3. Basic use of PyTorch

The Raspberry Pi motherboard series does not support PyTorch function yet.

3.1. About PyTorch

3.1.1. Introduction

PyTorch is an Open Source Python machine learning library, based on Torch, using for applications such as natural language processing.

3.1.2. Features

1） Powerful GPU-accelerated tensor calculations

2） Deep neural network for automatic derivation system

3） Dynamic graph mechanism

3.2. Tensors in PyTorch

3.2.1. Tensor

Tensor in English is Tensor, which is the basic unit of operation in PyTorch. Like Numpy's ndarray, it represents a multi-dimensional matrix. The biggest difference with ndarray is that PyTorch's Tensor can run on the GPU, while numpy's ndarray can only run on the CPU. Running on the GPU greatly speeds up the operation.

3.2.2. Create a tensor

1） There are many ways to create tensors. Different types of tensors can be created by calling APIs of different interfaces.

a = torch.empty(2,2):Create an uninitialized 2*2 tensor

b = torch.rand(5, 6)： Creates a uniformly distributed tensor with each element initialized from 0-1

c = torch.zeros(5, 5, dtype=torch.long)： Create an initialized all-zero tensor and specify the type of each element as long

d = c.new_ones(5, 3, dtype=torch.double) ： Create a new tensor d based on the known tensor c

d.size()： Get the shape of tensor d

2） Operations between tensors

Operations between tensors are actually operations between matrices. Due to the dynamic graph mechanism, mathematical calculations can be performed directly on tensors, for example,

- Add two tensors:

```
c = torch.zeros(5,3,dtype=torch.long)
d = torch.ones(5,3,dtype=torch.long)
e = c + d
print(e)
```

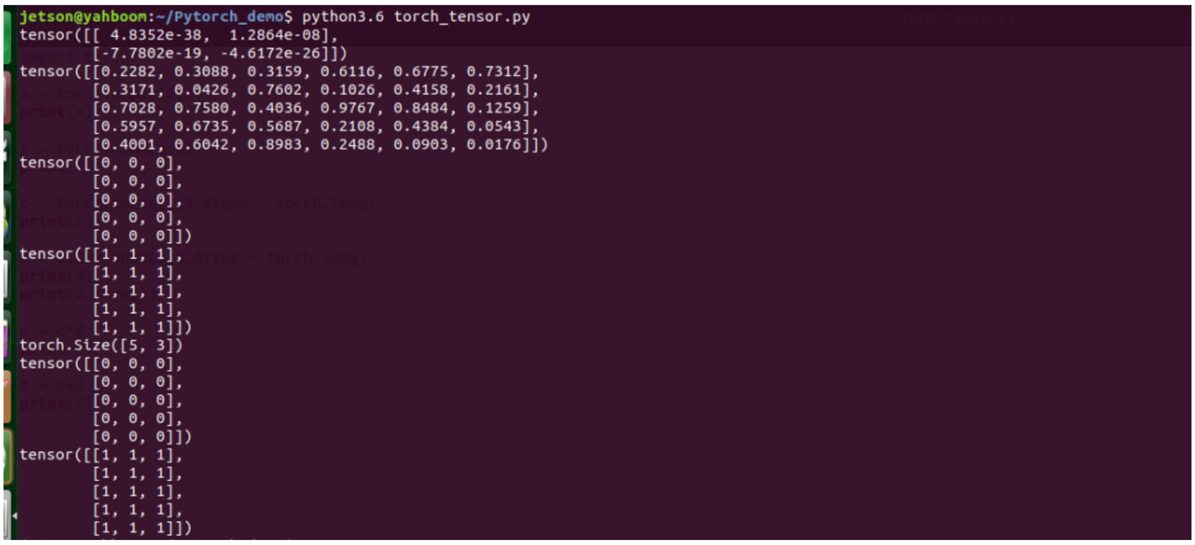
- Multiply two tensors

  ```
  c = torch.zeros(5,3,dtype=torch.long)
  d = torch.ones(5,3,dtype=torch.long)
  e = c * d
  print(e)
  ```

This part of the code can be referred to: ~/Pytorch_demo/torch_tensor.py

Run the code,

```
python3 torch_tensor.py
```



```
jetson@yahboom:~/Pytorch_demo$ python3.6 torch_tensor.py
tensor([[ 4.8352e-38,  1.2864e-08],
        [-7.7802e-19, -4.6172e-26]])
tensor([[0.2282, 0.3088, 0.3159, 0.6116, 0.6775, 0.7312],
        [0.3171, 0.0426, 0.7602, 0.1026, 0.4158, 0.2161],
        [0.7028, 0.7580, 0.4036, 0.9767, 0.8484, 0.1259],
        [0.5957, 0.6735, 0.5687, 0.2108, 0.4384, 0.0543],
        [0.4001, 0.6042, 0.8983, 0.2488, 0.0903, 0.0176]])
tensor([[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]])
tensor([[1, 1, 1],
        [1, 1, 1],
        [1, 1, 1],
        [1, 1, 1],
        [1, 1, 1]])
torch.Size([5, 3])
tensor([[0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0],
        [0, 0, 0]])
tensor([[1, 1, 1],
        [1, 1, 1],
        [1, 1, 1],
        [1, 1, 1],
        [1, 1, 1]])
```

3.3. torchvision package introduction

3.3.1. torchvision is a library specifically used to process images in Pytorch, including four major categories:

1) torchvision.datasets: Load data sets. Pytorch has many data sets such as CIFAR, MNIST, etc. You can use this class to load data sets. The usage is as follows:

```
cifar_train_data = torchvision.datasets.CIFAR10(root='./data', train=True,
                                            download=False, transform=transform)
```

2) torchvision.models: Load the trained model. The model includes the following VCG, ResNet, etc. The usage is as follows:

```
import torchvision.models as models
resnet18 = models.resnet18()
```

3) torchvision.transforms: Class for image conversion operations, usage is as follows:

```
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])
```

4) torchvision.untils: Arrange the pictures into a grid shape as follows:

```
torchvision.utils.make_grid(tensor, nrow=8, padding=2, normalize=False,
range=None, scale_each=False, pad_value=0)
```

For more information on the use of the torchvision package, please refer to the official website documentation: https://pytorch.org/vision/0.8/datasets.html

3.4. Convolutional neural network

3.4.1. Neural Network

1) The difference between neural networks and machine learning

Neural networks and machine learning are both used for classification tasks. The difference is that neural networks are more efficient than machine learning, the data are simpler, and fewer parameters are required to perform tasks. The following points are explained:

- Efficiency: The efficiency of neural networks is reflected in the extraction of features. It is different from the features of machine learning. It can train and "correct" itself. We only need to input data, and it will continuously update the features on its own.
- Data simplicity: In the machine learning process, we need to perform some processing on the data before inputting the data, such as normalization, format conversion, etc., but in neural networks, there is no need for too much processing.
- Fewer parameters to perform tasks: In machine learning, we need to adjust penalty factors, slack variables, etc. to achieve the most suitable effect, but for neural networks, we only need to give a weight w and a bias term b , during the training process, these two values will be continuously revised and adjusted to the optimum to minimize the error of the model.

3.4.2. Convolutional neural network

1) Convolution kernel

The convolution kernel can be understood as a feature extractor, filter (digital signal processing), etc. The neural network has three layers (input layer, hidden layer, output layer). The neurons in each layer can share the convolution kernel, so it will be very convenient to process high-level data. We only need to design the size, number and sliding step of the convolution kernel and let it train by itself.

2) Three basic layers of convolutional neural network:

- Convolutional layer

  Perform convolution operation, inner product operation of two matrices with the size of convolution kernel, multiply numbers at the same position and then add and sum. The convolution layer close to the input layer sets a small number of convolution kernels, and the later the convolution layer sets, the more convolution kernels it sets.

- Pooling layer

  Through downsampling, the image and parameters are compressed without destroying the quality of the image. There are two pooling methods, MaxPooling (that is, taking the maximum value in the sliding window) and AveragePooling (taking the average of all values in the sliding window).

- Flatten layer & Fully Connected layer

This layer is mainly about stacking layers. After passing through the pooling layer, the image is compressed and then enters the Flatten layer; the output of the Flatten layer is placed in the Fully Connected layer, and softmax is used to classify it.

3.5. Build LetNet neural network and train data set

3.5.1. Preparation before implementation

1） Environment

development board series are all installed with the project development environment, including:

- python 3.8.10
- torch 2.0.0
- torchvision 0.15.1

2） Dataset

CIFAR-10，50,000 training images of 32*32 size and 10,000 test images

3.5. Build LetNet neural network and train data set

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1). Environment

The ROSMASTER-jetson development board series are all installed with the project development environment, including:

-python 3.8.10
-torch 2.0.0

- torchvision 0.15.1

2), data set

CIFAR-10, 50,000 training images of 32*32 size and 10,000 test images

Note: The data set is stored in the ~/Pytorch_demo/data/cifar-10-batches-py directory,

3.5.2. Implementation process

1） Import relevant modules

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torchvision
import torchvision.transforms as transforms
import torch.optim as optim
```

2） Load data set

```
cifar_train_data = torchvision.datasets.CIFAR10(root='./data', train=True,
                                          download=False, transform=transform)
cifar_test_data = torchvision.datasets.CIFAR10(root='./data', train=False,
                                          transform=transform)
```

3) Encapsulated data set

```
train_data_loader = torch.utils.data.DataLoader(cifar_train_data, batch_size=32,
shuffle=True)
test_data_loader = torch.utils.data.DataLoader(cifar_test_data, batch_size=32,
shuffle=True
```

4) Build a convolutional neural network

```
class LeNet(nn.Module):
    #Define the operation operators required by the network, such as convolution,
fully connected operators, etc.
    def __init__(self):
        super(LeNet, self).__init__()
        #Conv2d parameter meaning: number of input channels, number of output
channels, kernel size
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16*5*5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)
        self.pool = nn.MaxPool2d(2, 2)
    def forward(self, x):
        x = F.relu(self.conv1(x))
        x = self.pool(x)
        x = F.relu(self.conv2(x))
        x = self.pool(x)
        x = x.view(-1, 16*5*5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x
```

5) Configure the training loss function and optimizer

```
criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.005, momentum=0.9)
```

6) Start training and testing

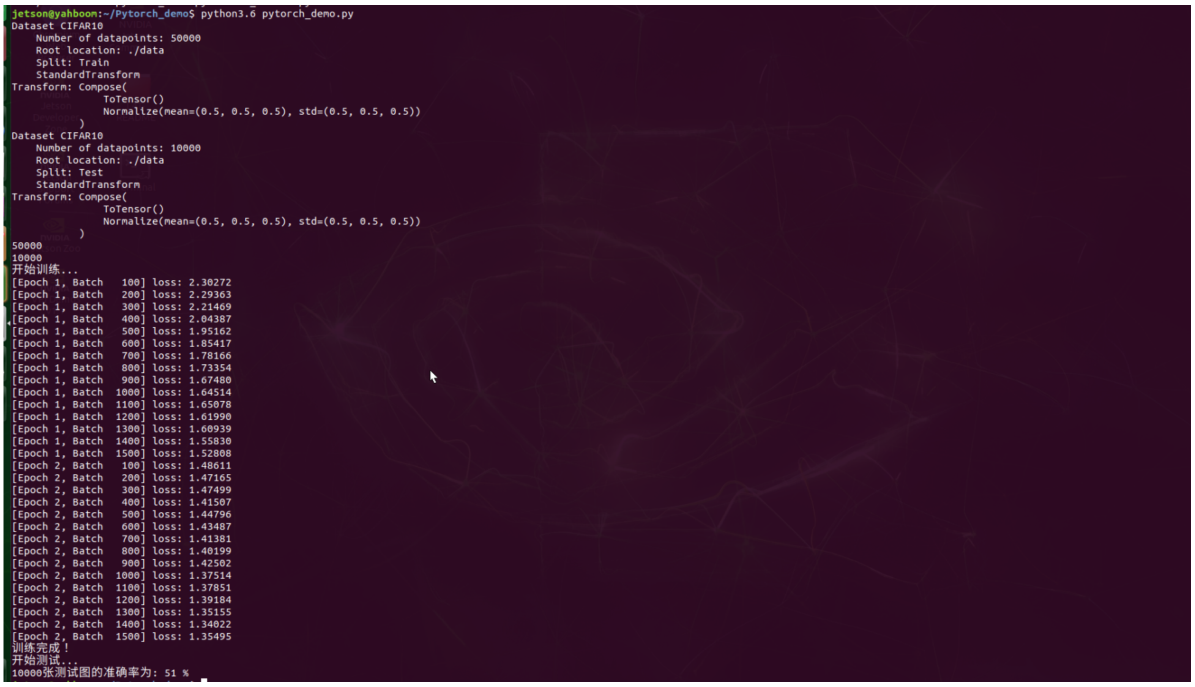
3.5.3. Running the program

1) Reference code path

```
~/Pytorch_demo/pytorch_demo.py
```

2) Run the program

```
cd  ~/Pytorch_demo
python3 pytorch_demo.py
```



```
jetson@yahboom:~/Pytorch_demo$ python3.6 pytorch_demo.py
Dataset CIFAR10
    Number of datapoints: 50000
    Root location: ./data
    Split: Train
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))
           )
Dataset CIFAR10
    Number of datapoints: 10000
    Root location: ./data
    Split: Test
    StandardTransform
Transform: Compose(
               ToTensor()
               Normalize(mean=(0.5, 0.5, 0.5), std=(0.5, 0.5, 0.5))
           )
50000
10000
开始训练...
[Epoch 1, Batch   100] loss: 2.30272
[Epoch 1, Batch   200] loss: 2.29363
[Epoch 1, Batch   300] loss: 2.21469
[Epoch 1, Batch   400] loss: 2.04387
[Epoch 1, Batch   500] loss: 1.95162
[Epoch 1, Batch   600] loss: 1.85417
[Epoch 1, Batch   700] loss: 1.78166
[Epoch 1, Batch   800] loss: 1.73354
[Epoch 1, Batch   900] loss: 1.67480
[Epoch 1, Batch  1000] loss: 1.64514
[Epoch 1, Batch  1100] loss: 1.65078
[Epoch 1, Batch  1200] loss: 1.61990
[Epoch 1, Batch  1300] loss: 1.60939
[Epoch 1, Batch  1400] loss: 1.55830
[Epoch 1, Batch  1500] loss: 1.52808
[Epoch 2, Batch   100] loss: 1.48611
[Epoch 2, Batch   200] loss: 1.47165
[Epoch 2, Batch   300] loss: 1.47499
[Epoch 2, Batch   400] loss: 1.41507
[Epoch 2, Batch   500] loss: 1.44796
[Epoch 2, Batch   600] loss: 1.43487
[Epoch 2, Batch   700] loss: 1.41381
[Epoch 2, Batch   800] loss: 1.40199
[Epoch 2, Batch   900] loss: 1.42502
[Epoch 2, Batch  1000] loss: 1.37514
[Epoch 2, Batch  1100] loss: 1.37851
[Epoch 2, Batch  1200] loss: 1.39184
[Epoch 2, Batch  1300] loss: 1.35155
[Epoch 2, Batch  1400] loss: 1.34022
[Epoch 2, Batch  1500] loss: 1.35495
训练完成！
开始测试...
10000张测试图的准确率为: 51 %
```

We have only trained 2 times here. You can modify the epoch value to modify the number of training times. The more times you train, the higher the accuracy.