实验四实验报告

1.实验介绍:

本实验使用pytorch完成MNIST任务,采用MLP和CNN两种网络结构完成.本次实验采用kaggle上的MNIST数据集并且提交了结果。

2.代码分析:

两种网络主要不同在于网络模型架构,其余数据载入等部分相同,因此放在一起说明:

• 载入必要的库

```
import os
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import torch
from torch import nn,functional
import torchvision
from torchvision import datasets,transforms
device = torch.device("cuda:4" if torch.cuda.is_available else "cpu")

from sklearn.model_selection import train_test_split

%matplotlib inline
```

• batch size=100,载入测试数据集并且以8:2的比例划分训练集和验证集

```
train_batch_size =100
validation_batch_size =100

#Loading data
train = pd.read_csv("./input/train.csv")
X = train.loc[:,train.columns != "label"].values/255  #Normalizing the values
Y = train.label.values

features_train, features_test, targets_train, targets_test =
    train_test_split(X,Y,test_size=0.2,random_state=42)
X_train = torch.from_numpy(features_train).to(device)
X_validation = torch.from_numpy(features_test).to(device)

Y_train = torch.from_numpy(targets_train).type(torch.LongTensor).to(device)
Y_validation = torch.from_numpy(targets_test).type(torch.LongTensor).to(device)
train = torch.utils.data.TensorDataset(X_train,Y_train)
```

```
validation = torch.utils.data.TensorDataset(X_validation,Y_validation)

train_loader = torch.utils.data.DataLoader(train, batch_size = train_batch_size,
    shuffle = False)
validation_loader = torch.utils.data.DataLoader(validation, batch_size =
    validation_batch_size, shuffle = False)
```

• 定义网络并实例化模型:

MLP版本: 采用了两个全连接层,使用softmax进行分类,并使用了drop层 和relu激活函数,采用SGD优化

```
#define network
class MLP(nn.Module):
   def __init__(self):
        super(MLP, self).__init__()
        self.fc1=nn.Linear(28*28,256)
        self.drop1=nn.Dropout(p=0.3)
        self.relu1=nn.ReLU()
        self.fc2=nn.Linear(256,64)
        self.drop2=nn.Dropout(p=0.3)
        self.relu2=nn.ReLU()
        self.fc3 = nn.Linear(64,10)
        self.softmax = nn.Softmax(dim=1)
    def forward(self,x):
        x = x.view(x.size(0), -1)
        out = self.fc1(x)
        out = self.drop1(out)
        out = self.relu1(out)
        out = self.fc2(out)
        out = self.drop2(out)
        out = self.relu2(out)
        out = self.fc3(out)
        out = self.softmax(out)
        return out
#create network criterion and optimizer
model = MLP()
model = model.double()
model = model.to(device)
criterion = nn.CrossEntropyLoss().to(device)
optimizer = torch.optim.SGD(model.parameters(),lr=0.1, momentum=0.8)
```

CNN版本:构建了两个卷基层,并采用了maxpool和relu激活函数 为了防止过拟合采用了dropout,优化器采用了SGD

```
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.cnn_1 = nn.Conv2d(in_channels = 1, out_channels = 16, kernel_size = 5,
stride=1, padding=0)
        self.relu1 = nn.ReLU()
        self.maxpool1 = nn.MaxPool2d(kernel_size=2)
        self.cnn_2 = nn.Conv2d(in_channels = 16, out_channels = 32, kernel_size = 5,
stride=1, padding=0)
        self.relu2 = nn.ReLU()
        self.maxpool2 = nn.MaxPool2d(kernel_size=2)
        self.fc1 = nn.Linear(32*4*4,10)
        self.drop=nn.Dropout(p=0.3)
        self.softmax = nn.Softmax(dim=1)
    def forward(self, x):
        out = self.cnn_1(x)
        out = self.relu1(out)
        out = self.maxpool1(out)
        out = self.cnn_2(out)
        out = self.relu2(out)
        out = self.maxpool2(out)
        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = self.drop(out)
        out = self.softmax(out)
        return out
model = CNN()
model = model.double()
model = model.to(device)
criterion = nn.CrossEntropyLoss().to(device)
optimizer = torch.optim.SGD(model.parameters(),lr=0.1, momentum=0.8)
```

• 训练和验证 采用15个epoch

```
#define network

class MLP(nn.Module):
```

```
def __init__(self):
    super(MLP, self).__init__()
    self.fc1=nn.Linear(28*28,256)
    self.drop1=nn.Dropout(p=0.3)
    self.relu1=nn.ReLU()
    self.fc2=nn.Linear(256,64)
    self.drop2=nn.Dropout(p=0.3)
    self.relu2=nn.ReLU()
    self.fc3 = nn.Linear(64,10)
    self.softmax = nn.Softmax(dim=1)
def forward(self, x):
    x = x.view(x.size(0), -1)
    out = self.fc1(x)
    out = self.drop1(out)
    out = self.relu1(out)
    out = self.fc2(out)
    out = self.drop2(out)
    out = self.relu2(out)
    out = self.fc3(out)
    out = self.softmax(out)
    return out
```

绘图

```
plt.plot(train_losses, label='Training loss')
plt.plot(validation_losses, label='Validation loss')
plt.plot(validation_accs, label='Validation Accuracy')
plt.legend(frameon=False)
```

• 测试集数据载入以及测试

```
test_images = pd.read_csv("./input/test.csv")
test_image = test_images.loc[:,test_images.columns != "label"].values/255
test_dataset = torch.from_numpy(test_image).to(device)
new_test_loader = torch.utils.data.DataLoader(test_dataset, batch_size = 1, shuffle = False)

top_classes = []
with torch.no_grad():
    model.eval()
```

3.结果分析:

本实验中超参数的选择如下:

batch_size = 100 总epoch次数15次

SGD学习率为 0.1 动量0.8

以下为两个网络模型的结果:

MLP:

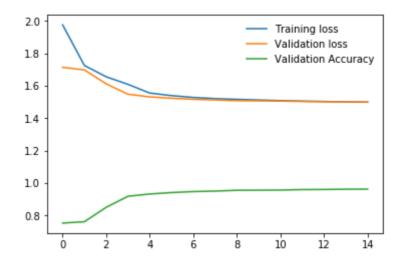
```
Epoch: 1/15.. Training Loss: 1.975.. Validation Loss: 1.714.. Validation Accuracy:
0.753
Epoch: 2/15.. Training Loss: 1.725.. Validation Loss: 1.698.. Validation Accuracy:
0.762
Epoch: 3/15.. Training Loss: 1.655.. Validation Loss: 1.612.. Validation Accuracy:
0.851
Epoch: 4/15.. Training Loss: 1.609.. Validation Loss: 1.548.. Validation Accuracy:
0.919
Epoch: 5/15.. Training Loss: 1.555.. Validation Loss: 1.531.. Validation Accuracy:
0.933
Epoch: 6/15.. Training Loss: 1.539.. Validation Loss: 1.523.. Validation Accuracy:
0.941
Epoch: 7/15.. Training Loss: 1.528.. Validation Loss: 1.516.. Validation Accuracy:
0.948
Epoch: 8/15.. Training Loss: 1.521.. Validation Loss: 1.512.. Validation Accuracy:
0.951
Epoch: 9/15.. Training Loss: 1.516.. Validation Loss: 1.508.. Validation Accuracy:
0.956
Epoch: 10/15.. Training Loss: 1.512.. Validation Loss: 1.507.. Validation Accuracy:
0.956
Epoch: 11/15.. Training Loss: 1.508.. Validation Loss: 1.505.. Validation Accuracy:
0.957
Epoch: 12/15.. Training Loss: 1.505.. Validation Loss: 1.503.. Validation Accuracy:
0.960
```

```
Epoch: 13/15.. Training Loss: 1.503.. Validation Loss: 1.502.. Validation Accuracy: 0.961

Epoch: 14/15.. Training Loss: 1.500.. Validation Loss: 1.500.. Validation Accuracy: 0.962

Epoch: 15/15.. Training Loss: 1.499.. Validation Loss: 1.500.. Validation Accuracy: 0.963
```

Loss和acc曲线:



在kaggle平台上提交了预测结果后 test_acc约为0.96

Your Best Entry 🛧

Your submission scored 0.96200, which is not an improvement of your best score. Keep trying!

CNN:

```
Epoch: 1/15.. Training Loss: 1.853.. Validation Loss: 1.522.. Validation Accuracy:
0.944
Epoch: 2/15.. Training Loss: 1.698.. Validation Loss: 1.500.. Validation Accuracy:
Epoch: 3/15.. Training Loss: 1.688.. Validation Loss: 1.492.. Validation Accuracy:
0.971
Epoch: 4/15.. Training Loss: 1.682.. Validation Loss: 1.490.. Validation Accuracy:
0.973
Epoch: 5/15.. Training Loss: 1.677.. Validation Loss: 1.487.. Validation Accuracy:
0.975
Epoch: 6/15.. Training Loss: 1.674.. Validation Loss: 1.485.. Validation Accuracy:
0.977
Epoch: 7/15.. Training Loss: 1.673.. Validation Loss: 1.485.. Validation Accuracy:
0.977
Epoch: 8/15.. Training Loss: 1.671.. Validation Loss: 1.485.. Validation Accuracy:
0.976
Epoch: 9/15.. Training Loss: 1.668.. Validation Loss: 1.483.. Validation Accuracy:
0.979
```

```
Epoch: 10/15.. Training Loss: 1.669.. Validation Loss: 1.482.. Validation Accuracy: 0.980

Epoch: 11/15.. Training Loss: 1.670.. Validation Loss: 1.480.. Validation Accuracy: 0.982

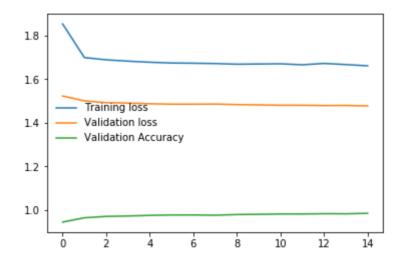
Epoch: 12/15.. Training Loss: 1.665.. Validation Loss: 1.480.. Validation Accuracy: 0.982

Epoch: 13/15.. Training Loss: 1.672.. Validation Loss: 1.478.. Validation Accuracy: 0.983

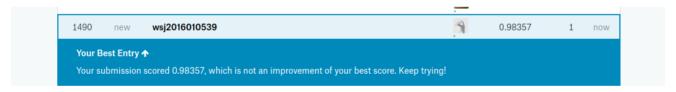
Epoch: 14/15.. Training Loss: 1.666.. Validation Loss: 1.479.. Validation Accuracy: 0.982

Epoch: 15/15.. Training Loss: 1.661.. Validation Loss: 1.477.. Validation Accuracy: 0.985
```

Loss和acc曲线:



在kaggle平台上提交了预测结果后 test_acc约为0.983



经过分析可以看见,MLP和CNN都能在MNIST数据集上取得比较好的效果。在验证集上MLP能够取得0.96+的准确率,CNN在验证集上能够取得0.98+的准确率。从网络训练速度上看,MLP相比较CNN架构速度更快一些,而收敛速度都比较快,大约在1第十个epoch下达到收敛。

通过图片我们可以看见,validation loss始终低于training loss,这主要是因为在validation的过程中采用了eval()模式,不再dropout,因此所有的神经元都处于激活状态,所以loss更低。这一现象在cnn上比较明显。

通过不同的网络架构对比,可以发现,CNN在图像分类识别的任务上取得的效果更好.通过validation和test的准确率比较,发现相差不大,未出现过拟合的情况。

本次试验使用pytorch库,pytorch封装的一些结构和函数大大增加了搭建神经网络的方便性,并且支持GPU运算, 比较简单易学,相比较前几次的作业,我深深地感到轮子的伟大。