q3

February 20, 2025

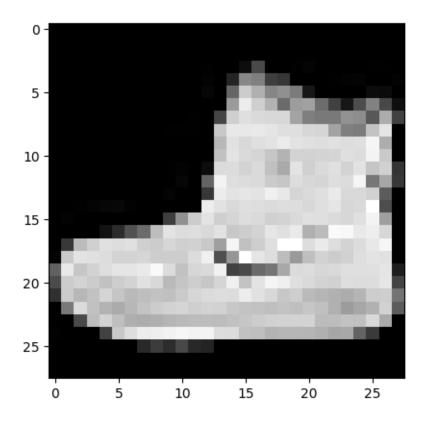
```
[1]: # import the libraries
     import numpy as np
     import torch
     import torchvision
[2]: trainingdata = torchvision.datasets.FashionMNIST('./FashionMNIST/
     , train=True, download=True, transform=torchvision.transforms.ToTensor())
     testdata = torchvision.datasets.FashionMNIST('./FashionMNIST/

¬',train=False,download=True,transform=torchvision.transforms.ToTensor())

    Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
    images-idx3-ubyte.gz
    Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
    images-idx3-ubyte.gz to ./FashionMNIST/FashionMNIST/raw/train-images-
    idx3-ubyte.gz
    100%|
               | 26.4M/26.4M [00:02<00:00, 12.6MB/s]
    Extracting ./FashionMNIST/FashionMNIST/raw/train-images-idx3-ubyte.gz to
    ./FashionMNIST/FashionMNIST/raw
    Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
    labels-idx1-ubyte.gz
    Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-
    labels-idx1-ubyte.gz to ./FashionMNIST/FashionMNIST/raw/train-labels-
    idx1-ubyte.gz
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    Extracting ./FashionMNIST/FashionMNIST/raw/train-labels-idx1-ubyte.gz to
    ./FashionMNIST/FashionMNIST/raw
    Downloading http://fashion-mnist.s3-website.eu-
    central-1.amazonaws.com/t10k-images-idx3-ubyte.gz
    Downloading http://fashion-mnist.s3-website.eu-
    central-1.amazonaws.com/t10k-images-idx3-ubyte.gz to
    ./FashionMNIST/FashionMNIST/raw/t10k-images-idx3-ubyte.gz
    100%|
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```

```
./FashionMNIST/FashionMNIST/raw
    Downloading http://fashion-mnist.s3-website.eu-
    central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz
    Downloading http://fashion-mnist.s3-website.eu-
    central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz to
    ./FashionMNIST/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz
    100%|
               | 5.15k/5.15k [00:00<00:00, 11.9MB/s]
    Extracting ./FashionMNIST/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to
    ./FashionMNIST/FashionMNIST/raw
[3]: print(len(trainingdata))
     print(len(testdata))
    60000
    10000
[4]: image, label = trainingdata[0]
     print(image.shape, label)
    torch.Size([1, 28, 28]) 9
[5]: print(image.squeeze().shape)
    torch.Size([28, 28])
[6]: import matplotlib.pyplot as plt
     %matplotlib inline
     plt.imshow(image.squeeze(), cmap=plt.cm.gray)
[6]: <matplotlib.image.AxesImage at 0x7bcceaa85250>
```

Extracting ./FashionMNIST/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to



```
[7]: trainDataLoader = torch.utils.data.
       →DataLoader(trainingdata,batch_size=64,shuffle=True)
      testDataLoader = torch.utils.data.
       →DataLoader(testdata,batch_size=64,shuffle=False)
 [8]: print(len(trainDataLoader))
      print(len(testDataLoader))
     938
     157
 [9]: print(len(trainDataLoader) * 64) # batch_size from above
      print(len(testDataLoader) * 64)
     60032
     10048
[10]: images, labels = next(iter(trainDataLoader))
      plt.figure(figsize=(10,4))
      for index in np.arange(0,5):
        plt.subplot(1,5,index+1)
```

```
plt.title(f'Label: {labels[index].item()}')
plt.imshow(images[index].squeeze(),cmap=plt.cm.gray)
```

```
Label: 4 Label: 2 Label: 0 Label: 5 Label: 4 Label: 4 Label: 4 Label: 4 Label: 5 Label: 4 Label: 4 Label: 5 Label: 4 Label: 5 Label: 4 Label: 4 Label: 5 Label: 6 Lab
```

```
[17]: class FashionMNISTModel(torch.nn.Module):
        def __init__(self):
          super(FashionMNISTModel,self).__init__()
          self.fc1 = torch.nn.Linear(28*28, 256)
          self.fc2 = torch.nn.Linear(256, 128)
          self.fc3 = torch.nn.Linear(128, 64)
          self.fc4 = torch.nn.Linear(64, 10)
          self.relu = torch.nn.ReLU()
        def forward(self, x):
          x = x.view(-1, 28*28)
          x = self.relu(self.fc1(x))
          x = self.relu(self.fc2(x))
          x = self.relu(self.fc3(x))
          x = self.fc4(x)
          return x
      model = FashionMNISTModel().cuda() # Step 1: architecture
      loss = torch.nn.CrossEntropyLoss() # Step 2: loss
      optimizer = torch.optim.SGD(model.parameters(), lr=0.01) # Step 3: training_
       \rightarrowmethod
```

```
[19]: train_loss_history = []
    test_loss_history = []

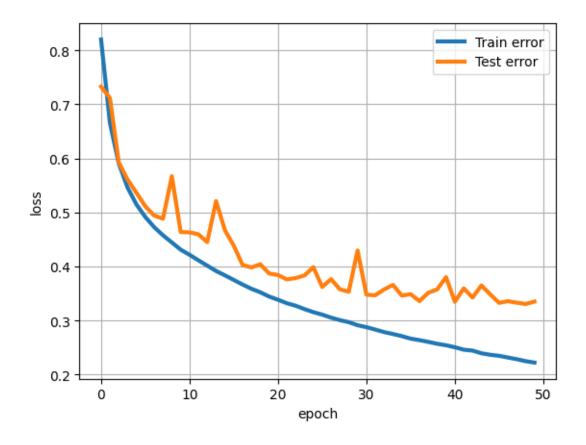
    for epoch in range(50):
        train_loss = 0.0
        test_loss = 0.0

        model.train()
        for i, data in enumerate(trainDataLoader):
        images, labels = data
        images = images.cuda()
```

```
labels = labels.cuda()
  optimizer.zero_grad() # zero out any gradient values from the previous_
\rightarrow iteration
  predicted_output = model(images) # forward propagation
  fit = loss(predicted_output, labels) # calculate our measure of goodness
  fit.backward() # backpropagation
  optimizer.step() # update the weights of our trainable parameters
  train loss += fit.item()
model.eval()
for i, data in enumerate(testDataLoader):
  with torch.no_grad():
    images, labels = data
    images = images.cuda()
    labels = labels.cuda()
    predicted_output = model(images)
    fit = loss(predicted_output, labels)
    test_loss += fit.item()
train_loss = train_loss / len(trainDataLoader)
test_loss = test_loss / len(testDataLoader)
train_loss_history += [train_loss]
test loss history += [test loss]
print(f'Epoch {epoch}, Train loss {train_loss}, Test loss {test_loss}')
```

```
Epoch 0, Train loss 0.8200335381572434, Test loss 0.7326804498198686
Epoch 1, Train loss 0.665718307690834, Test loss 0.7116923011412286
Epoch 2, Train loss 0.5906475426228062, Test loss 0.5926861100515742
Epoch 3, Train loss 0.5457974640863028, Test loss 0.5606379247015449
Epoch 4, Train loss 0.5148079536362752, Test loss 0.5363499848705948
Epoch 5, Train loss 0.49167311339299563, Test loss 0.5114035538047742
Epoch 6, Train loss 0.4729746097663064, Test loss 0.4943873890835768
Epoch 7, Train loss 0.4577874707927836, Test loss 0.48849217717055304
Epoch 8, Train loss 0.4445181418297642, Test loss 0.5671002291570044
Epoch 9, Train loss 0.43125458921133075, Test loss 0.4638637961096065
Epoch 10, Train loss 0.4216652001176816, Test loss 0.46319339448099683
Epoch 11, Train loss 0.411558430713377, Test loss 0.4597173428079884
Epoch 12, Train loss 0.401729068665235, Test loss 0.44516734247374684
Epoch 13, Train loss 0.3918211419445111, Test loss 0.5210342504036655
Epoch 14, Train loss 0.383749128746262, Test loss 0.46723415251750094
Epoch 15, Train loss 0.37521459705539856, Test loss 0.4385564943217927
Epoch 16, Train loss 0.3666893032822273, Test loss 0.4028862781205754
Epoch 17, Train loss 0.35885209242291033, Test loss 0.3982689765038764
Epoch 18, Train loss 0.35241075597210986, Test loss 0.40421634219634306
Epoch 19, Train loss 0.3445079951668218, Test loss 0.3870985234618946
Epoch 20, Train loss 0.3386262595764737, Test loss 0.38436001814474724
Epoch 21, Train loss 0.33214848486980647, Test loss 0.3761763641978525
Epoch 22, Train loss 0.32754341848909474, Test loss 0.3787363739150345
```

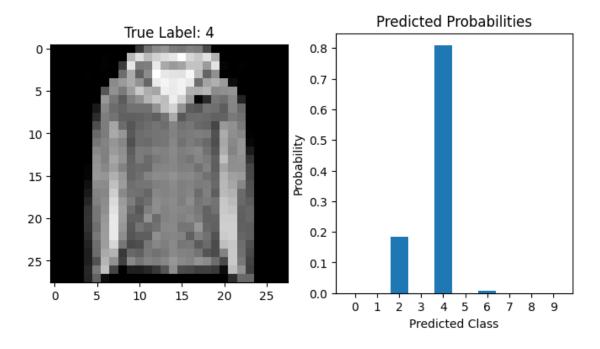
```
Epoch 23, Train loss 0.32119926396431697, Test loss 0.3835079055872692
     Epoch 24, Train loss 0.3156572524259594, Test loss 0.39882386765282624
     Epoch 25, Train loss 0.31103204473503615, Test loss 0.36221614185791867
     Epoch 26, Train loss 0.3055283787217476, Test loss 0.3767634172728107
     Epoch 27, Train loss 0.3008508968597917, Test loss 0.3578552864729219
     Epoch 28, Train loss 0.29715881352898665, Test loss 0.3533400070325584
     Epoch 29, Train loss 0.2914532613573171, Test loss 0.42966997471584634
     Epoch 30, Train loss 0.2879214670135777, Test loss 0.3479153208292214
     Epoch 31, Train loss 0.28345096788839746, Test loss 0.34679541428377675
     Epoch 32, Train loss 0.27875598672547064, Test loss 0.3576511265176117
     Epoch 33, Train loss 0.2752353979437463, Test loss 0.36603504855921315
     Epoch 34, Train loss 0.27129416232869064, Test loss 0.34637003463165017
     Epoch 35, Train loss 0.2666461776727552, Test loss 0.3488483873142558
     Epoch 36, Train loss 0.2638548987347688, Test loss 0.33612170483276343
     Epoch 37, Train loss 0.2606392344956332, Test loss 0.35152637569388007
     Epoch 38, Train loss 0.25712381808488355, Test loss 0.35781701440644115
     Epoch 39, Train loss 0.25437884713445647, Test loss 0.3804061690903014
     Epoch 40, Train loss 0.2507424075593318, Test loss 0.33481416794335006
     Epoch 41, Train loss 0.24622550944307212, Test loss 0.35968598581043776
     Epoch 42, Train loss 0.2445218058457888, Test loss 0.3427320975501826
     Epoch 43, Train loss 0.2396058153662918, Test loss 0.365043097668013
     Epoch 44, Train loss 0.23681550292270398, Test loss 0.34848266802016337
     Epoch 45, Train loss 0.23487135837835543, Test loss 0.33279177323458303
     Epoch 46, Train loss 0.2317561384941787, Test loss 0.3359520827319212
     Epoch 47, Train loss 0.2286240428702028, Test loss 0.3331539783697979
     Epoch 48, Train loss 0.22498356889703, Test loss 0.3307615016011675
     Epoch 49, Train loss 0.2223383083081703, Test loss 0.3352103267031111
[20]: plt.plot(range(50), train_loss_history, '-', linewidth=3, label='Train error')
      plt.plot(range(50),test_loss_history,'-',linewidth=3,label='Test_error')
      plt.xlabel('epoch')
      plt.ylabel('loss')
      plt.grid(True)
      plt.legend()
      plt.show()
```



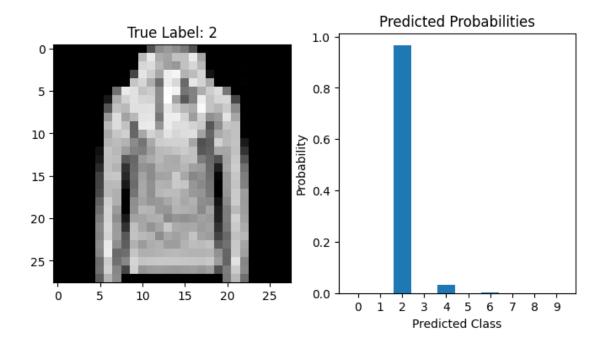
```
[27]: # draw any 3 random image samples from the test dataset, visualize the
      # predicted class probabilities for each sample, and comment on what you can \Box
       ⇔observe from these plots.
      import matplotlib.pyplot as plt
      import random
      # Select 3 random indices from the test dataset
      random_indices = random.sample(range(len(testdata)), 3)
      # Get the images and labels for the selected samples
      images = [testdata[i][0] for i in random_indices]
      labels = [testdata[i][1] for i in random_indices]
      device = torch.device("cuda" if torch.cuda.is_available() else "cpu") #
      print(f"Using device: {device}")
      model.to(device)
      # Get predicted probabilities
      model.eval()
      with torch.no_grad():
```

```
predicted_probabilities = [
        torch.softmax(model(image.unsqueeze(0).to(device)), dim=1).squeeze()
         for image in images]
# Visualize and comment on predicted probabilities
for i in range(3):
   plt.figure(figsize=(8, 4))
   plt.subplot(1, 2, 1)
   plt.imshow(images[i].squeeze(), cmap=plt.cm.gray)
   plt.title(f"True Label: {labels[i]}")
   plt.subplot(1, 2, 2)
   plt.bar(range(10), predicted_probabilities[i].cpu().numpy())
   plt.xticks(range(10))
   plt.xlabel("Predicted Class")
   plt.ylabel("Probability")
   plt.title(f"Predicted Probabilities")
   plt.show()
   print(f"Observation for sample {i+1}:")
   print(f"The model predicts class {torch.argmax(predicted_probabilities[i])}__
 ⇔with the highest probability.")
   print(f"The true label is {labels[i]}.")
   print("-"*20)
```

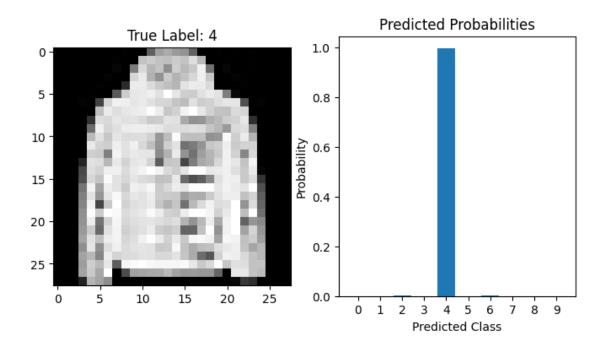
Using device: cuda



Observation for sample 1: The model predicts class 4 with the highest probability. The true label is 4.



Observation for sample 2: The model predicts class 2 with the highest probability. The true label is 2.



Observation for sample 3: The model predicts class 4 with the highest probability. The true label is 4.

Comment on these plots:

- 1. The training loss decreases gradually as the epoch increases.
- 2. From the loss curves, the training loss continues to decrease while the testing loss tends to level off, indicating that the model generalizes well on the test set.
- 3. On 3 randomly selected test images, we visualized the model's category probability distribution, showing its strong categorization ability.