
```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 import torch
4 from torchvision import transforms, datasets
```

```
1 transform = transforms.Compose([
2     transforms.ToTensor(),
3     transforms.Normalize((0.5,), (0.5,))
4 ])
5
6 device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

```
1 data_path = './MNIST'
2
3 data_test  = datasets.MNIST(root = data_path, train= True, download=True, transform= transform)
4 data_train = datasets.MNIST(root = data_path, train= False, download=True, transform= transform)
```

Downloading <http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz> to ./MNIST/MNIST/raw/train-images-idx3-ubyte.gz

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```
1 print("the number of your training data (must be 10,000) = ", data_train.__len__())
```

```
2 print("hte number of your testing data (must be 60,000) = ", data_test.__len__())
```

the number of your training data (must be 10,000) = 10000

hte number of your testing data (must be 60,000) = 60000

Downloading <http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz> to ./MNIST/MNIST/raw/train-images-idx3-ubyte.gz

```
1 train_loader = torch.utils.data.DataLoader(data_train, batch_size = 64, num_workers=0)
```

```
2 test_loader = torch.utils.data.DataLoader(data_test, batch_size=64, num_workers=0)
```

Downloading <http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz> to ./MNIST/MNIST/raw/train-images-idx3-ubyte.gz

```
1 import torch.nn as nn
```

```
2
```

```
3 def calc_out(in_layers, stride, padding, kernel_size, pool_stride):
```

```
4     """
```

```
5     Helper function for computing the number of outputs from a
```

```
6     conv layer
```

```
7     """
```

```
8     return int((1+(in_layers - kernel_size + (2*padding))/stride)/pool_stride)
```

```
9
```

```
10 class Net(nn.Module):
```

```
11     def __init__(self):
```

```
12         super(Net, self).__init__()
```

```
13
```

```
14         # Some helpful values
```

```
15         inputs      = [1,32,64,64] # MNIST data shape
```

```
16         kernel_size = [5,5,3]
```

```
17         stride      = [1,1,1]
```

```
18         pool_stride = [2,2,2]
```

```
19
```

```
20         # Layer lists
```

```
21         layers = []
```

```
22
```

```
23         self.out  = 28
```

```
24         self.depth = inputs[-1]
```

```
25         for i in range(len(kernel_size)):
```

```

25         for i in range(len(kernel_size)):
26             # Get some variables
27             padding = int(kernel_size[i]/2)
28
29             # Define the output from this layer
30             self.out = calc_out(self.out, stride[i], padding,
31                                 kernel_size[i], pool_stride[i])
32
33             # convolutional layer 1
34             layers.append(nn.Conv2d(inputs[i], inputs[i+1], kernel_size[i],
35                                     stride=stride[i], padding=padding))
36             layers.append(nn.BatchNorm2d(inputs[i+1]))
37             layers.append(nn.ReLU())
38
39             # convolutional layer 2
40             layers.append(nn.Conv2d(inputs[i+1], inputs[i+1], kernel_size[i],
41                                     stride=stride[i], padding=padding))
42             layers.append(nn.BatchNorm2d(inputs[i+1]))
43             layers.append(nn.ReLU())
44             # maxpool layer
45             layers.append(nn.MaxPool2d(pool_stride[i], pool_stride[i]))
46             layers.append(nn.Dropout(p=0.2))
47
48         self.cnn_layers = nn.Sequential(*layers)
49
50         print(self.depth*self.out*self.out)
51
52         # Now for our fully connected layers
53         layers2 = []
54         layers2.append(nn.Dropout(p=0.2))
55         layers2.append(nn.Linear(self.depth*self.out*self.out, 512))
56         layers2.append(nn.Dropout(p=0.2))
57         layers2.append(nn.Linear(512, 256))
58         layers2.append(nn.Dropout(p=0.2))
59         layers2.append(nn.Linear(256, 256))
60         layers2.append(nn.Dropout(p=0.2))
61         layers2.append(nn.Linear(256, 10))
62
63         self.fc_layers = nn.Sequential(*layers2)

```

```
63         self.fc_layers = nn.Sequential(*layers2)
64
65     def forward(self, x):
66         x = self.cnn_layers(x)
67         x = x.view(-1, self.depth*self.out*self.out)
68         x = self.fc_layers(x)
69         return x
70
71 # create a complete CNN
72 model = Net()
73 model
```

```
1 tLoss, vLoss = [], []
2 tacc, vacc = [], []
```

```
1 import torch.optim as optim
2
3 # specify loss function
4 criterion = nn.CrossEntropyLoss()
5
6 # specify optimizer
7 optimizer = optim.Adam(model.parameters(), lr=0.0005)
```

```
1 # number of epochs to train the model
2 n_epochs = 30
3
4 # Get the device
5 model.to(device)
6
7 for epoch in range(n_epochs):
8     # keep track of training and validation loss
9     train_loss = 0.0
10    test_loss = 0.0
11    train_correct = 0
12    test_correct = 0
13
```

```
14 # train #
15 model.train()
16 for data, target in train_loader:
17     # move tensors to GPU if CUDA is available
18     data = data.to(device)
19     target = target.to(device)
20
21     # clear the gradients of all optimized variables
22     optimizer.zero_grad()
23     output = model(data)
24
25     # calculate the batch loss
26     loss = criterion(output, target)
27     loss.backward()
28     optimizer.step()
29     train_loss += loss.item()*data.size(0)
30
31     prediction = output.data.max(1)[1] # first column has actual prob.
32     correct = prediction.eq(target.data).sum()
33     train_correct += correct
34
35
36 # test #
37 model.eval()
38 for data, target in test_loader:
39     # move tensors to GPU if CUDA is available
40     data = data.to(device)
41     target = target.to(device)
42
43     output = model(data)
44
45     # calculate the batch loss
46     loss = criterion(output, target)
47     test_loss += loss.item()*data.size(0)
48
49     prediction = output.data.max(1)[1] # first column has actual prob.
50     correct = prediction.eq(target.data).sum()
51     test_correct += correct
```

```

51         test_loss = test_loss + test_loader.dataset
52
53     # calculate average losses
54     train_loss = train_loss/len(train_loader.dataset)
55     test_loss = test_loss/len(test_loader.dataset)
56     tLoss.append(train_loss)
57     vLoss.append(test_loss)
58
59     # calculate average accuracy
60     train_accuracy = train_correct / len(train_loader.dataset)
61     test_accuracy = test_correct / len(test_loader.dataset)
62     tacc.append(train_accuracy)
63     vacc.append(test_accuracy)
64
65     # print training/validation statistics
66     print('Epoch: {} WtTraining Loss: {:.5f} WtTesting Loss: {:.5f}'.format(
67         epoch, train_loss, test_loss))
68     print('Epoch: {} WtTraining acc: {:.5f} WtTesting acc: {:.5f}'.format(
69         epoch, train_accuracy, test_accuracy))

```

cuda

Epoch: 0	Training Loss: 0.48889	Testing Loss: 0.24120
Epoch: 0	Training acc: 0.83620	Testing acc: 0.93440
Epoch: 1	Training Loss: 0.12925	Testing Loss: 0.19014
Epoch: 1	Training acc: 0.95930	Testing acc: 0.94888
Epoch: 2	Training Loss: 0.09355	Testing Loss: 0.15203
Epoch: 2	Training acc: 0.96970	Testing acc: 0.96112
Epoch: 3	Training Loss: 0.06981	Testing Loss: 0.09111
Epoch: 3	Training acc: 0.97840	Testing acc: 0.97465
Epoch: 4	Training Loss: 0.05037	Testing Loss: 0.10475
Epoch: 4	Training acc: 0.98300	Testing acc: 0.97467
Epoch: 5	Training Loss: 0.05559	Testing Loss: 0.10922
Epoch: 5	Training acc: 0.98190	Testing acc: 0.97373
Epoch: 6	Training Loss: 0.05032	Testing Loss: 0.08810
Epoch: 6	Training acc: 0.98460	Testing acc: 0.97850
Epoch: 7	Training Loss: 0.04541	Testing Loss: 0.09403
Epoch: 7	Training acc: 0.98440	Testing acc: 0.97637
Epoch: 8	Training Loss: 0.03695	Testing Loss: 0.08212
Epoch: 8	Training acc: 0.98780	Testing acc: 0.97995
Epoch: 9	Training Loss: 0.03521	Testing Loss: 0.11271

Epoch: 9	Training acc: 0.98900	Testing acc: 0.97473
Epoch: 10	Training Loss: 0.03152	Testing Loss: 0.06703
Epoch: 10	Training acc: 0.99000	Testing acc: 0.98387
Epoch: 11	Training Loss: 0.03275	Testing Loss: 0.06449
Epoch: 11	Training acc: 0.98950	Testing acc: 0.98433
Epoch: 12	Training Loss: 0.02276	Testing Loss: 0.08469
Epoch: 12	Training acc: 0.99160	Testing acc: 0.98163
Epoch: 13	Training Loss: 0.02510	Testing Loss: 0.05986
Epoch: 13	Training acc: 0.99270	Testing acc: 0.98657
Epoch: 14	Training Loss: 0.01584	Testing Loss: 0.08609
Epoch: 14	Training acc: 0.99500	Testing acc: 0.98363
Epoch: 15	Training Loss: 0.02910	Testing Loss: 0.10357
Epoch: 15	Training acc: 0.99080	Testing acc: 0.97780
Epoch: 16	Training Loss: 0.02150	Testing Loss: 0.05728
Epoch: 16	Training acc: 0.99360	Testing acc: 0.98757
Epoch: 17	Training Loss: 0.01902	Testing Loss: 0.07424
Epoch: 17	Training acc: 0.99360	Testing acc: 0.98402
Epoch: 18	Training Loss: 0.02480	Testing Loss: 0.09501
Epoch: 18	Training acc: 0.99380	Testing acc: 0.97943
Epoch: 19	Training Loss: 0.02785	Testing Loss: 0.08328
Epoch: 19	Training acc: 0.99300	Testing acc: 0.98238
Epoch: 20	Training Loss: 0.01852	Testing Loss: 0.06883
Epoch: 20	Training acc: 0.99460	Testing acc: 0.98535
Epoch: 21	Training Loss: 0.01451	Testing Loss: 0.10794
Epoch: 21	Training acc: 0.99540	Testing acc: 0.98095
Epoch: 22	Training Loss: 0.01561	Testing Loss: 0.08543
Epoch: 22	Training acc: 0.99400	Testing acc: 0.98485
Epoch: 23	Training Loss: 0.02758	Testing Loss: 0.08960
Epoch: 23	Training acc: 0.99160	Testing acc: 0.98168
Epoch: 24	Training Loss: 0.01557	Testing Loss: 0.07596
Epoch: 24	Training acc: 0.99420	Testing acc: 0.98552
Epoch: 25	Training Loss: 0.02221	Testing Loss: 0.09837
Epoch: 25	Training acc: 0.99300	Testing acc: 0.98017
Epoch: 26	Training Loss: 0.01557	Testing Loss: 0.07513
Epoch: 26	Training acc: 0.99570	Testing acc: 0.98502
Epoch: 27	Training Loss: 0.01268	Testing Loss: 0.09921
Epoch: 27	Training acc: 0.99650	Testing acc: 0.98045
Epoch: 28	Training Loss: 0.01817	Testing Loss: 0.06952
Epoch: 28	Training acc: 0.99450	Testing acc: 0.98652



▼ Output

▼ 1. Plot the training and testing losses over epochs [2pt]

```
1 plt.plot([i for i in range(len(tLoss))], tLoss, label = 'training loss' , c = 'blue')
2 plt.plot([i for i in range(len(vLoss))], vLoss, label = 'testing loss' , c = 'red')
3
4 plt.legend()
5 plt.xlabel("epochs")
6 plt.ylabel("loss")
7 plt.title("training and testing losses over epochs")
8 plt.show()
```



▼ 2. Plot the training and testing accuracies over epochs [2pt]

```
1 plt.plot([i for i in range(len(tacc))], tacc, label = 'training acc' , c = 'blue')
2 plt.plot([i for i in range(len(vacc))], vacc, label = 'testing acc' , c = 'red')
3
```



```

4 plt.legend()
5 plt.xlabel("epochs")
6 plt.ylabel("accuracy")
7 plt.title("training and testing accuracies over epochs")
8 plt.show()

```



▼ 3. Print the final training and testing losses at convergence [2pt]

```
1 print('Training loss: {:.5f} \nTesting loss: {:.5f}'.format(tLoss[-1], vLoss[-1]))
```

```

Training loss: 0.01050
Testing loss: 0.08998

```

▼ 4. Print the final training and testing accuracies at convergence [20pt]

```
1 print('Training acc: {:.5f} \nTesting acc: {:.5f}'.format(tacc[-1], vacc[-1]))
```

```

Training acc: 0.99660

```

Testing acc: 0.98395

▼ 5. Print the testing accuracies within the last 10 epochs [5pt]

```
1 vacc_last_10_epochs = vacc[n_epochs - 10:]
2
3 for i in range(len(vacc_last_10_epochs)):
4     print("[epoch = {}] WtTesting acc : {:.5f}".format(n_epochs - 10 + i, vacc_last_10_epochs[i]))
```

```
[epoch = 20]    Testing acc : 0.98535
[epoch = 21]    Testing acc : 0.98095
[epoch = 22]    Testing acc : 0.98485
[epoch = 23]    Testing acc : 0.98168
[epoch = 24]    Testing acc : 0.98552
[epoch = 25]    Testing acc : 0.98017
[epoch = 26]    Testing acc : 0.98502
[epoch = 27]    Testing acc : 0.98045
[epoch = 28]    Testing acc : 0.98652
[epoch = 29]    Testing acc : 0.98395
```

