cs101aFinal

May 10, 2022

[1]:
```
import numpy as np
import pandas as pd
import torch
import torch.nn.functional as F
import torch.optim as optim
import torchvision
import matplotlib.pyplot as plt
from torchvision import datasets, transforms
from torch import nn, optim
from torch.utils.data import Dataset, DataLoader, random_split
from tqdm import tqdm
from PIL import Image as im
```

0, Define the hyper parameters

[2]:
```
n_epochs = 100 #Initially 3.
batch_size_train = 16
batch_size_test = 16
```

1, Loading training and testing data

Organizing images First, we need to create a directory structure to hold our images. The directory training2 will hold 10 directories, corresponding to class labels.

This is so we can load the images using torchvision.datasets.ImageFolder, which expects the format described above.

[3]:
```
import os

#Make training2 directory
if not os.path.exists('training2'):
    os.mkdir("training2")
#Create the subdirectories corresponding to class labels
for i in range(10):
    if not os.path.exists("training2/{:02d}".format(i+1)):
        os.mkdir("training2/{:02d}".format(i + 1))
```

[4]:
```python
import shutil

#Iterate through labels.txt, copying images from training into training2 based on their class label
file = open("labels.txt","r")
for line in file.readlines():
    text = line.strip().split("\t")
    shutil.copy("training/" + text[0], "training2/{:02d}/".format(int(text[1])))
file.close()
```

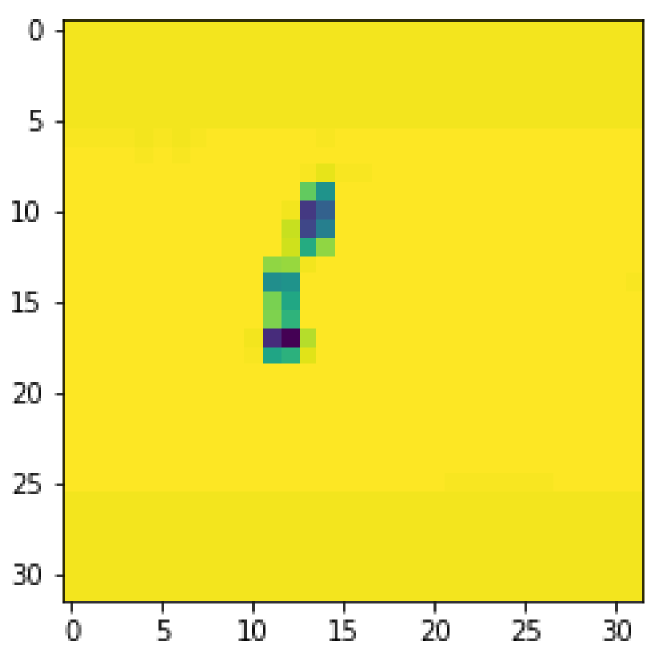
[5]:
```python
transform = transforms.Compose([transforms.Grayscale(),
                                transforms.Resize((32,32)),
                                transforms.ToTensor(),
                                transforms.Normalize((0.5,), (0.5,))
                               ])

dataset = datasets.ImageFolder('training2',transform=transform)
```

[6]:
```python
def display_img(img,label):
    print(f"Label : {dataset.classes[label]}")
    plt.imshow(img.permute(1,2,0))

#display the first image in the dataset
display_img(*dataset[0])
```

```
Label : 01
```



```
[7]: #Splitting the dataset into a testing and training set
trainset,testset = random_split(dataset,[600,260])
```

Passing the dataset to a dataloader

```
[8]: trainloader = torch.utils.data.DataLoader(trainset,␣
    ↪batch_size=batch_size_train, shuffle=True)
testloader = torch.utils.data.DataLoader(testset, batch_size_test=16,␣
    ↪shuffle=True)
```

2 Define the model

```
[10]: class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3,␣
    ↪stride=1, padding=1)
        self.pool = nn.MaxPool2d(kernel_size=2, stride=2)
        self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3,␣
    ↪stride=1, padding=1)
        self.fc1 = nn.Linear(64*8*8, 10)

    # x represents our data
    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.reshape(x.shape[0], -1)
        x = self.fc1(x)

        return x
```

3 Write the training function and the testing function

```
[11]: def test(model, test_loader, device):
    # evaluation, freeze
    model.eval()
    total_num = 0
    total_correct = 0
    with torch.no_grad():
        for _, (data, target) in enumerate(test_loader):

            data = data.to(device)
            target = target.to(device)

            predict_one_hot = model(data)
```

```
            _, predict_label = torch.max(predict_one_hot, 1)

            total_correct += (predict_label == target).sum().item()
            total_num += target.size(0)

    return (total_correct / total_num)
```

[12]:
```
def train(model, train_loader, test_loader, num_epoch, learning_rate, momentum,␣
↪device):
    train_losses = []

    # 1, define optimizer
    optimizer = optim.Adam(network.parameters()) #Using default learning rate␣
↪of 1e-3

    for epoch in tqdm(range(num_epoch)):
        # train the model
        model.train()

        for i, (data, target) in enumerate(train_loader):

            data = data.to(device)
            target = target.to(device)

            optimizer.zero_grad()

            # 2, forward
            output = network(data)


            # 3, calculate the loss
            loss = F.cross_entropy(output, target)

            # 4, backward
            loss.backward()


            optimizer.step()

        # evaluate the accuracy on test data for each epoch
        accuracy = test(model, test_loader, device)
        print('accuracy', accuracy)


    # 5, save model
```

[13]:

```python
device0 = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
# use cpu if you do not have gpu installed in your computer
network = Net().to(device0)
train(model=network, train_loader=trainloader, test_loader=testloader,␣
↪num_epoch=n_epochs, learning_rate=learning_rate, momentum=momentum,␣
↪device=device0)
```

```
  1%|          | 1/100 [00:01<02:49,  1.71s/it]

accuracy 0.12692307692307692

  2%|          | 2/100 [00:03<02:36,  1.59s/it]

accuracy 0.12307692307692308

  3%|          | 3/100 [00:04<02:33,  1.58s/it]

accuracy 0.25384615384615383

  4%|          | 4/100 [00:06<02:35,  1.62s/it]

accuracy 0.36153846153846153

  5%|          | 5/100 [00:08<02:31,  1.59s/it]

accuracy 0.34615384615384615

  6%|          | 6/100 [00:09<02:33,  1.64s/it]

accuracy 0.36923076923076925

  7%|          | 7/100 [00:11<02:34,  1.66s/it]

accuracy 0.43846153846153846

  8%|          | 8/100 [00:13<02:32,  1.66s/it]

accuracy 0.46923076923076923

  9%|          | 9/100 [00:14<02:29,  1.64s/it]

accuracy 0.4346153846153846

 10%|          | 10/100 [00:16<02:27,  1.64s/it]

accuracy 0.4807692307692308

 11%|          | 11/100 [00:17<02:25,  1.64s/it]

accuracy 0.5192307692307693

 12%|          | 12/100 [00:19<02:27,  1.67s/it]

accuracy 0.4307692307692308

 13%|          | 13/100 [00:21<02:27,  1.70s/it]

accuracy 0.5576923076923077

 14%|          | 14/100 [00:23<02:23,  1.67s/it]
```

```
accuracy 0.5538461538461539
 15%|                                       | 15/100 [00:24<02:19,  1.64s/it]
accuracy 0.5384615384615384
 16%|                                       | 16/100 [00:26<02:18,  1.64s/it]
accuracy 0.5423076923076923
 17%|                                      | 17/100 [00:27<02:17,  1.65s/it]
accuracy 0.5423076923076923
 18%|                                      | 18/100 [00:29<02:17,  1.67s/it]
accuracy 0.5923076923076923
 19%|                                      | 19/100 [00:31<02:17,  1.70s/it]
accuracy 0.5846153846153846
 20%|                                     | 20/100 [00:33<02:13,  1.67s/it]
accuracy 0.5884615384615385
 21%|                                     | 21/100 [00:34<02:10,  1.65s/it]
accuracy 0.6192307692307693
 22%|                                    | 22/100 [00:36<02:09,  1.67s/it]
accuracy 0.5923076923076923
 23%|                                    | 23/100 [00:38<02:08,  1.67s/it]
accuracy 0.6076923076923076
 24%|                                    | 24/100 [00:39<02:09,  1.70s/it]
accuracy 0.6423076923076924
 25%|                                   | 25/100 [00:41<02:07,  1.71s/it]
accuracy 0.6076923076923076
 26%|                                   | 26/100 [00:43<02:10,  1.76s/it]
accuracy 0.6653846153846154
 27%|                                  | 27/100 [00:45<02:10,  1.79s/it]
accuracy 0.6423076923076924
 28%|                                  | 28/100 [00:46<02:02,  1.71s/it]
accuracy 0.6576923076923077
 29%|                                 | 29/100 [00:48<01:57,  1.65s/it]
accuracy 0.6615384615384615
 30%|                                 | 30/100 [00:50<01:58,  1.69s/it]
```

```
accuracy 0.6615384615384615
 31%|                                        | 31/100 [00:51<01:58,  1.72s/it]
accuracy 0.6576923076923077
 32%|                                       | 32/100 [00:53<01:59,  1.75s/it]
accuracy 0.6730769230769231
 33%|                                       | 33/100 [00:55<01:58,  1.77s/it]
accuracy 0.6576923076923077
 34%|                                      | 34/100 [00:57<01:57,  1.79s/it]
accuracy 0.65
 35%|                                      | 35/100 [00:59<01:56,  1.80s/it]
accuracy 0.6692307692307692
 36%|                                      | 36/100 [01:00<01:54,  1.80s/it]
accuracy 0.6692307692307692
 37%|                                     | 37/100 [01:02<01:53,  1.80s/it]
accuracy 0.676923076923077
 38%|                                     | 38/100 [01:04<01:52,  1.81s/it]
accuracy 0.6653846153846154
 39%|                                    | 39/100 [01:06<01:50,  1.81s/it]
accuracy 0.6653846153846154
 40%|                                    | 40/100 [01:08<01:48,  1.81s/it]
accuracy 0.6807692307692308
 41%|                                   | 41/100 [01:10<01:47,  1.82s/it]
accuracy 0.6692307692307692
 42%|                                   | 42/100 [01:11<01:45,  1.82s/it]
accuracy 0.6653846153846154
 43%|                                   | 43/100 [01:13<01:43,  1.82s/it]
accuracy 0.6653846153846154
 44%|                                  | 44/100 [01:15<01:42,  1.83s/it]
accuracy 0.6730769230769231
 45%|                                  | 45/100 [01:17<01:43,  1.88s/it]
accuracy 0.6730769230769231
 46%|                                 | 46/100 [01:19<01:40,  1.86s/it]
```

```
accuracy 0.6692307692307692
 47%|                                 | 47/100 [01:21<01:36,  1.82s/it]
accuracy 0.6615384615384615
 48%|                                | 48/100 [01:22<01:33,  1.80s/it]
accuracy 0.6807692307692308
 49%|                                | 49/100 [01:24<01:30,  1.78s/it]
accuracy 0.6961538461538461
 50%|                                | 50/100 [01:26<01:28,  1.77s/it]
accuracy 0.6730769230769231
 51%|                               | 51/100 [01:28<01:26,  1.76s/it]
accuracy 0.7
 52%|                               | 52/100 [01:29<01:23,  1.75s/it]
accuracy 0.6692307692307692
 53%|                              | 53/100 [01:31<01:21,  1.74s/it]
accuracy 0.6846153846153846
 54%|                              | 54/100 [01:33<01:19,  1.74s/it]
accuracy 0.6730769230769231
 55%|                              | 55/100 [01:34<01:18,  1.74s/it]
accuracy 0.676923076923077
 56%|                             | 56/100 [01:36<01:16,  1.74s/it]
accuracy 0.6807692307692308
 57%|                             | 57/100 [01:38<01:14,  1.74s/it]
accuracy 0.6730769230769231
 58%|                            | 58/100 [01:40<01:12,  1.73s/it]
accuracy 0.676923076923077
 59%|                            | 59/100 [01:41<01:11,  1.73s/it]
accuracy 0.6923076923076923
 60%|                           | 60/100 [01:43<01:09,  1.74s/it]
accuracy 0.6653846153846154
 61%|                           | 61/100 [01:45<01:07,  1.73s/it]
accuracy 0.6807692307692308
 62%|                           | 62/100 [01:47<01:05,  1.74s/it]
```

```
accuracy 0.6923076923076923
 63%|                              | 63/100 [01:48<01:05,  1.77s/it]
accuracy 0.6923076923076923
 64%|                              | 64/100 [01:50<01:04,  1.78s/it]
accuracy 0.6884615384615385
 65%|                             | 65/100 [01:52<01:02,  1.79s/it]
accuracy 0.6807692307692308
 66%|                             | 66/100 [01:54<01:01,  1.80s/it]
accuracy 0.7
 67%|                            | 67/100 [01:56<00:59,  1.81s/it]
accuracy 0.6807692307692308
 68%|                            | 68/100 [01:58<00:57,  1.81s/it]
accuracy 0.676923076923077
 69%|                            | 69/100 [01:59<00:56,  1.81s/it]
accuracy 0.6961538461538461
 70%|                           | 70/100 [02:01<00:54,  1.82s/it]
accuracy 0.6884615384615385
 71%|                           | 71/100 [02:03<00:52,  1.82s/it]
accuracy 0.6961538461538461
 72%|                          | 72/100 [02:05<00:50,  1.82s/it]
accuracy 0.6884615384615385
 73%|                          | 73/100 [02:07<00:49,  1.82s/it]
accuracy 0.7076923076923077
 74%|                          | 74/100 [02:08<00:47,  1.81s/it]
accuracy 0.6961538461538461
 75%|                         | 75/100 [02:10<00:44,  1.78s/it]
accuracy 0.6961538461538461
 76%|                         | 76/100 [02:12<00:42,  1.76s/it]
accuracy 0.7038461538461539
 77%|                        | 77/100 [02:14<00:40,  1.78s/it]
accuracy 0.7038461538461539
 78%|                        | 78/100 [02:16<00:39,  1.80s/it]
```

```
accuracy 0.7076923076923077
 79%|                             | 79/100 [02:17<00:37,  1.81s/it]
accuracy 0.7115384615384616
 80%|                             | 80/100 [02:19<00:36,  1.80s/it]
accuracy 0.6923076923076923
 81%|                             | 81/100 [02:21<00:33,  1.77s/it]
accuracy 0.6884615384615385
 82%|                            | 82/100 [02:23<00:31,  1.76s/it]
accuracy 0.6884615384615385
 83%|                            | 83/100 [02:24<00:29,  1.76s/it]
accuracy 0.6923076923076923
 84%|                            | 84/100 [02:26<00:28,  1.75s/it]
accuracy 0.7
 85%|                            | 85/100 [02:28<00:26,  1.75s/it]
accuracy 0.7076923076923077
 86%|                            | 86/100 [02:30<00:24,  1.74s/it]
accuracy 0.7
 87%|                           | 87/100 [02:31<00:22,  1.72s/it]
accuracy 0.7038461538461539
 88%|                           | 88/100 [02:33<00:19,  1.65s/it]
accuracy 0.6884615384615385
 89%|                           | 89/100 [02:34<00:17,  1.60s/it]
accuracy 0.7192307692307692
 90%|                           | 90/100 [02:36<00:16,  1.67s/it]
accuracy 0.7076923076923077
 91%|                          | 91/100 [02:38<00:15,  1.72s/it]
accuracy 0.7115384615384616
 92%|                          | 92/100 [02:40<00:14,  1.75s/it]
accuracy 0.7038461538461539
 93%|                          | 93/100 [02:42<00:12,  1.78s/it]
accuracy 0.7153846153846154
 94%|                          | 94/100 [02:43<00:10,  1.80s/it]
```

```
accuracy 0.7076923076923077

 95%|                        | 95/100 [02:45<00:09,  1.81s/it]

accuracy 0.7038461538461539

 96%|                        | 96/100 [02:47<00:07,  1.82s/it]

accuracy 0.7038461538461539

 97%|                        | 97/100 [02:49<00:05,  1.83s/it]

accuracy 0.7038461538461539

 98%|                        | 98/100 [02:50<00:03,  1.74s/it]

accuracy 0.7

 99%|                        | 99/100 [02:52<00:01,  1.67s/it]

accuracy 0.6923076923076923

100%|                        | 100/100 [02:53<00:00,  1.74s/it]

accuracy 0.7115384615384616
```

0.0.1 Saving the model

[14]:
```
torch.save(network, './Final_Model.pt')
```