set, num_replicas=args.world_size, rank=args.rank)
    tr_loader = DataLoader(tr_set, batch_size=batch, sampler=tr_sampler, shuffle=False,
        drop_last=True)
### Settings for distributed training. Create a sampler for data distribution to ensure that
different processes load different data. ###

    val_loader = DataLoader(val_set, batch_size=batch, shuffle=False)

    lr = args.lr * gpus_per_node * args.world_size
    max_epoch = args.epochs
    model = ResNet(Block).cuda() if args.enable_gpu else ResNet(Block)

### Settings for distributed training. Build a DistributedDataParallel model. ###
    model = nn.parallel.DistributedDataParallel(model)
### Settings for distributed training. Build a DistributedDataParallel model. ###

    optimizer = optim.Adam(model.parameters(), lr=lr)
    loss_func = torch.nn.CrossEntropyLoss()

    os.makedirs(args.output_dir, exist_ok=True)

    for epoch in range(1, max_epoch + 1):
        model.train()
        train_loss = 0

### Settings for distributed training. DistributedDataParallel sampler. Random numbers are set
for the DistributedDataParallel sampler based on the current epoch number to avoid loading
duplicate data. ###
        tr_sampler.set_epoch(epoch)
### Settings for distributed training. DistributedDataParallel sampler. Random numbers are set
for the DistributedDataParallel sampler based on the current epoch number to avoid loading
duplicate data. ###

        for step, (tr_x, tr_y) in enumerate(tr_loader):
            if args.enable_gpu:
                tr_x, tr_y = tr_x.cuda(), tr_y.cuda()
            out = model(tr_x)
            loss = loss_func(out, tr_y)
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
            train_loss += loss.item()

```

```
print('train | epoch: %d | loss: %.4f' % (epoch, train_loss / len(tr_loader)))

val_loss = 0
pred_record = []
real_record = []
model.eval()
with torch.no_grad():
    for step, (val_x, val_y) in enumerate(val_loader):
        if args.enable_gpu:
            val_x, val_y = val_x.cuda(), val_y.cuda()
            out = model(val_x)
            pred_record += list(np.argmax(out.cpu().numpy(), axis=1))
            real_record += list(val_y.cpu().numpy())
            val_loss += loss_func(out, val_y).item()
        val_accu = accuracy_score(real_record, pred_record)
    print('val | epoch: %d | loss: %.4f | accuracy: %.4f' % (epoch, val_loss / len(val_loader),
val_accu), '\n')

    if args.rank == 0:
        # save ckpt every epoch
        torch.save(model.state_dict(), os.path.join(args.output_dir, f'epoch_{epoch}.pth'))

if __name__ == '__main__':
    main()
```

FAQs

1. How Do I Use Different Datasets in the Sample Code?

- To use the CIFAR-10 dataset in the preceding code, [download](#) and decompress the dataset and upload it to the OBS bucket. The file directory structure is as follows:

```
DDP
|-- main.py
|-- input_dir
|----- cifar-10-batches-py
|----- data_batch_1
|----- data_batch_2
|----- ...
```

DDP is the code directory specified during training job creation, **main.py** is the preceding code example (the boot file specified during training job creation), and **cifar-10-batches-py** is the decompressed dataset folder (stored in the **input_dir** folder).

Figure 7-3 Creating a training job

The screenshot shows a configuration form for creating a training job. It includes the following fields and options:

- Algorithm Type:** Custom algorithm (selected), My algorithm (with a help icon).
- Boot Mode:** Preset image (selected), Custom image.
- Code Directory:** /DDP/ (with a Select button and help icon).
- Boot File:** /main.py (with a Select button and help icon).
- Local Code Directory:** /home/ma-user/modelarts/user-job-dir.
- Work Directory:** /home/ma-user/modelarts/user-job-dir (with a Select button).

- To use user-defined random data, change the value of **custom_data** in the code example to **true**.

```
parser.add_argument('--custom_data', default='true')
```

Then, run **main.py**. The parameters for creating a training job are the same as those shown in the preceding figure.

2. Why Can I Leave the IP Address of the Master Node Blank for DDP?

The **init method** parameter in `parser.add_argument('--init_method', default=None, help='tcp_port')` contains the IP address and port number of the master node, which are automatically input by the platform.

7.6 Example of Starting PyTorch DDP Training Based on a Training Job

This topic describes three methods of using a training job to start PyTorch DDP training and provides their sample code.

- Use PyTorch preset images and run the **mp.spawn** command.
- Use custom images.
 - Run the **torch.distributed.launch** command.
 - Run the **torch.distributed.run** command.

Creating a Training Job

- Use PyTorch preset images and run the **mp.spawn** command.
Set **Boot Mode** to **Preset image**, select a PyTorch preset image below, set **Code Directory** to the OBS path where the code folder is stored, and choose the **main.py** file as the boot file.

Figure 7-4 Creating a training job

* Algorithm Type
 Custom algorithm
 My algorithm
 My subscription

* Boot Mode
 Preset image
 Custom image

PyTorch pytorch_1.8.0-cuda_10.2-py_3.7...

* Code Directory ? Select

* Boot File ? Select

Local Code Directory

Work Directory X Select

If you select a resource flavor with multiple cards on one node, specify the hyperparameters **world_size** and **rank** when creating a training job. If you select a resource flavor with multiple nodes (more than one compute node in a training job), you do not need to set these hyperparameters. **world_size** and **rank** are automatically injected by ModelArts.

Figure 7-5 Hyperparameters

Hyperparameter

= 🗑️

= 🗑️

⊕ Add

- Use the custom image and run the **torch.distributed.launch** command. Set **Boot Mode** to **Custom image**, select a custom image, and set **Code Directory** to the OBS path where the code folder is stored. The boot command is as follows:

```
bash ${MA_JOB_DIR}/code/torchlaunch.sh
```

Figure 7-6 Creating a training job

* Algorithm Type
 Custom algorithm
 My algorithm
 My subscription

* Boot Mode
 Preset image
 Custom image

* Image Select

Code Directory Select

* Boot Command ?

1 bash \$ {MA_JOB_DIR} /code/torchlaunch.sh

- Use the custom image and run the **torch.distributed.run** command. Set **Boot Mode** to **Custom image**, select a custom image, and set **Code Directory** to the OBS path where the code folder is stored. The boot command is as follows:

```
bash ${MA_JOB_DIR}/code/torchrun.sh
```

Figure 7-7 Creating a training job

* Algorithm Type

* Boot Mode

* Image

Code Directory

* Boot Command ?

```
1 bash ${MA_JOB_DIR} /code/torchrun.sh
```

Code Examples

Upload the following files to an OBS bucket:

```
code                # Root directory of the code
├── torch_ddp.py    # Code file for PyTorch DDP training
├── main.py        # Boot file for starting training using the PyTorch preset image and the mp.spawn
command
├── torchlaunch.sh # Boot file for starting training using the custom image and the
torch.distributed.launch command
├── torchrun.sh    # Boot file for starting training using the custom image and the
torch.distributed.run command
```

torch_ddp.py

```
import os
import torch
import torch.distributed as dist
import torch.nn as nn
import torch.optim as optim
from torch.nn.parallel import DistributedDataParallel as DDP

# Start training by running mp.spawn.
def init_from_arg(local_rank, base_rank, world_size, init_method):
    rank = base_rank + local_rank
    dist.init_process_group("nccl", rank=rank, init_method=init_method, world_size=world_size)
    ddp_train(local_rank)

# Start training by running torch.distributed.launch or torch.distributed.run.
def init_from_env():
    dist.init_process_group(backend='nccl', init_method='env://')
    local_rank=int(os.environ["LOCAL_RANK"])
    ddp_train(local_rank)

def cleanup():
    dist.destroy_process_group()

class ToyModel(nn.Module):
    def __init__(self):
        super(ToyModel, self).__init__()
        self.net1 = nn.Linear(10, 10)
        self.relu = nn.ReLU()
        self.net2 = nn.Linear(10, 5)
    def forward(self, x):
        return self.net2(self.relu(self.net1(x)))

def ddp_train(device_id):
    # create model and move it to GPU with id rank
    model = ToyModel().to(device_id)
    ddp_model = DDP(model, device_ids=[device_id])
```



```
loss_fn = nn.MSELoss()
optimizer = optim.SGD(ddp_model.parameters(), lr=0.001)
optimizer.zero_grad()
outputs = ddp_model(torch.randn(20, 10))
labels = torch.randn(20, 5).to(device_id)
loss_fn(outputs, labels).backward()
optimizer.step()
cleanup()

if __name__ == "__main__":
    init_from_env()
```

main.py

```
import argparse
import torch
import torch.multiprocessing as mp

parser = argparse.ArgumentParser(description='ddp demo args')
parser.add_argument('--world_size', type=int, required=True)
parser.add_argument('--rank', type=int, required=True)
parser.add_argument('--init_method', type=str, required=True)
args, unknown = parser.parse_known_args()

if __name__ == "__main__":
    n_gpus = torch.cuda.device_count()
    world_size = n_gpus * args.world_size
    base_rank = n_gpus * args.rank
    # Call the start function in the DDP sample code.
    from torch_ddp import init_from_arg
    mp.spawn(init_from_arg,
             args=(base_rank, world_size, args.init_method),
             nprocs=n_gpus,
             join=True)
```

torchlaunch.sh

```
#!/bin/bash
# Default system environment variables. Do not modify them.
MASTER_HOST="$VC_WORKER_HOSTS"
MASTER_ADDR="${VC_WORKER_HOSTS%%,*}"
MASTER_PORT="6060"
JOB_ID="1234"
NNODES="$MA_NUM_HOSTS"
NODE_RANK="$VC_TASK_INDEX"
NGPUS_PER_NODE="$MA_NUM_GPUS"

# Custom environment variables to specify the Python script and parameters.
PYTHON_SCRIPT=${MA_JOB_DIR}/code/torch_ddp.py
PYTHON_ARGS=""

CMD="python -m torch.distributed.launch \
  --nnodes=$NNODES \
  --node_rank=$NODE_RANK \
  --nproc_per_node=$NGPUS_PER_NODE \
  --master_addr $MASTER_ADDR \
  --master_port=$MASTER_PORT \
  --use_env \
  $PYTHON_SCRIPT \
  $PYTHON_ARGS"

echo $CMD
$CMD
```

torchrn.sh

NOTICE

In PyTorch 2.1, you must set **rdzv_backend** to **static**: **--rdzv_backend=static**.

```
#!/bin/bash
# Default system environment variables. Do not modify them.
MASTER_HOST="${VC_WORKER_HOSTS}"
MASTER_ADDR="${VC_WORKER_HOSTS%%,*}"
MASTER_PORT="6060"
JOB_ID="1234"
NNODES="$MA_NUM_HOSTS"
NODE_RANK="$VC_TASK_INDEX"
NGPUS_PER_NODE="$MA_NUM_GPUS"

# Custom environment variables to specify the Python script and parameters.
PYTHON_SCRIPT=${MA_JOB_DIR}/code/torch_ddp.py
PYTHON_ARGS=""

if [[ $NODE_RANK == 0 ]]; then
    EXT_ARGS="--rdzv_conf=is_host=1"
else
    EXT_ARGS=""
fi

CMD="python -m torch.distributed.run \
    --nnodes=$NNODES \
    --node_rank=$NODE_RANK \
    $EXT_ARGS \
    --nproc_per_node=$NGPUS_PER_NODE \
    --rdzv_id=$JOB_ID \
    --rdzv_backend=c10d \
    --rdzv_endpoint=$MASTER_ADDR:$MASTER_PORT \
    $PYTHON_SCRIPT \
    $PYTHON_ARGS
"
echo $CMD
$CMD
```

8 Automatic Model Tuning (AutoSearch)

8.1 Introduction to Hyperparameter Search

The new version of ModelArts training jobs supports hyperparameter search, which can automatically search for optimal hyperparameters for your models.

During model training, many hyperparameters, such as **learning_rate** and **weight_decay**, need to be adjusted based on actual requirements. This may cost an experienced algorithm engineer a lot of time and effort on manual optimization. However, the hyperparameter search supported by ModelArts can automatically optimize hyperparameters without the help of algorithm engineers and has higher optimization speed and precision than manual optimization.

ModelArts supports the following hyperparameter search algorithms:

- [Bayesian Optimization \(SMAC\)](#)
- [TPE Algorithm](#)
- [Simulated Annealing Algorithm](#)

8.2 Search Algorithm

8.2.1 Bayesian Optimization (SMAC)

In Bayesian optimization, it is assumed that there exists a functional relationship between hyperparameters and the objective function. Based on the evaluation values of the searched hyperparameters, the mean and variance of the objective function values at other search points are estimated through Gaussian process regression. The mean and variance are then used to construct the acquisition function. The next search point is the maximum value of the acquisition function. Compared with grid search, Bayesian optimization uses the previous evaluation results to reduce the number of iterations and shorten the search time. The disadvantage is that it is difficult to find the global optimal solution.

Table 8-1 Bayesian optimization parameters

Parameter	Description	Recommended Value
num_samples	Number of times to sample from the hyperparameter space	The value is an integer ranging from 10 to 20. The larger the value, the longer the search time and the better the effect.
kind	Acquisition function type	This value is string type. The default value is ucb and other value options are ei and poi . Do not change the default one.
kappa	Adjustment parameter of acquisition function type ucb , which is the upper confidence boundary	This value is a float. You are advised not to change it.
xi	Adjustment parameter of acquisition function types poi and ei	This value is a float. You are advised not to change it.

8.2.2 TPE Algorithm

The tree-structured parzen estimator (TPE) algorithm uses the Gaussian mixture model to learn the model hyperparameters. On each trial, for each parameter, TPE fits one Gaussian mixture model $l(x)$ to the set of parameter values associated with the best objective values, and another Gaussian mixture model $g(x)$ to the remaining parameter values. It chooses the hyperparameter value that maximizes the ratio $l(x)/g(x)$.

Table 8-2 TPE algorithm parameters

Parameter	Description	Recommended Value
num_samples	Number of times to sample from the hyperparameter space	The value is an integer ranging from 10 to 20. The larger the value, the longer the search time and the better the effect.
n_initial_points	Number of random evaluations of the objective function before starting to approximate it with tree parzen estimators	The value is an integer. You are advised not to change it.
gamma	Quantile of the TPE algorithm to divide $l(x)$ and $g(x)$	This value is a float ranging from 0 to 1. You are advised not to change it.

8.2.3 Simulated Annealing Algorithm

The simulated annealing algorithm is a simple but effective variant on random search that leverages smoothness in the response surface. The annealing rate is not adaptive. The annealing algorithm is to choose one of the previous trial points as a starting point, and then to sample each hyperparameter from a similar distribution to the one specified in the prior, but whose density is more concentrated around the selected trial point. The algorithm tends over time to sample from points closer and closer to the best ones. During the sampling, this algorithm may draw a runner-up trial as the best trail to avoid local optima at a certain probability.

Table 8-3 Parameters of the simulated annealing algorithm

Parameter	Description	Recommended Value
num_samples	Number of times to sample from the hyperparameter space	The value is an integer ranging from 10 to 20. The larger the value, the longer the search time and the better the effect.
avg_best_idx	Mean of geometric distribution over which trial to explore around, selecting from trials sorted by score	This value is a float. You are advised not to change it.
shrink_coef	Rate of reduction in the size of sampling neighborhood as more points have been explored	This value is a float. You are advised not to change it.

8.3 Creating a Hyperparameter Search Job

Background

Hyperparameters that you want to optimize need to be defined when you configure **Hyperparameters**. You can specify the name, type, default value, and constraints. For details, see [Defining Hyperparameters](#).

If the AI engine is `pytorch_1.8.0-cuda_10.2-py_3.7-ubuntu_18.04-x86_64` or `tensorflow_2.1.0-cuda_10.1-py_3.7-ubuntu_18.04-x86_64` and the hyperparameter to be optimized is of the float type, you can use hyperparameter search on ModelArts.

You can perform the hyperparameter search without any code modification. The procedure is as follows:

1. [Preparations](#)
2. [Creating an Algorithm](#)
3. [Creating a Training Job](#)
4. [Viewing Details About a Hyperparameter Search Job](#)

Preparations

- Data has been prepared. Specifically, you have created an available dataset in ModelArts, or you have uploaded the dataset used for training to the OBS directory.
- Prepare the training script and upload it to the OBS directory. For details about how to develop a training script, see [Developing a Custom Script](#).
- In the training code, print the search indicator parameters.
- At least one empty folder has been created in OBS for storing the training output.
- The account is not in arrears because resources are consumed when training jobs are running.
- The OBS directory you use and ModelArts are in the same region.

Creating an Algorithm

Log in to the ModelArts management console and create an algorithm by referring to [Creating an Algorithm](#). When configuring parameters of the algorithm, pay attention to the configuration of **Hyperparameters** and **Supported Policies**.

Figure 8-1 Parameters of hyperparameter search

Hyperparameters

Delete Clear

<input type="checkbox"/>	Name	Type
--------------------------	------	------

+ Add hyperparameter

Supported Policies

autoSearch(S)

Hyperparameters that you want to optimize need to be defined when you configure **Hyperparameters**. You can specify the name, type, default value, and constraints. For details, see [Defining Hyperparameters](#).

Select **autoSearch(S)** to enable the auto search function for the algorithm. During an auto search, ModelArts uses a regular expression to obtain the search indicator parameters and performs hyperparameter optimization based on the optimization direction. Print search parameters in the code and configure the following parameters:

- Search Indicator
The search indicator is the value of the objective function, which can be loss, accuracy, and so on. By optimizing and converging this value based on the optimization direction, the optimal hyperparameter can be found to improve the model precision and convergence speed.

Table 8-4 Search indicator parameters

Parameter	Description
Name	search indicator name. This parameter must be identical to the search indicator parameter in the code.
Optimization Direction	This parameter can be max or min .
Counter regularization	A regular expression needs to be entered. You can click Generate Intelligently to generate a regular expression automatically.

- **Setting Automatic Search Parameters**
Select hyperparameters that can be used for search optimization from what you configured for **Hyperparameters**. Only hyperparameters of the float type are supported. After **autoSearch(S)** is selected, set the value range.
- **Search Algorithm Configuration**
ModelArts has three built-in algorithms for hyperparameter search. You can select one or more algorithms as needed. The algorithms and their parameter description are as follows:
 - bayes_opt_search: **Bayesian Optimization (SMAC)**
 - tpe_search: **TPE Algorithm**
 - anneal_search: **Simulated Annealing Algorithm**

After you submit the request for creating the algorithm, wait until the algorithm is available on the algorithm management page. When the newly created algorithm is available, you can perform other operations.

Creating a Training Job

Log in to the ModelArts management console and create a training job by referring to **Creating a Training Job**. Pay attention to operations described in this section before you enable the hyperparameter search.

If you select an algorithm that supports hyperparameter search, click the button for range setting to enable hyperparameter search.

Figure 8-2 Range setting

Hyperparameter

learning_rate	=	0.01	⊗
batch_size	=	64	▼
weight_decay	=	0.01	⊗

⊕ Add

After the hyperparameter search is enabled, you can configure the search indicator, search algorithm, and parameters of the selected algorithm. These parameters need to have the same values as the hyperparameters of the algorithm you created.

After a hyperparameter search job is created, it will take a period of time to run it.

Viewing Details About a Hyperparameter Search Job

After a training job is complete, you can view the job details to determine whether the training job is satisfactory.

You can go to the ModelArts management console to view the details. For details, see [Viewing Training Job Details](#). If the training job is an auto hyperparameter search job, you can view the results after it is completed.

9 Converting a Model

9.1 Model Conversion

NOTE

ModelArts model conversion will be taken offline on February 29, 2024. You will be provided with links to download the [ATC](#) model conversion tool or [MindSpore Lite](#). ATC converts your model into OM format, and MindSpore Lite converts your model into MindIR format for inference. ModelArts development environment supports the conversion of ONNX or PyTorch models into MindIR format in the CN Southwest-Guiyang1 region.

To deploy the models created in ModelArts or a local PC on the Ascend chip, convert the models to the required formats beforehand.

ModelArts supports model conversion, allowing you to convert a model to a required format.

Model conversion applies to the following scenarios:

- If you use the Caffe (in **.caffemodel** format) or TensorFlow framework (in **frozen_graph** or **saved_model** format) to train a model, you can convert the model to the **.om** format. The converted model can be deployed and run on Ascend chips.

Constraints

- Only TensorFlow models can be converted. For a TensorFlow model, the input data type is of the INT32, BOOL, UINT8, or FLOAT type.
- ModelArts provides conversion templates for you to choose. For details about the supported templates, see [Conversion Templates](#).
- An OBS directory must be specified in compression/conversion tasks. Ensure that the OBS directory you use and ModelArts are in the same region.
- When importing the converted model to ModelArts, use [a model template](#).
- For a TensorFlow model, the FrozenGraphDef and SavedModel formats are supported. If a model is in the SavedModel format, the model is converted to the FrozenGraphDef format and then to the OM format.
- Inputs with dynamic shapes are not supported, for example, NHWC = [?, ?, ?, 3]. A fixed value needs to be specified during model conversion.

- The input can be up to 4-dimensional. Operators involving dimension changes (such as reshape and expanddim) cannot output five dimensions.
- Except the const operator, the input and output at all layers in a model must meet the condition **dim!=0**.
- Model conversion does not support models that contain training operators.
- A UINT8 quantized model cannot be converted.
- Model operators support only 2D convolution but do not support 3D convolution. The batch_normalization_1 and FusedBatchNorm operators cannot be converted in batches.

Creating a Model Conversion Task

1. Log in to the ModelArts management console and choose **AI Application Management > Model Conversion** in the navigation pane. The **Model Conversion** page is displayed.
2. Click **Create Task** in the upper left corner to create a task.
3. On the **Create Task** page, set the conversion task parameters.
 - a. Enter the name and description of the conversion task.
 - b. Set the parameters of the conversion task. For details, see [Table 9-1](#).

Table 9-1 Parameters

Parameter	Description
Input Framework	Caffe and TensorFlow frameworks support conversion.
Conversion Input Path	Path to the model to be converted. The path must be an OBS path and comply with the ModelArts specifications. For details about the specifications, see Conversion Input Path .
Output Framework	MindSpore is supported.
Conversion Output Path	Path to the converted model. The path must comply with the ModelArts specifications. For details about the specifications, see Conversion Output Path .

Parameter	Description
Conversion Template	<p>ModelArts provides various templates to define model conversion and the parameters required during the conversion. Conversion Templates details the supported model conversion templates. The drop-down list on the right of the conversion template displays the matching templates based on the selected input and output frameworks.</p> <p>After you select a template from the drop-down list, the advanced parameters of the template are displayed in the lower part of the page, for example, the precision.</p> <p>Different conversion templates support different advanced settings. For details about the parameters supported by each template, see Conversion Templates.</p>

Figure 9-1 Creating a model conversion task

The screenshot shows a form for creating a model conversion task. It includes the following fields and options:

- Input Framework:** Radio buttons for Caffe and TensorFlow.
- Conversion Input Path:** A text input field with a placeholder "Select a conversion input path." and a file selection icon.
- Output Framework:** A radio button for MindSpore.
- Conversion Output Path:** A text input field with a placeholder "Select a conversion output path." and a file selection icon.
- Conversion Template:** A dropdown menu showing "Caffe to Ascend" with sub-options "ascend", "Caffe", and "caffemodel". A tooltip indicates "Caffe models can be converted into mo...".
- framework:** A separate dropdown menu.

- After entering the task information, click **Create now** in the lower right corner.

After the task is created, the system automatically switches to the **Model Conversion Tasks** page. The created conversion task is displayed on the page and is in the **Initializing** status. The conversion task takes several minutes to complete. When the task status changes to **Successful**, the task is complete and the model has been converted.

If the task status changes to **Failed**, click the task name to go to the task details page, view the log information, adjust task parameters based on the log information, and create another conversion task.

Deleting a Model Conversion Task

You can delete unnecessary conversion tasks. However, tasks in the **Running** or **Initializing** status cannot be deleted.

NOTE

Deleted tasks cannot be recovered. Exercise caution when performing this operation.

- Deleting a single task:
On the **Model Conversion Tasks** page, click **Delete** in the **Operation** column of the target task.
- Deleting a batch of tasks:
On the **Model Conversion Tasks** page, select multiple tasks to be deleted and click **Delete** in the upper left corner.

9.2 Conversion Input Path

Ascend Chip

The requirements for converting the models run on the Ascend chip are as follows:

- For Caffe-based models, the input path must comply with the following specifications during model conversion:
 - |---xxx.caffemodel (Mandatory) Model parameter file. Only one model parameter file can exist in the input path.
 - |---xxx.prototxt (Mandatory) Model network file. Only one model network file can exist in the input path.
 - |---insert_op_conf.cfg (Optional) Insertion operator configuration file. Only one insertion operator configuration file can exist in the input path.
 - |---plugin (Optional) Custom operator directory. The input directory can contain only one plugin folder. Only custom operators developed based on Tensor Engine (TE) are supported.

- For TensorFlow-based models (in **frozen_graph** or **saved_model** format), the input path must comply with the following specifications during model conversion:

frozen_graph format

- |---xxx.pb (Mandatory) Model network file. Only one model network file can exist in the input path. The model must be in **frozen_graph** or **saved_model** format.
- |---insert_op_conf.cfg (Optional) Insertion operator configuration file. Only one insertion operator configuration file can exist in the input path.
- |---plugin (Optional) Custom operator directory. The input directory can contain only one plugin folder. Only custom operators developed based on Tensor Engine (TE) are supported.

saved_model format

- |---saved_model.pb (Mandatory) Model network file. Only one model network file can exist in the input path. The model must be in **frozen_graph** or **saved_model** format.
- |---variables (Mandatory) Fixed subdirectory name, including the model weight deviation.
 - |---variables.index Mandatory
 - |---variables.data-00000-of-00001 Mandatory
- |---insert_op_conf.cfg (Optional) Insertion operator configuration file. Only one insertion operator configuration file can exist in the input path.
- |---plugin (Optional) Custom operator directory. The input directory can contain only one plugin folder. Only custom operators developed based on Tensor Engine (TE) are supported.

9.3 Conversion Output Path

Ascend Chip

The following describes the output path of the model run on the Ascend chip after conversion:

- For Caffe-based models, the output path must comply with the following specifications during model conversion:

```
|
|---xxx.om      Converted model to run on the Ascend chip. The model file name extension is .om.
|---job_log.txt Conversion log file
```

- For TensorFlow-based models, the output path must comply with the following specifications during model conversion:

```
|
|---xxx.om      Converted model to run on the Ascend chip. The model file name extension is .om.
|---job_log.txt Conversion log file
```

9.4 Conversion Templates

ModelArts provides the following conversion templates based on different AI frameworks:

- [Caffe to Ascend](#)
- [TF-FrozenGraph-To-Ascend](#)
- [TF-SavedModel-To-Ascend](#)

Caffe to Ascend

Convert the model trained by the Caffe framework. The converted model can run on the Ascend chip.

This template has no advanced settings.

TF-FrozenGraph-To-Ascend

Convert the model trained by the TensorFlow framework and saved in **frozen_graph** format. The converted model can run on the Ascend. The custom operators (TE operators) developed based on TE can be used for conversion.

Table 9-2 Advanced settings of the custom operator conversion template

Parameter	Description
input_shape	Enter the shape of the input data of the model, for example, input_name1:n1,c1,h1,w1;input_name2:n2,c2,h2,w2 . input_name must be the node name in the network model before model conversion. This parameter is mandatory when the model has dynamic shape input. For example, in input_name1:?,h,w,c , the question mark (?) indicates the batch size, that is, the number of images processed at a time. It is used to convert the original model with a dynamic shape into an offline model with a fixed shape. The batch feature is not supported. The batch value of the input_shape can only be 1. During the conversion, the system parses the input model to obtain the input tensor and prints it in the log. If you do not know the input tensor of the used model, refer to the parsing result in the log.

Parameter	Description
input_format	NCHW and NHWC are supported. The default format is NHWC . For the TensorFlow framework, the default value is NHWC . To use the NCHW format, you need to specify NCHW . For the Caffe framework, only the NCHW format is supported.
out_nodes	Specifies the output node, for example, node_name1:0;node_name1:1;node_name2:0 . node_name must be the node name in the network model before model conversion. The digit after each colon (:) indicates the sequence number of the output. For example, node_name1:0 indicates the 0th output of node_name1 . If the output node is not specified, the output of the last operator layer serves as the model output by default. To check the parameters of a specific operator layer, specify the operator layer by using this parameter. During the conversion, the system parses the input model to obtain the output node and prints it in the log. If you do not know the input tensor of the used model, refer to the parsing result in the log.
net_format	Specifies the preferred data format for network operators. Possible values are ND (N cannot be more than 4) and 5D . This parameter only takes effect if the input data of operators on the network supports both ND and 5D formats. ND indicates that operators in the model are converted into the NCHW format. 5D indicates that operators in the model are converted into the Huawei-developed 5D format. 5D is the default value.
fp16_high_prec	Specifies whether to generate a high-precision FP16 Davinci model. 0 is the default value, indicating that a common FP16 Da Vinci model with better inference performance is generated. The value 1 indicates that a high-precision FP16 Da Vinci model with better inference precision is generated. High-precision models support only Caffe operators (Convolution, Pooling, and FullConnection) and TensorFlow operators (tf.nn.conv2d and tf.nn.max_poo).
output_type	FP32 is the default value and is recommended for classification and detection networks. For image super-resolution networks, UINT8 is recommended for better inference performance.

TF-SavedModel-To-Ascend

Convert the model trained by the TensorFlow framework and saved in **saved_model** format. The converted model can run on the Ascend. The custom operators (TE operators) developed based on TE can be used for conversion.

Table 9-3 Advanced settings of the custom operator conversion template

Parameter	Description
input_shape	Enter the shape of the input data of the model, for example, input_name1:n1,c1,h1,w1;input_name2:n2,c2,h2,w2 . input_name must be the node name in the network model before model conversion. This parameter is mandatory when the model has dynamic shape input. For example, in input_name1:?,h,w,c , the question mark (?) indicates the batch size, that is, the number of images processed at a time. It is used to convert the original model with a dynamic shape into an offline model with a fixed shape. The batch feature is not supported. The batch value of the input_shape can only be 1 . During the conversion, the system parses the input model to obtain the input tensor and prints it in the log. If you do not know the input tensor of the used model, refer to the parsing result in the log.
input_format	NCHW and NHWC are supported. The default format is NHWC . For the TensorFlow framework, the default value is NHWC . To use the NCHW format, you need to specify NCHW . For the Caffe framework, only the NCHW format is supported.
out_nodes	Specifies the output node, for example, node_name1:0;node_name1:1;node_name2:0 . node_name must be the node name in the network model before model conversion. The digit after each colon (:) indicates the sequence number of the output. For example, node_name1:0 indicates the 0th output of node_name1 . If the output node is not specified, the output of the last operator layer serves as the model output by default. To check the parameters of a specific operator layer, specify the operator layer by using this parameter. During the conversion, the system parses the input model to obtain the output node and prints it in the log. If you do not know the input tensor of the used model, refer to the parsing result in the log.
net_format	Specifies the preferred data format for network operators. Possible values are ND (N cannot be more than 4) and 5D . This parameter only takes effect if the input data of operators on the network supports both ND and 5D formats. ND indicates that operators in the model are converted into the NCHW format. 5D indicates that operators in the model are converted into the Huawei-developed 5D format. 5D is the default value.

Parameter	Description
fp16_high_prec	Specifies whether to generate a high-precision FP16 Davinci model. 0 is the default value, indicating that a common FP16 Da Vinci model with better inference performance is generated. The value 1 indicates that a high-precision FP16 Da Vinci model with better inference precision is generated. High-precision models support only Caffe operators (Convolution, Pooling, and FullConnection) and TensorFlow operators (tf.nn.conv2d and tf.nn.max_poo).
output_type	FP32 is the default value and is recommended for classification and detection networks. For image super-resolution networks, UINT8 is recommended for better inference performance.

10 Change History

Released On	Description
2023-12-29	<p>Supported folder permission control when SFS Turbo is mounted to a training job. For details, see Creating a Training Job.</p> <p>Provided the ATC model conversion tool and MindSpore Lite offline model conversion tool in Model Conversion.</p>
2023-10-01	<p>Added the user ID parameter for running a container. For details, see Creating a Training Job.</p> <p>Enabled CloudShell fault locating tips. For details, see Logging In to a Training Container Using Cloud Shell.</p>
2023-08-01	<p>Added the function of filtering training jobs by resource pool. For details, see Stopping, Rebuilding, or Searching for a Training Job.</p>