Cloud GPU Service

Best Practices

Product Documentation

Contents

Best Practices

Using Docker to Install TensorFlow and Set GPU/CPU Support

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Note:

This document is written by a Cloud GPU Service user and is for study and reference only.

Overview

You can use Docker to run TensorFlow in a GPU instance quickly. In this way, you only need to install the NVIDIA® driver program in the instance and don't need to install NVIDIA® CUDA® Toolkit.

This document describes how to use Docker to install TensorFlow and configure GPU/CPU support in a GPU instance.

Notes

This document uses a GPU instance on Ubuntu 20.04 as an example.

The GPU driver has been installed in your GPU instance.

Note:

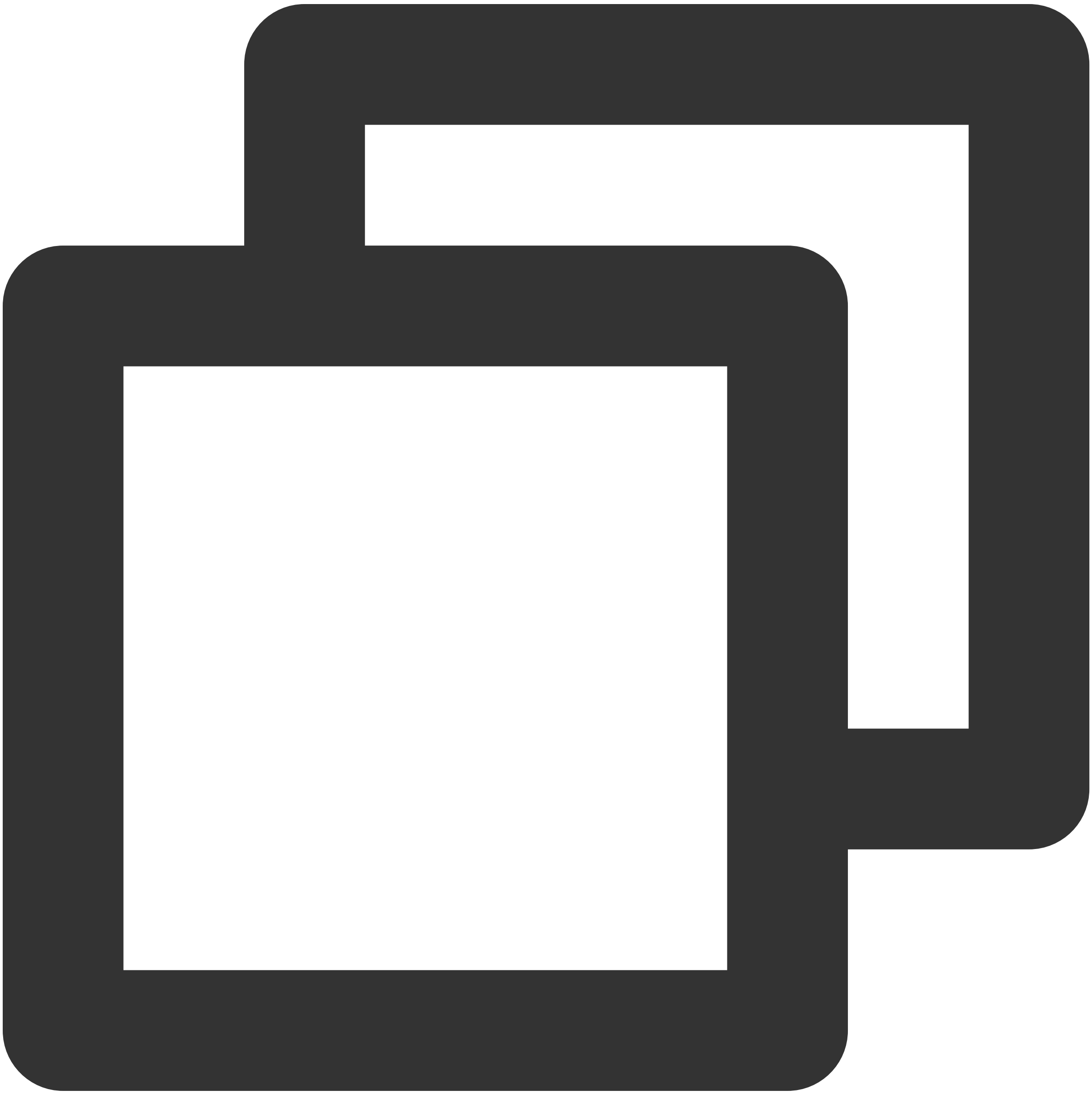
We recommend you use a public image to create a GPU instance. If you select a public image, then select **Automatically install GPU driver on the backend** to preinstall the driver on the corresponding version. This method only supports certain Linux public images.

Directions

Installing Docker

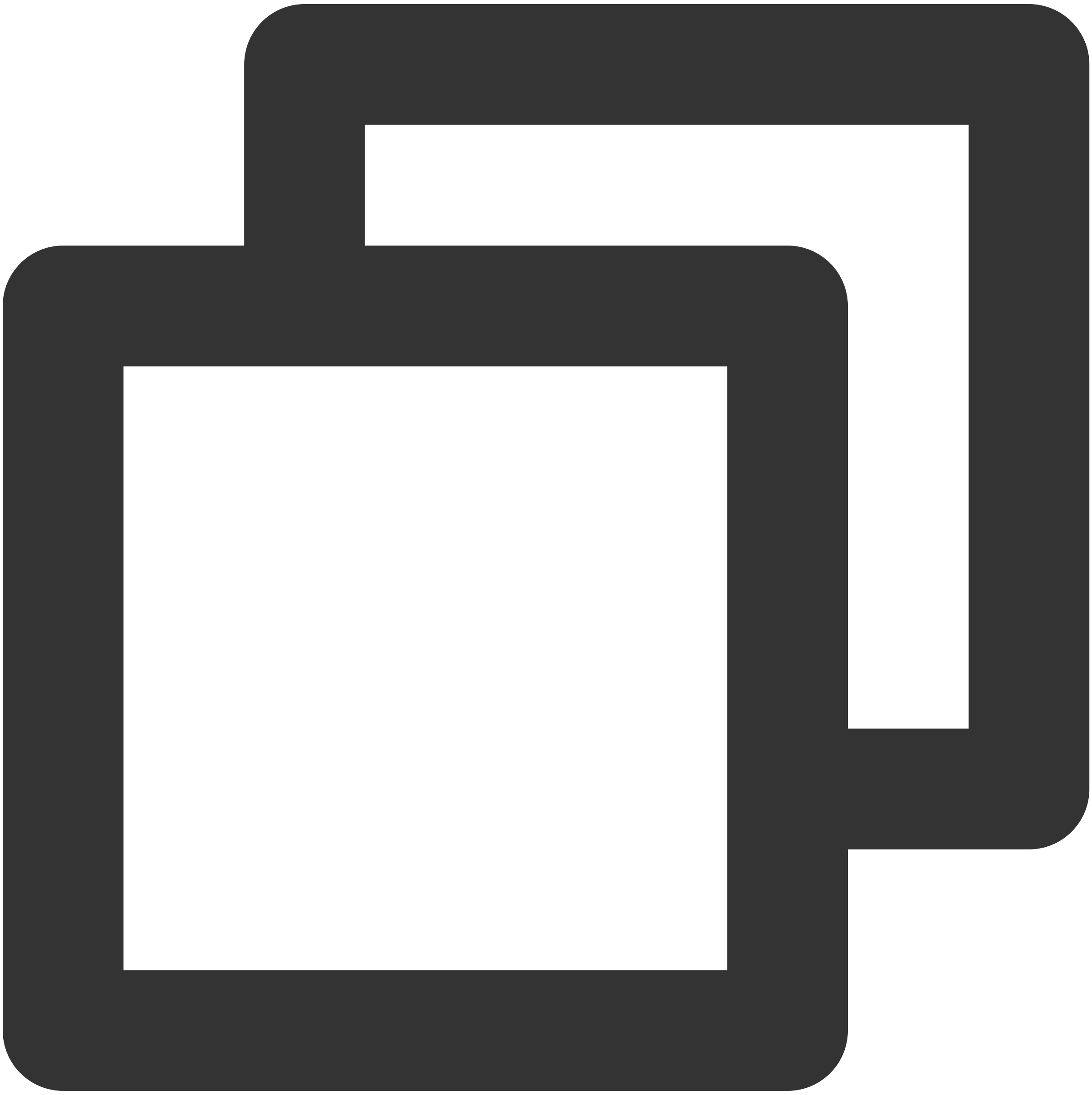
1. Log in to the instance and run the following commands to install the required system tools:

```
sudo apt-get update
```

```
sudo apt-get install \\
ca-certificates \\
curl \\
gnupg \\
lsb-release
```

2. Run the following command to install the GPG certificate to write the software source information:



```
sudo mkdir -p /etc/apt/keyrings
 curl -fsSL https://download.docker.com/linux/ubuntu/gpg | sudo gpg --dearmor -o /e
 echo \\
  "deb [arch=$(dpkg --print-architecture) signed-by=/etc/apt/keyrings/docker.gpg] h
  $(lsb_release -cs) stable" | sudo tee /etc/apt/sources.list.d/docker.list > /dev/
```

3. Run the following commands to update and install Docker-CE:

```
sudo apt-get update
```

```
sudo apt-get install docker-ce docker-ce-cli containerd.io docker-compose-plugin
```

Installing TensorFlow

Setting the NVIDIA container toolkit

1. Run the following command to set the package repository and GPG key as instructed in Setting up NVIDIA Container Toolkit:


```
distribution=$(. /etc/os-release;echo $ID$VERSION_ID) \\
   && curl -fsSL https://nvidia.github.io/libnvidia-container/gpgkey | sudo gpg --d
   && curl -s -L https://nvidia.github.io/libnvidia-container/$distribution/libnvid
         sed 's#deb https://#deb [signed-by=/usr/share/keyrings/nvidia-container-to
         sudo tee /etc/apt/sources.list.d/nvidia-container-toolkit.list
```

2. Run the following command to install the nvidia-docker2 package and its dependencies:


```
sudo apt-get update
```

```
sudo apt-get install -y nvidia-docker2
```

3. Run the following command to set the default runtime and restart the Docker daemon to complete installation:

```
sudo systemctl restart docker
```

4. Then, you can run the following command to run the base CUDA container to test the job settings:


```
sudo docker run --rm --gpus all nvidia/cuda:11.0.3-base-ubuntu20.04 nvidia-smi
```

The following information will appear:

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 450.51.06    Driver Version: 450.51.06    CUDA Version: 11.0     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|                               |                      |               MIG M. |
|===============================+======================+======================|
|   0  Tesla T4            On   | 00000000:00:1E.0 Off |                    0 |
| N/A   34C    P8     9W /  70W |      0MiB / 15109MiB |      0%      Default |
|                               |                      |                  N/A |
+-------------------------------+----------------------+----------------------+
```



```
+-----------------------------------------------------------------------------+
| Processes:                                                                  |
|  GPU   GI   CI        PID   Type   Process name                  GPU Memory |
|        ID   ID                                                   Usage      |
|=============================================================================|
|  No running processes found                                                 |
+-----------------------------------------------------------------------------+
```

Downloading a TensorFlow Docker image

The official TensorFlow Docker images are in the tensorflow/tensorflow code repository in Docker Hub. Image tags are defined in the following format as listed in Tags:

Tag	Description
latest	Latest (default) tag of the binary TensorFlow CPU image.
nightly	Nightly tag of the TensorFlow image, which is unstable.
version	Tag of the TensorFlow binary image, such as `2.1.0`.
devel	TensorFlow masterNightly tag of the development environment, which contains the TensorFlow source code.
custom-op	Special experimental image for custom TensorFlow operation development. For more information, see tensorflow/custom-op.

Each basic tag has variants with new or modified features:

Tag Variant	Description
tag -gpu	Specified tag supporting GPU.
tag -jupyter	Specified tag for Jupyter, which contains the TensorFlow tutorial laptop.

You can use multiple variants at a time. For example, the following command will download the TensorFlow image tags to your computer:


```
docker pull tensorflow/tensorflow                     # latest stable release
docker pull tensorflow/tensorflow:devel-gpu           # nightly dev release w/ GPU
docker pull tensorflow/tensorflow:latest-gpu-jupyter  # latest release w/ GPU suppo
```

Starting the TensorFlow Docker container

Run the following command to start and configure the TensorFlow container. For more information, see Docker run reference.

```
docker run [-it] [--rm] [-p hostPort:containerPort] tensorflow/tensorflow[:tag] [co
```

Examples

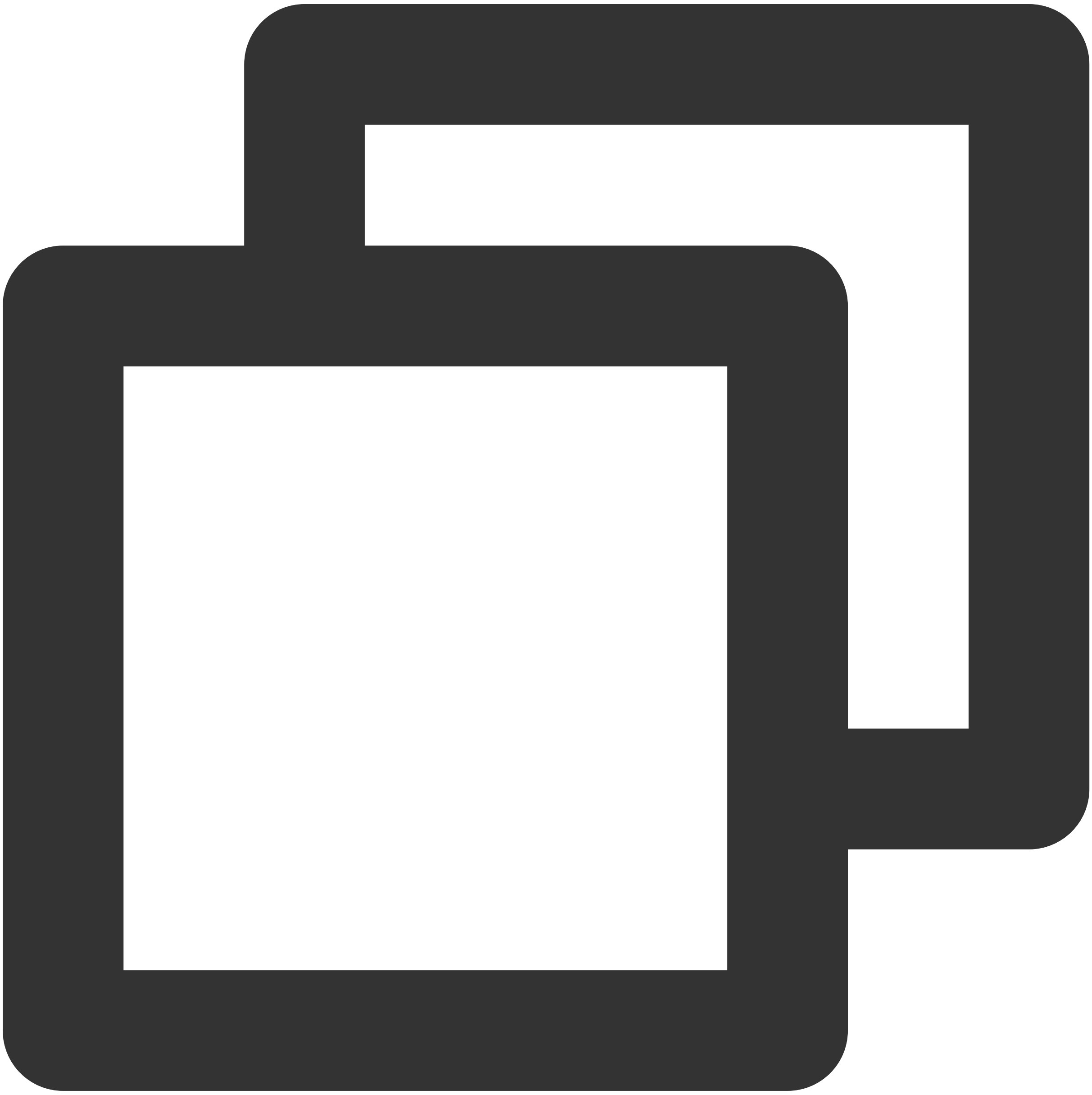
Using an image supporting only CPU

Use an image with the `latest` tag to verify the TensorFlow installation result. Docker will download the latest TensorFlow image when it runs for the first time.

```
docker run -it --rm tensorflow/tensorflow \\
   python -c "import tensorflow as tf; print(tf.reduce_sum(tf.random.normal([1000,
```

Below are the samples of other TensorFlow Docker solutions:

Start the `bash` shell session in the container where TensorFlow is configured:



```
docker run -it tensorflow/tensorflow bash
```

To run the TensorFlow program developed on the host in the container, use the `-v hostDir:containerDir -w workDir` parameter to load the server directory and change the container working directory as follows:


```
docker run -it --rm -v $PWD:/tmp -w /tmp tensorflow/tensorflow python ./script.py
```

Note:

When you allow the host to access the files created in the container, permission problems may occur. Generally, we recommend you modify files on the host system.

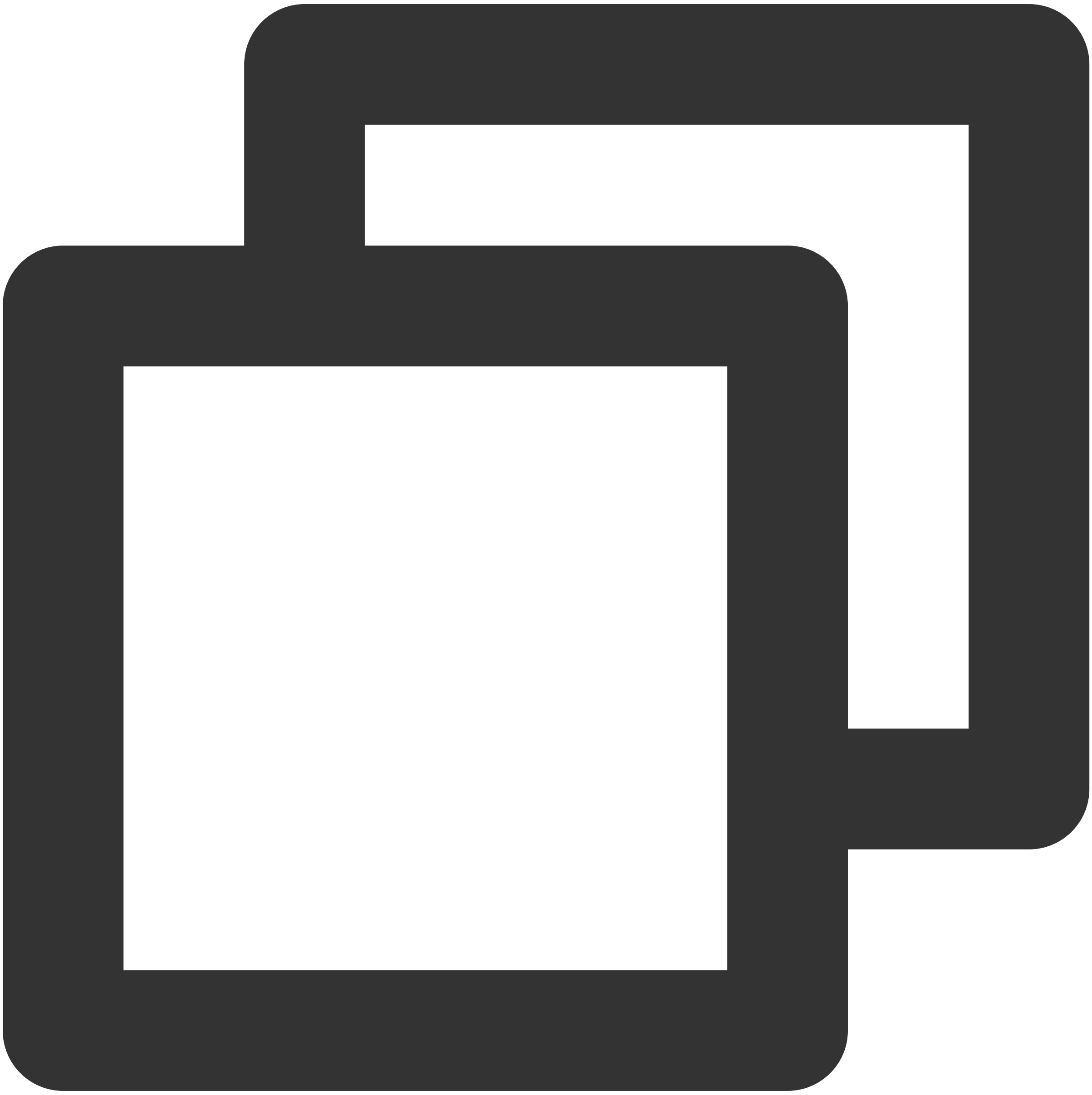
Use TensorFlow with the `nightly` tag to start Jupyter laptop server:

```
docker run -it -p 8888:8888 tensorflow/tensorflow:nightly-jupyter
```

Use a browser to visit `http://127.0.0.1:8888/?token=...` as instructed at the Jupyter website.

Using an image supporting GPU

Run the following command to download and run the TensorFlow image supporting GPU:



```
docker run --gpus all -it --rm tensorflow/tensorflow:latest-gpu \\
   python -c "import tensorflow as tf; print(tf.reduce_sum(tf.random.normal([1000,
```

It may take a while to set the image supporting GPU. To run the GPU-based script repeatedly, you can use `docker exec` to use the container repeatedly.

Run the following command to use the latest TensorFlow GPU image to start the `bash` shell session in the container:


```
docker run --gpus all -it tensorflow/tensorflow:latest-gpu bash
```

Using GPU Instance to Train ViT Model

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Note:

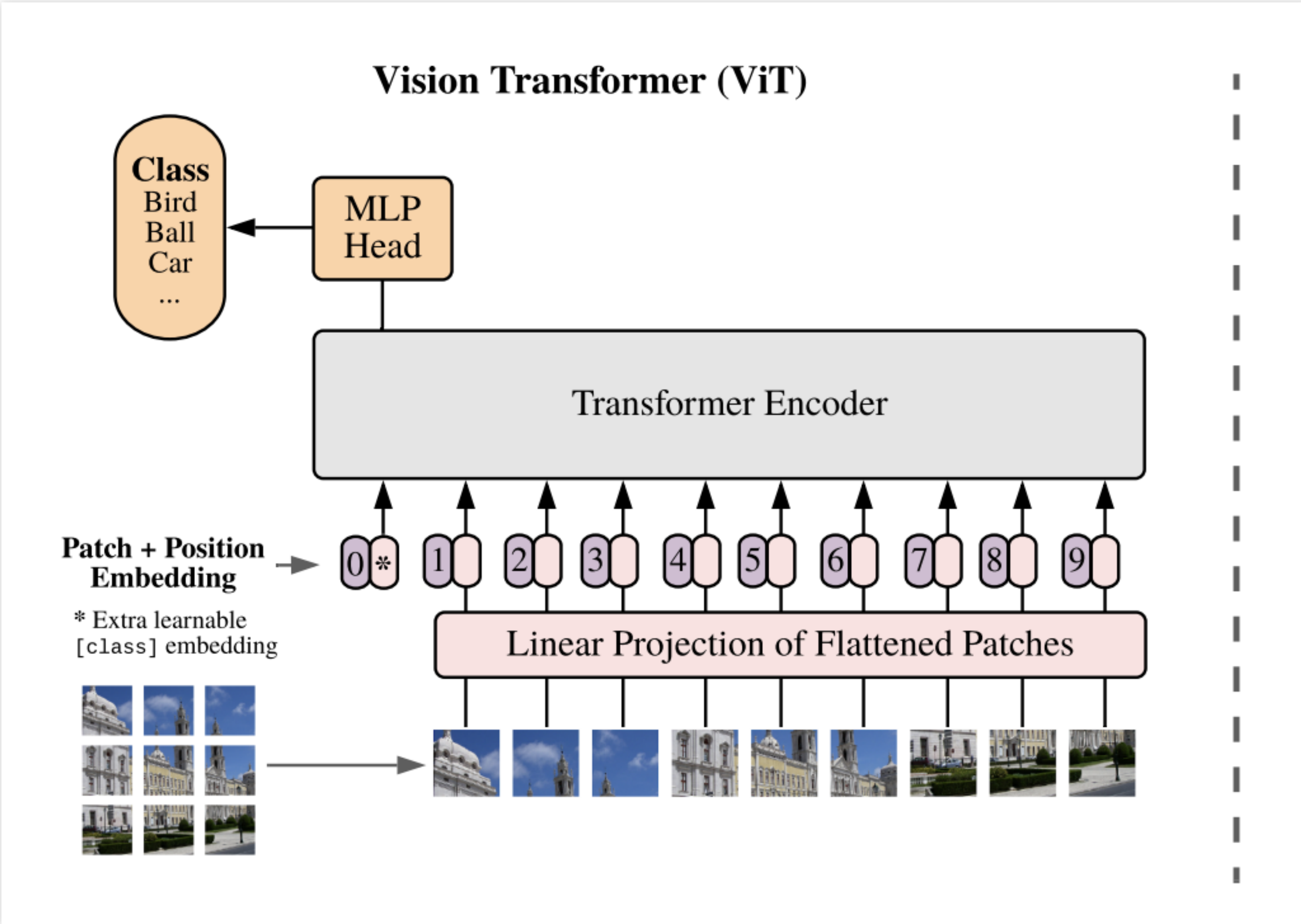
This document is written by a Cloud GPU Service user and is for study and reference only.

Overview

This document describes how to use a GPU instance to train a ViT model offline to complete a simple image classification task.

ViT Model Overview

The Vision Transformer (ViT) model is proposed by Alexey Dosovitskiy to get the state-of-the-art (SOTA) result from multiple tasks.



For an input image, ViT splits it into multiple subimage patches. Each patch is spliced with position embedding and combined with class labels to be input to transformer encoder together. After the corresponding output layer results of the class label positions pass through a network, the ViT result will be output. In the pretraining status, the ground truth of the result can replaced by a patch of the mask.

Instance Environment

Instance type: In this document, you can select a GN7 or GN8 model. Based on the GPU performance comparison provided in Tesla P40 vs Tesla T4, the performance of T4 in Turing architecture is higher than that of P40 in Pascal architecture. Therefore, GN7.5XLARGE80 is selected in this document.

Region: As large datasets may need to be uploaded, we recommend you select the region with the lowest latency. This document uses the online ping tool for testing. As the latency between the test region and Chongqing region where GN7 resides is the lowest, Chongqing region is selected in this example.

System disk: 100 GB Premium Cloud Storage disk.

Operating system: Ubuntu 18.04.

Bandwidth: 5 Mbps.

Local operating system: macOS

Directions

Setting passwordless login for your instance (optional)

1. (Optional) You can configure the server alias in `~/.ssh/config` on your local server. In this document, the alias `tcg` is used.
2. Run the `ssh-copy-id` command to copy the SSH public key of the local server to the GPU instance.
3. Run the following command in the GPU instance to disable password login to enhance security:

```
echo 'PasswordAuthentication no' | sudo tee -a /etc/ssh/ssh\\_config
```

4. Run the following command to restart the SSH service.

```
sudo systemctl restart sshd
```

Configuring the PyTorch-GPU development environment

To use pytorch-gpu for development, you need to further configure the environment as follows:

1. Install the NVIDIA graphics card driver.

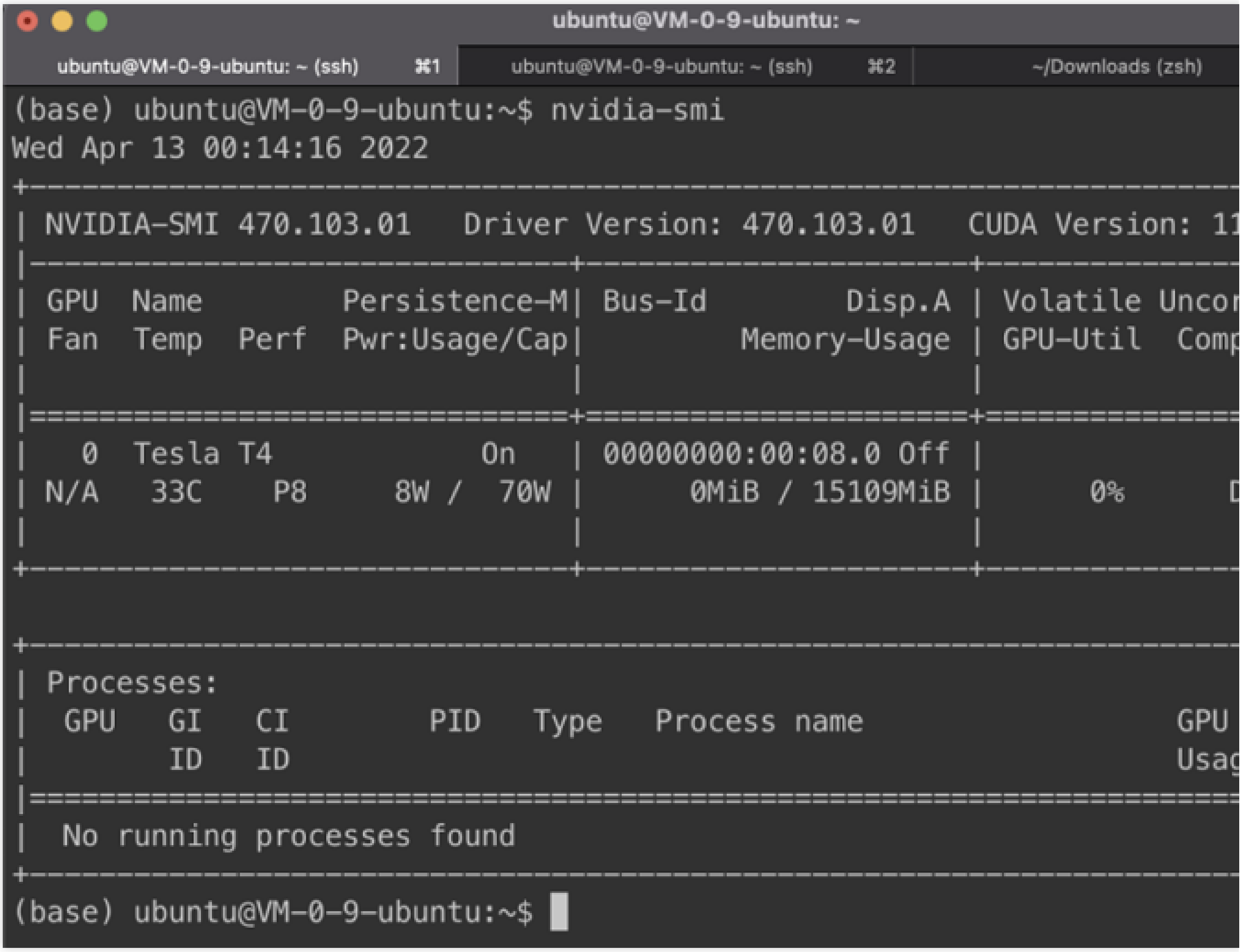
Run the following command to install the NVIDIA graphics card driver:


```
sudo apt install nvidia-driver-418
```

After the installation is completed, run the following command to check whether the installation is successful:

```
nvidia-smi
```

If the following result is returned, the installation is successful.

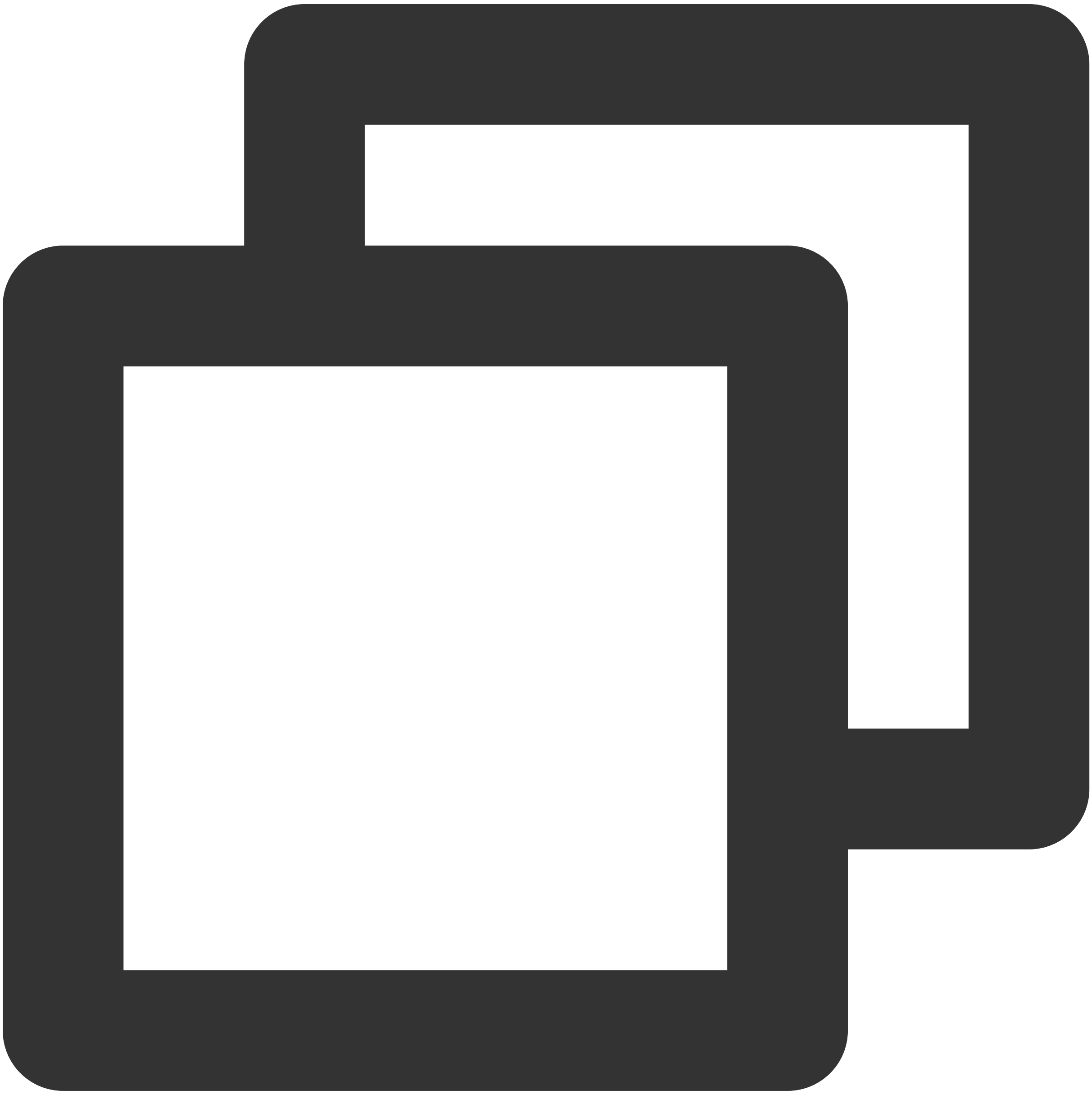


```
ubuntu@VM-0-9-ubuntu: ~
ubuntu@VM-0-9-ubuntu: ~ (ssh)    ⌘1    ubuntu@VM-0-9-ubuntu: ~ (ssh)    ⌘2    ~/Downloads (zsh)
(base) ubuntu@VM-0-9-ubuntu:~$ nvidia-smi
Wed Apr 13 00:14:16 2022
+------------------------------------------------------------------------------
| NVIDIA-SMI 470.103.01   Driver Version: 470.103.01   CUDA Version: 11
|-------------------------------+----------------------+-----------------------
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncor
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Comp
|                               |                      |
|===============================+======================+=======================
|   0  Tesla T4            On   | 00000000:00:08.0 Off |
| N/A   33C    P8     8W /  70W |      0MiB / 15109MiB |      0%      D
|                               |                      |
+-------------------------------+----------------------+-----------------------

+------------------------------------------------------------------------------
| Processes:
|  GPU   GI   CI        PID   Type   Process name                         GPU
|        ID   ID                                                          Usag
|==============================================================================
|  No running processes found
+------------------------------------------------------------------------------
(base) ubuntu@VM-0-9-ubuntu:~$
```

2. Configure the conda environment.

Run the following commands to configure the conda environment:


```
wget https://repo.anaconda.com/miniconda/Miniconda3-py39\\_4.11.0-Linux-x86\\_64.sh
```



```
chmod +x Miniconda3-py39\\_4.11.0-Linux-x86\\_64.sh
```

```
./Miniconda3-py39\\_4.11.0-Linux-x86\\_64.sh
```

```
rm Miniconda3-py39\\_4.11.0-Linux-x86\\_64.sh
```

3. Compile the `~/.condarc` file to add the following software source information and replace the conda software source with the Qinghua source.


```
channels:

- defaults

show\\_channel\\_urls: true

default\\_channels:

- https://mirrors.tuna.tsinghua.edu.cn/anaconda/pkgs/main

- https://mirrors.tuna.tsinghua.edu.cn/anaconda/pkgs/r
```

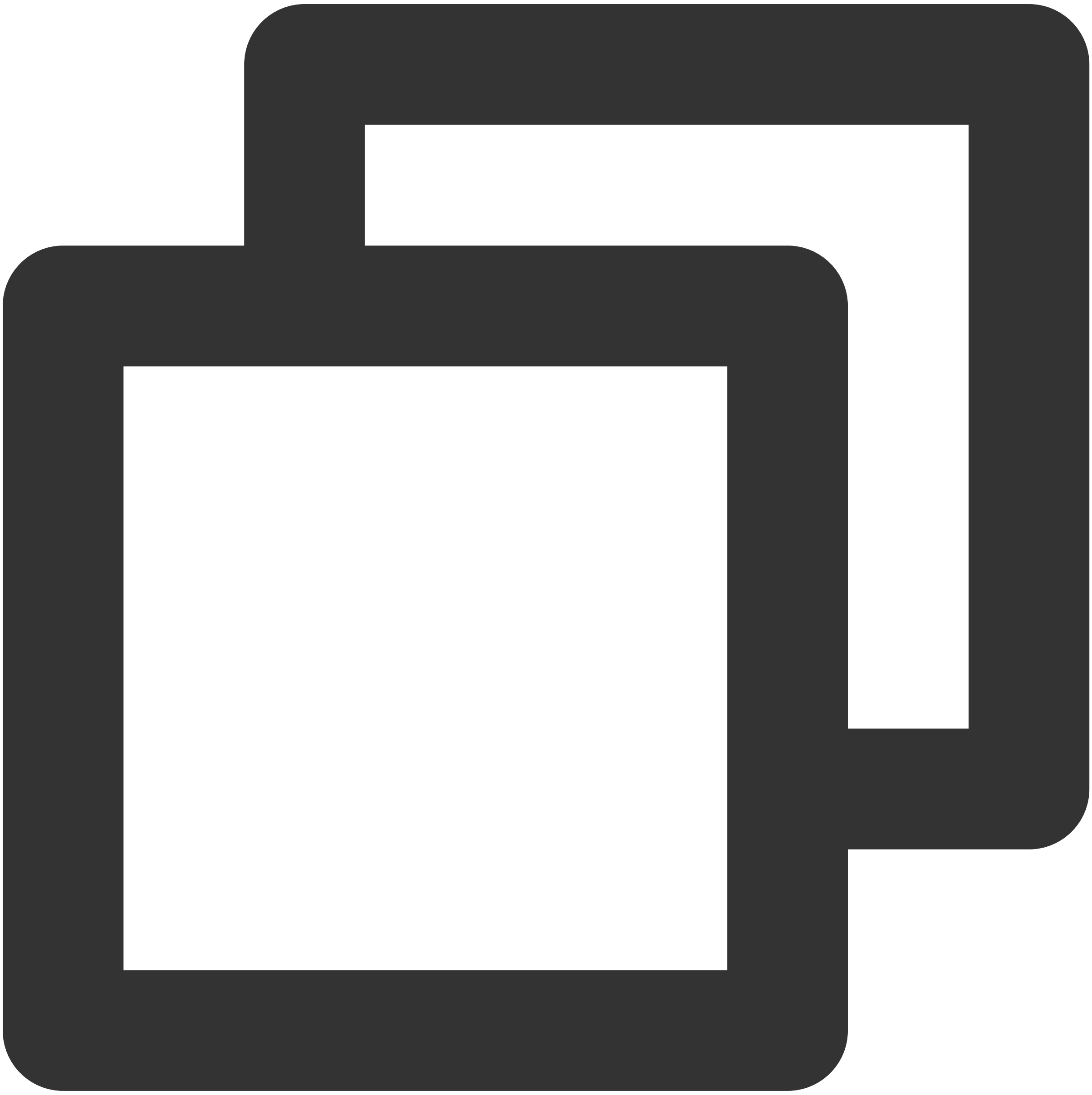
```
- https://mirrors.tuna.tsinghua.edu.cn/anaconda/pkgs/msys2

custom\\_channels:

  conda-forge: https://mirrors.tuna.tsinghua.edu.cn/anaconda/cloud

  msys2: https://mirrors.tuna.tsinghua.edu.cn/anaconda/cloud

  bioconda: https://mirrors.tuna.tsinghua.edu.cn/anaconda/cloud

  menpo: https://mirrors.tuna.tsinghua.edu.cn/anaconda/cloud

  pytorch: https://mirrors.tuna.tsinghua.edu.cn/anaconda/cloud

  pytorch-lts: https://mirrors.tuna.tsinghua.edu.cn/anaconda/cloud

  simpleitk: https://mirrors.tuna.tsinghua.edu.cn/anaconda/cloud
```

4. Run the following command to set the `pip` source to the Tencent Cloud image source.

```
pip config set global.index-url https://mirrors.cloud.tencent.com/pypi/simple
```

5. Install PyTorch.

Run the following command to install PyTorch:



```
conda install pytorch torchvision cudatoolkit=11.4 -c pytorch --yes
```

Run the following commands to view whether PyTorch is installed successfully:

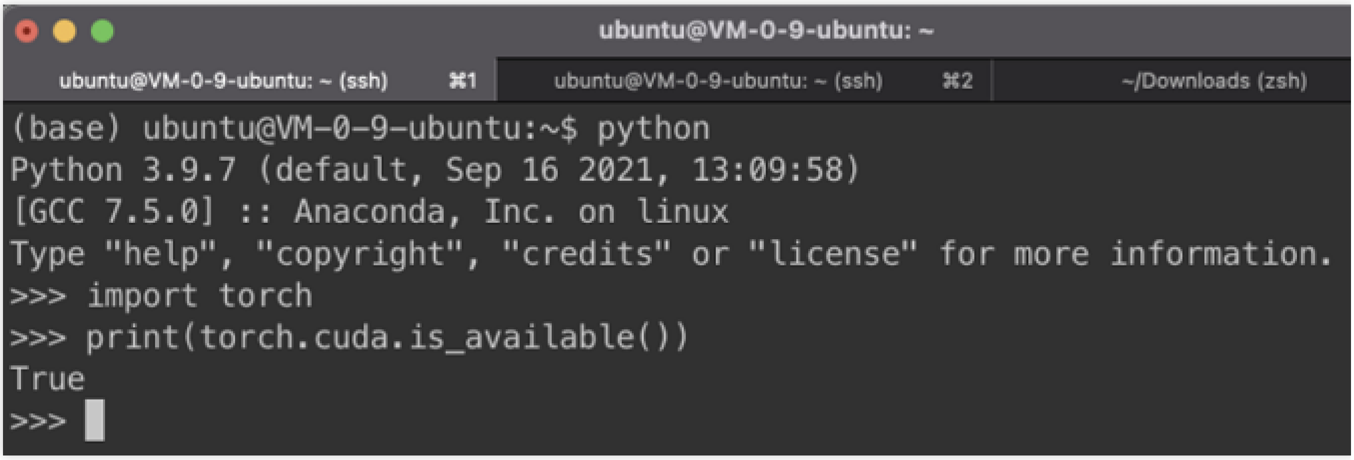

```
python
```



```
import torch
```

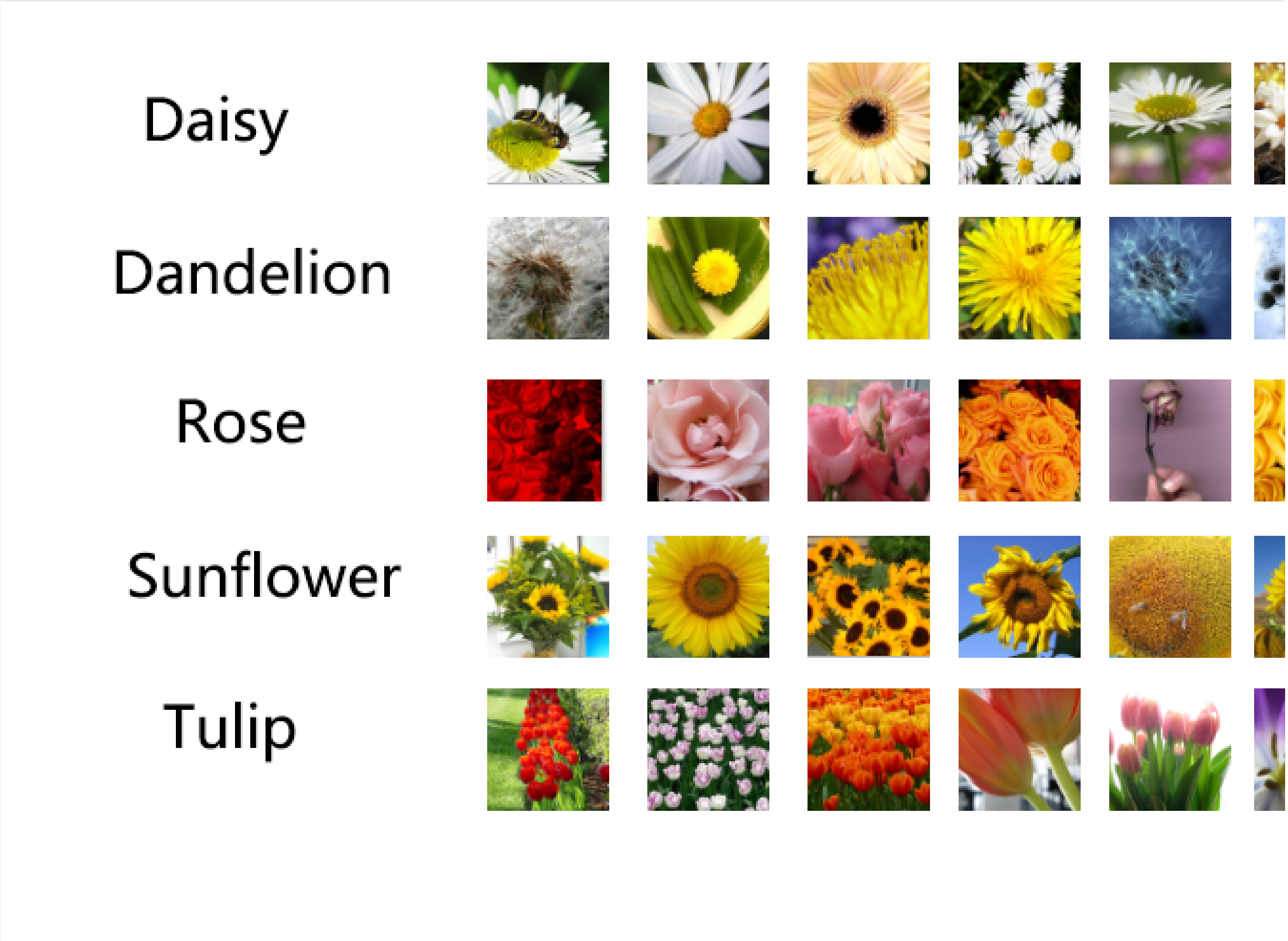
```
print(torch.cuda.is_avaliable())
```

If the following result is returned, PyTorch is installed successfully:



Preparing the experiment data

The test task in this training is an image classification task and uses the flower image classification dataset in the Tencent Cloud online document. The dataset contains five classes of flowers and is 218 MB in size. Below are the sampled dataset results (examples of images of flowers in each class):



The data of each class in the raw dataset is stored in the folder of the corresponding class. You need to convert it to the standard format of ImageNet and divide the training and verification datasets at the ratio of 4:1. Use the following code to convert the format:


```
# split data into train set and validation set, train:val=scale

import shutil

import os

import math

scale = 4

data\\_path = '../raw'
```



```
data\\_dst = '../train\\_val'

#create imagenet directory structure

os.mkdir(data\\_dst)

os.mkdir(os.path.join(data\\_dst, 'train'))

os.mkdir(os.path.join(data\\_dst, 'validation'))

for item in os.listdir(data\\_path):

    item\\_path = os.path.join(data\\_path, item)

 if os.path.isdir(item\\_path):

        train\\_dst = os.path.join(data\\_dst, 'train', item)

        val\\_dst = os.path.join(data\\_dst, 'validation', item)

        os.mkdir(train\\_dst)

        os.mkdir(val\\_dst)

        files = os.listdir(item\\_path)

 print(f'Class {item}:\\n\\t Total sample count is {len(files)}')

        split\\_idx = math.floor(len(files) \\* scale / ( 1 + scale ))

 print(f'\\t Train sample count is {split\\_idx}')

 print(f'\\t Val sample count is {len(files) - split\\_idx}\\n')

 for idx, file in enumerate(files):

            file\\_path = os.path.join(item\\_path, file)

 if idx <= split\\_idx:

                shutil.copy(file\\_path, train\\_dst)

 else:

                shutil.copy(file\\_path, val\\_dst)
```

```
print(f'Split Complete. File path: {data\\_dst}')
```

Below is the dataset overview:

```
Class roses:

    Total sample count is 641

    Train sample count is 512

    Validation sample count is 129
```

```
Class sunflowers:

      Total sample count is 699

      Train sample count is 559

      Validation sample count is 140

Class tulips:

      Total sample count is 799

      Train sample count is 639

      Validation sample count is 160

Class daisy:

      Total sample count is 633

      Train sample count is 506

      Validation sample count is 127

Class dandelion:

      Total sample count is 898

      Train sample count is 718

      Validation sample count is 180
```

To accelerate the training process, you need to further convert the dataset to a GPU-friendly format such as NVIDIA Data Loading Library (DALI). The DALI library can use GPU to replace CPU to accelerate data preprocessing. When data in the ImageNet format already exists, you can simply run the following command to use DALI:

```
git clone https://github.com/ver217/imagenet-tools.git

cd imagenet-tools && python3 make\\_tfrecords.py \\

  --raw\\_data\\_dir="../train\\_val" \\

  --local\\_scratch\\_dir="../train\\_val\\_tfrecord" && \\

python3 make\\_idx.py --tfrecord\\_root="../train\\_val\\_tfrecord"
```

Model training result

To facilitate subsequent training of large distributed models, this document describes how to train and develop a model based on the distributed training framework Colossal-AI. Colossal-AI provides a set of easy-to-use APIs, which enables you to easily perform data, model, pipeline, and mixed parallel training.

Based on the demo provided by Colossal-AI, this document uses ViT integrated in the pytorch-image-models repository for implementation. The minimum `vit\\_tiny\\_patch16\\_224` model at a resolution of 224*224 is used, where each sample is divided into 16 `patches` .

1. Run the following command to install Colossal-AI and pytorch-image-models as instructed in Start Locally:

```
pip install colossalai==0.1.5+torch1.11cu11.3 -f https://release.colossalai.org
```

```
pip install timm
```

2. Write the following model training code based on the demo provided by Colossal-AI:

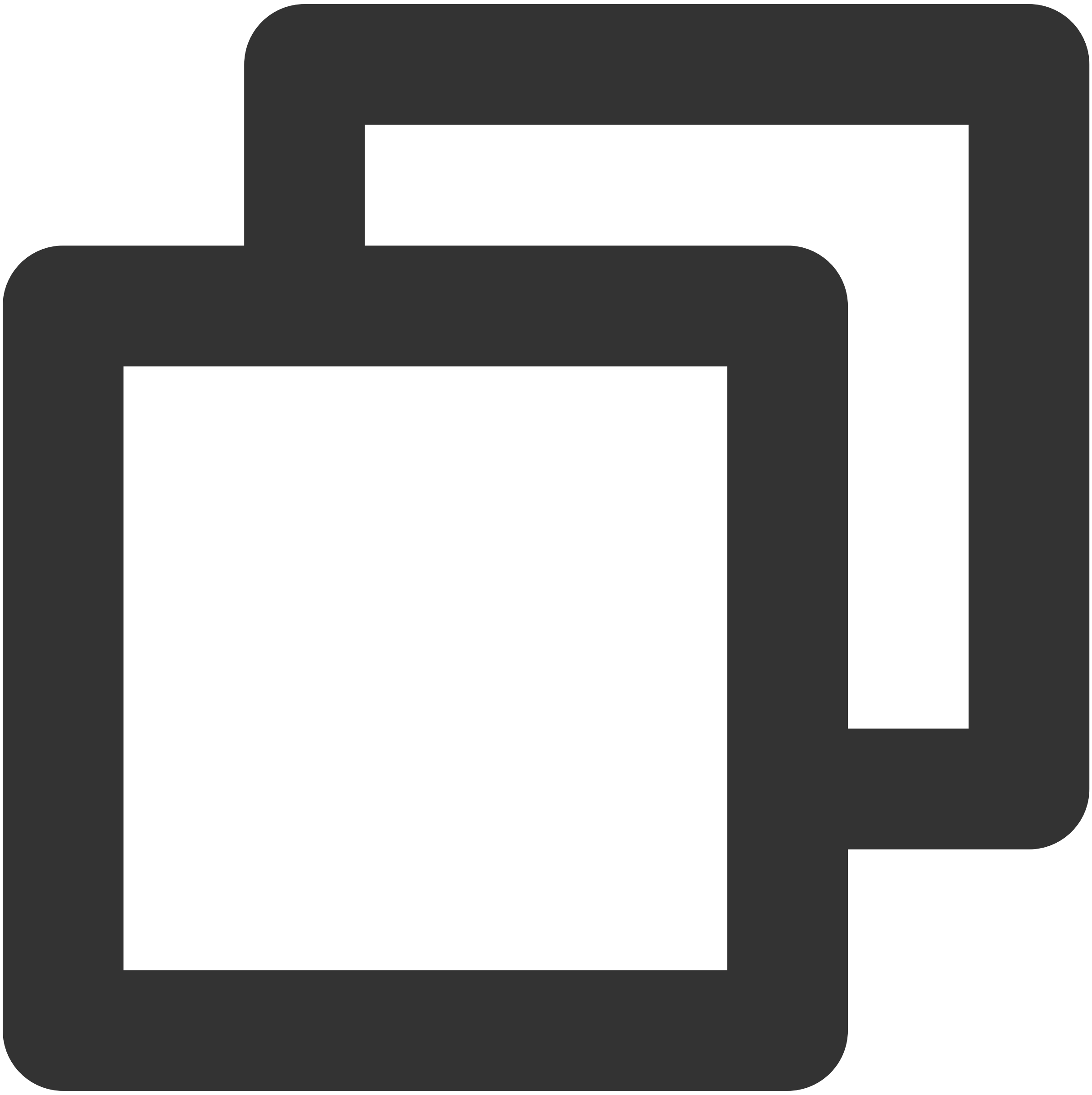

```
from pathlib import Path

from colossalai.logging import get\\_dist\\_logger

import colossalai

import torch

import os

from colossalai.core import global\\_context as gpc
```

```
from colossalai.utils import get\\_dataloader, MultiTimer

from colossalai.trainer import Trainer, hooks

from colossalai.nn.metric import Accuracy

from torchvision import transforms

from colossalai.nn.lr\\_scheduler import CosineAnnealingLR

from tqdm import tqdm

from titans.utils import barrier\\_context

from colossalai.nn.lr\\_scheduler import LinearWarmupLR

from timm.models import vit\\_tiny\\_patch16\\_224

from titans.dataloader.imagenet import build\\_dali\\_imagenet

from mixup import MixupAccuracy, MixupLoss

def main():

 parser = colossalai.get\\_default\\_parser()

 args = parser.parse\\_args()

 colossalai.launch\\_from\\_torch(config='./config.py')

 logger = get\\_dist\\_logger()

 # build model

 model = vit\\_tiny\\_patch16\\_224(num\\_classes=5, drop\\_rate=0.1)

 # build dataloader

 root = os.environ.get('DATA', '../train\\_val\\_tfrecord')

 train\\_dataloader, test\\_dataloader = build\\_dali\\_imagenet(

     root, rand\\_augment=True)

 # build criterion
```

```
criterion = MixupLoss(loss\\_fn\\_cls=torch.nn.CrossEntropyLoss)

# optimizer

optimizer = torch.optim.SGD(

    model.parameters(), lr=0.1, momentum=0.9, weight\\_decay=5e-4)

# lr\\_scheduler

lr\\_scheduler = CosineAnnealingLR(

   optimizer, total\\_steps=gpc.config.NUM\\_EPOCHS)

engine, train\\_dataloader, test\\_dataloader, \\_ = colossalai.initialize(

    model,

    optimizer,

    criterion,

    train\\_dataloader,

    test\\_dataloader,

)

# build a timer to measure time

timer = MultiTimer()

# create a trainer object

trainer = Trainer(engine=engine, timer=timer, logger=logger)

# define the hooks to attach to the trainer

hook\\_list = [

    hooks.LossHook(),

    hooks.LRSchedulerHook(lr\\_scheduler=lr\\_scheduler, by\\_epoch=True),

    hooks.AccuracyHook(accuracy\\_func=MixupAccuracy()),

    hooks.LogMetricByEpochHook(logger),
```

```
        hooks.LogMemoryByEpochHook(logger),

        hooks.LogTimingByEpochHook(timer, logger),

        hooks.TensorboardHook(log\\_dir='./tb\\_logs', ranks=[0]),

        hooks.SaveCheckpointHook(checkpoint\\_dir='./ckpt')

    ]

    # start training

    trainer.fit(train\\_dataloader=train\\_dataloader,

                epochs=gpc.config.NUM\\_EPOCHS,

                test\\_dataloader=test\\_dataloader,

                test\\_interval=1,

                hooks=hook\\_list,

                display\\_progress=True)

if \\_\\_name\\_\\_ == '\\_\\_main\\_\\_':

    main()
```

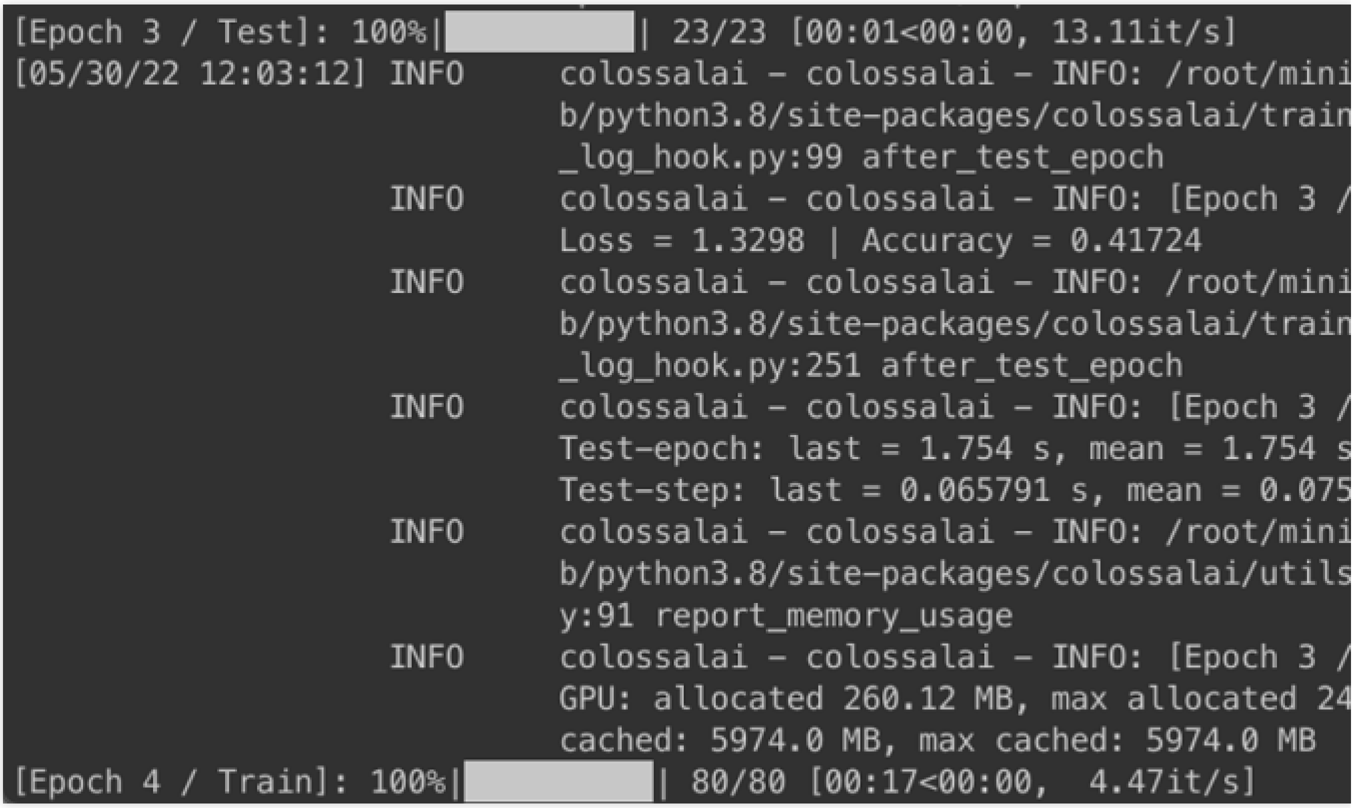
Below is the specific model configuration:



```
from colossalai.amp import AMP\\_TYPE

BATCH\\_SIZE = 128

DROP\\_RATE = 0.1

NUM\\_EPOCHS = 200

CONFIG = dict(fp16=dict(mode=AMP\\_TYPE.TORCH))

gradient\\_accumulation = 16
```

```
clip\\_grad\\_norm = 1.0

dali = dict(

 gpu\\_aug=True,

 mixup\\_alpha=0.2

)
```

Below is the model execution process. Each epoch time is within 20s:



```
[Epoch 3 / Test]: 100%|          | 23/23 [00:01<00:00, 13.11it/s]
[05/30/22 12:03:12] INFO     colossalai - colossalai - INFO: /root/mini
                             b/python3.8/site-packages/colossalai/train
                             _log_hook.py:99 after_test_epoch
                    INFO     colossalai - colossalai - INFO: [Epoch 3 /
                             Loss = 1.3298 | Accuracy = 0.41724
                    INFO     colossalai - colossalai - INFO: /root/mini
                             b/python3.8/site-packages/colossalai/train
                             _log_hook.py:251 after_test_epoch
                    INFO     colossalai - colossalai - INFO: [Epoch 3 /
                             Test-epoch: last = 1.754 s, mean = 1.754 s
                             Test-step: last = 0.065791 s, mean = 0.075
                    INFO     colossalai - colossalai - INFO: /root/mini
                             b/python3.8/site-packages/colossalai/utils
                             y:91 report_memory_usage
                    INFO     colossalai - colossalai - INFO: [Epoch 3 /
                             GPU: allocated 260.12 MB, max allocated 24
                             cached: 5974.0 MB, max cached: 5974.0 MB
[Epoch 4 / Train]: 100%|          | 80/80 [00:17<00:00,  4.47it/s]
```

The result shows that the highest accuracy of the model with the verification dataset is 66.62%. You can also increase the number of model parameters; for example, you can change the model to `v.

```
[Epoch 3 / Test]: 100%|██████████| 23/23 [00:01<00:00, 13.11it/s]
[05/30/22 12:03:12] INFO     colossalai - colossalai - INFO: /root/mini
                             b/python3.8/site-packages/colossalai/train
                             _log_hook.py:99 after_test_epoch
                    INFO     colossalai - colossalai - INFO: [Epoch 3 /
                             Loss = 1.3298 | Accuracy = 0.41724
                    INFO     colossalai - colossalai - INFO: /root/mini
                             b/python3.8/site-packages/colossalai/train
                             _log_hook.py:251 after_test_epoch
                    INFO     colossalai - colossalai - INFO: [Epoch 3 /
                             Test-epoch: last = 1.754 s, mean = 1.754 s
                             Test-step: last = 0.065791 s, mean = 0.075
                    INFO     colossalai - colossalai - INFO: /root/mini
                             b/python3.8/site-packages/colossalai/utils
                             y:91 report_memory_usage
                    INFO     colossalai - colossalai - INFO: [Epoch 3 /
                             GPU: allocated 260.12 MB, max allocated 24
                             cached: 5974.0 MB, max cached: 5974.0 MB
[Epoch 4 / Train]: 100%|██████████| 80/80 [00:17<00:00,  4.47it/s]
```

.

Summary

The biggest problem encountered in this example was that cloning from GitHub was very slow. To solve this, a tunnel and ProxyChains were used for acceleration. However, such operations violated the CVM use rules and caused a period of unavailability. Eventually, this problem was solved by deleting the proxy and submitting a ticket.

Using a public network proxy doesn't comply with the CVM use regulations. To guarantee the stable operations of your business, do not violate the regulations.

References

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