Homework Assignment - 1

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OK, thus far we have been talking about linear models. All these can be viewed as a single-layer neural net. The next step is to move on to multi-layer nets. Training these is a bit more involved, and implementing from scratch requires time and effort. Instead, we just use well-established libraries. I prefer PyTorch, which is based on an earlier library called Torch (designed for training neural nets via backprop).

```
import numpy as np
import torch
import torchvision
```

Torch handles data types a bit differently. Everything in torch is a *tensor*.

```
a = np.random.rand(2,3)
b = torch.from_numpy(a)

# Q4.1 Display the contents of a, b
print('a: ',a)
print('b: ',b)
```

```
a:  [[0.85717764 0.62909467 0.46403862]
 [0.60939195 0.57009568 0.0865028 ]]
b:  tensor([[0.8572, 0.6291, 0.4640],
        [0.6094, 0.5701, 0.0865]], dtype=torch.float64)
```

The idea in Torch is that tensors allow for easy forward (function evaluations) and backward (gradient) passes.

```
A = torch.rand(2,2)
b = torch.rand(2,1)
x = torch.rand(2,1, requires_grad=True)

y = torch.matmul(A,x) + b

print(y)
z = y.sum()
print(z)
```

```
z.backward()
print(x.grad)
print(x)
```

```
tensor([[0.9474],
        [1.1385]], grad_fn=<AddBackward0>)
tensor(2.0859, grad_fn=<SumBackward0>)
tensor([[1.8082],
        [1.0379]])
tensor([[0.2059],
        [0.5857]], requires_grad=True)
```

Notice how the backward pass computed the gradients using autograd. OK, enough background. Time to train some networks. Let us load the *Fashion MNIST* dataset, which is a database of grayscale images of clothing items.

```
trainingdata = torchvision.datasets.FashionMNIST('./FashionMNIST/',train=True,downloac
testdata = torchvision.datasets.FashionMNIST('./FashionMNIST/',train=False,download=Tı
```

Let us examine the size of the dataset.

```
# Q4.2 How many training and testing data points are there in the dataset?
# What is the number of features in each data point?
print('Training Points: ',len(trainingdata))
print('Test Points: ',len(testdata))
print('Features in each Data Point: ',trainingdata[0][0].size())
```

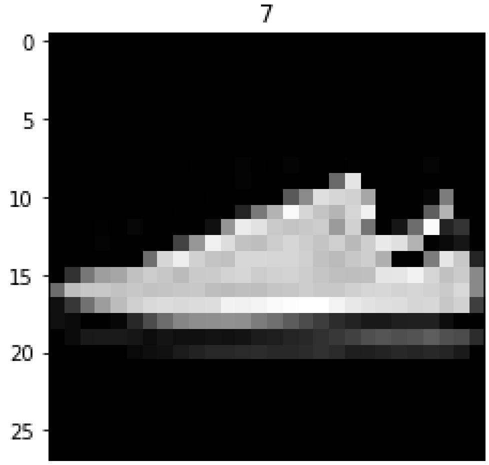
```
Training Points:  60000
Test Points:  10000
Features in each Data Point:  torch.Size([1, 28, 28])
```

Let us try to visualize some of the images. Since each data point is a tensor (not an array) we need to postprocess to use matplotlib.

```
import matplotlib.pyplot as plt
%matplotlib inline
import random

image, label = trainingdata[0]
# Q4.3 Assuming each sample is an image of size 28x28, show it in matplotlib.
idx = random.randint(0,9)
plt.imshow(trainingdata[idx][0][0].numpy(), cmap='gray')
plt.title('%i'% trainingdata[idx][1])
```

```
Text(0.5, 1.0, '7')
```

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import matplotlib.pyplot as plt
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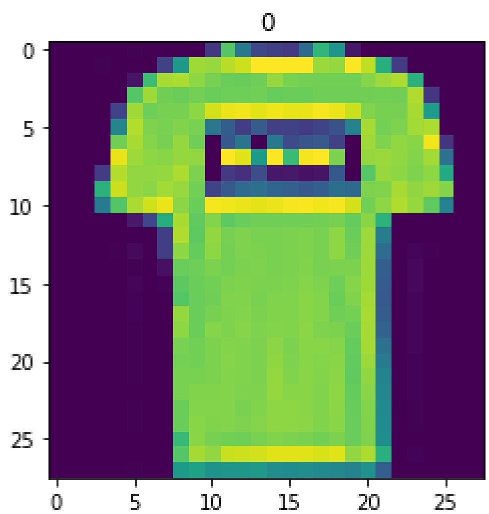
idx = random.randint(0,9)
plt.imshow(trainingdata[idx][0][0].numpy())
plt.title('%i'% trainingdata[idx][1])
```

```
Text(0.5, 1.0, '0')
```



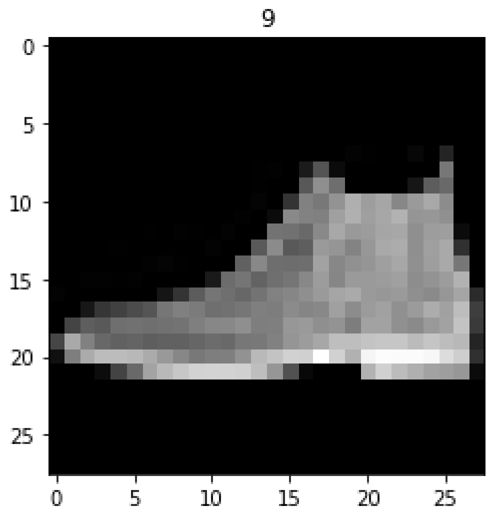
Let's try plotting several images. This is conveniently achieved in PyTorch using a *data loader*, which loads data in batches.

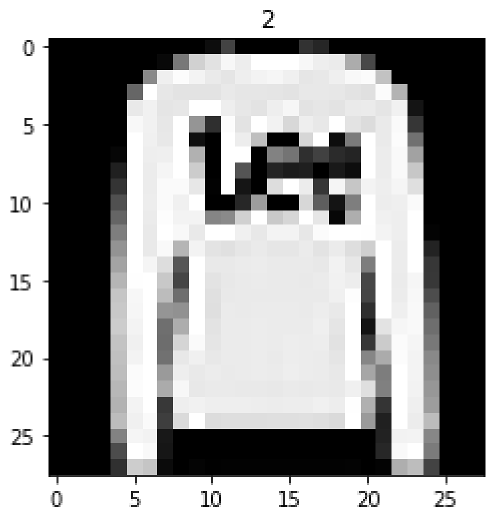
```
trainDataLoader = torch.utils.data.DataLoader(trainingdata, batch_size=64, shuffle=Tru
testDataLoader = torch.utils.data.DataLoader(testdata, batch_size=64, shuffle=False)
images, labels = iter(trainDataLoader).next()
print(images.size(), labels)
```

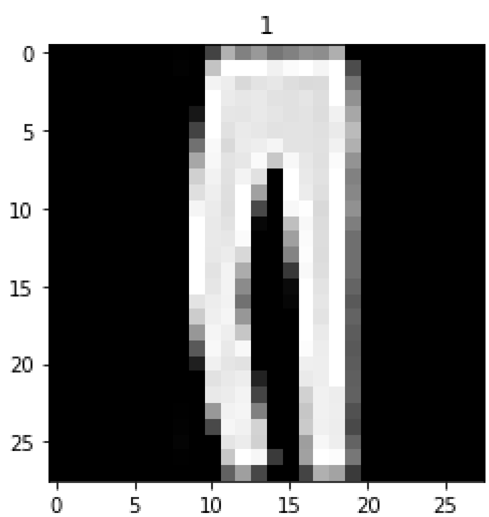
```
torch.Size([64, 1, 28, 28]) tensor([8, 5, 2, 3, 5, 4, 0, 8, 1, 0, 7, 6, 5, 0, 4,
        1, 6, 7, 5, 6, 9, 4, 3, 4, 2, 9, 5, 2, 8, 4, 0, 3, 3, 2, 0, 0, 8, 6, 5,
```

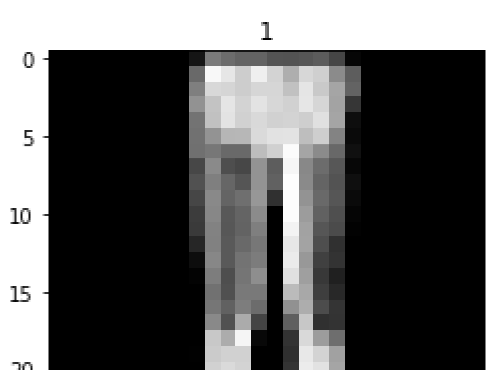
```
        6, 8, 2, 3, 2, 1, 4, 5, 6, 7, 0, 6, 6, 2, 2, 9])
```

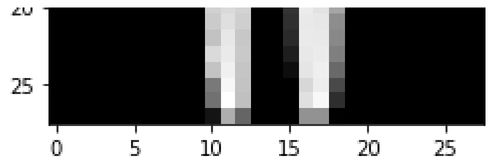
```
# Q4.4 Visualize the first 10 images of the first minibatch
# returned by testDataLoader.
images, labels = iter(testDataLoader).next()
for i in range(10):
  plt.imshow(images[i][0].numpy(), cmap='gray')
  plt.title('%i'% labels[i])
  plt.show()
```


9
0
5
10
15
20
25
0
5
10
15
20
25

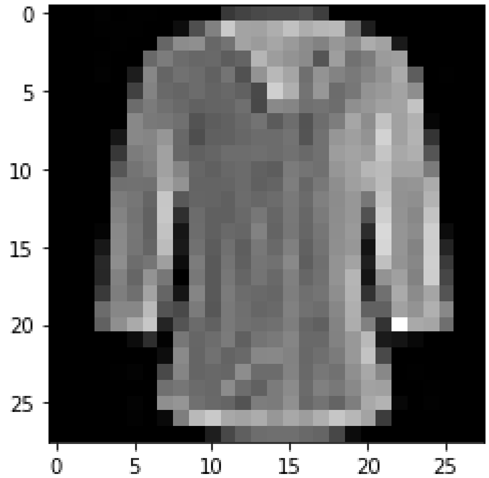

2
0
5
10
15
20
25
0
5
10
15
20
25


1
0
5
10
15
20
25
0
5
10
15
20
25

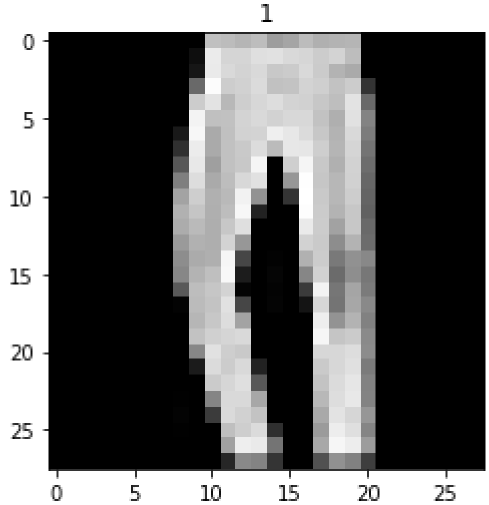

1
0
5
10
15



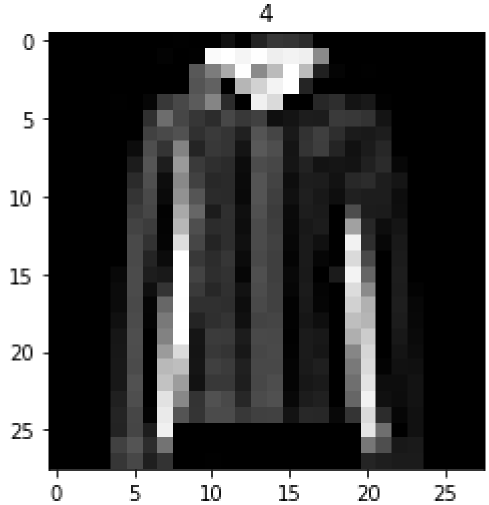
6



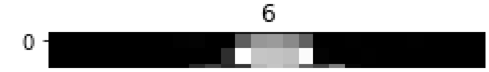
1



4

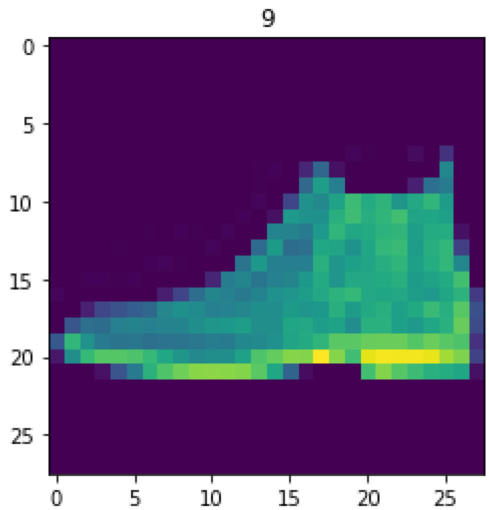


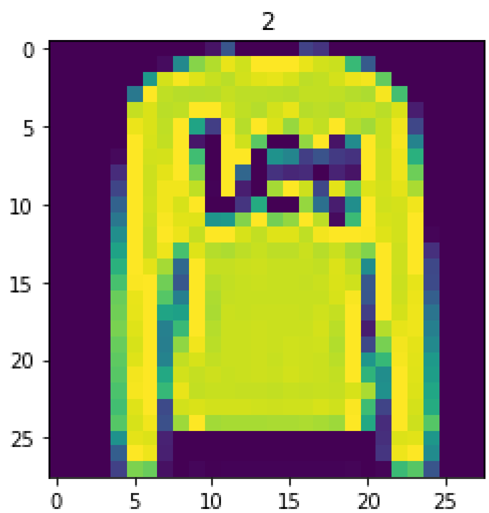
6

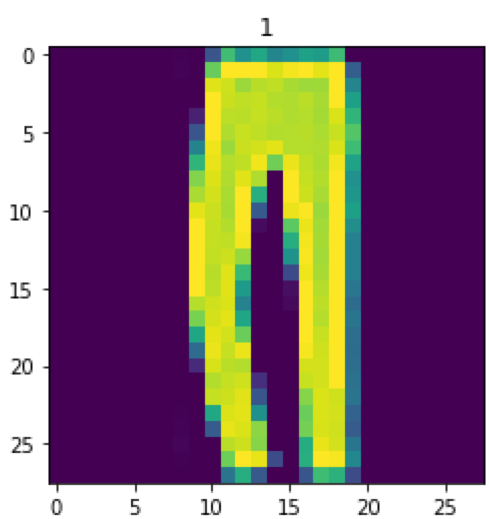


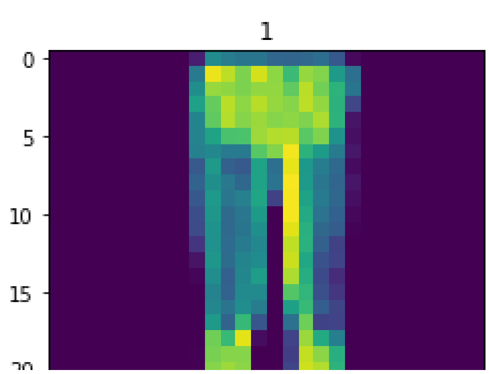

```
images, labels = iter(testDataLoader).next()
for i in range(10):
  plt.imshow(images[i][0].numpy())
```

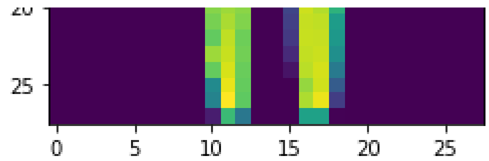
```
    plt.title('%i'% labels[i])
    plt.show()
```

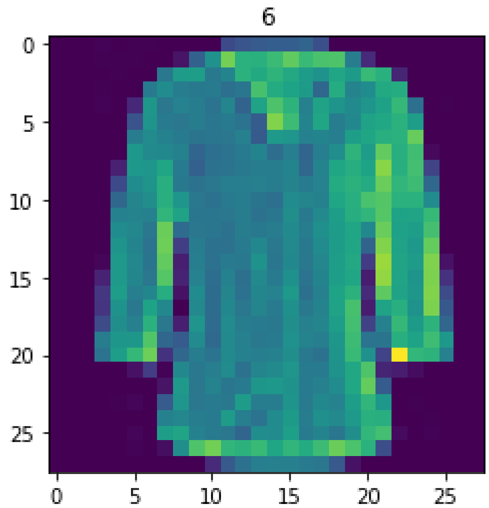

9

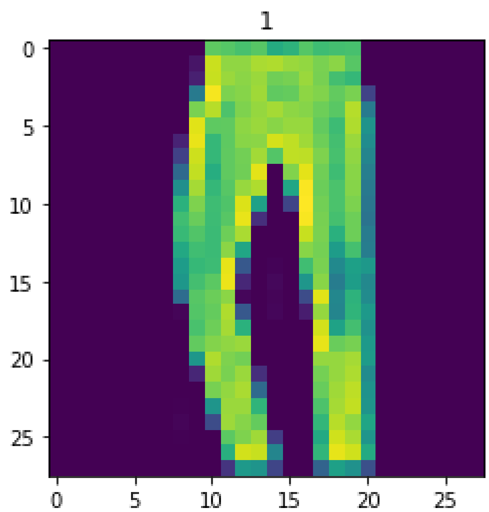

2

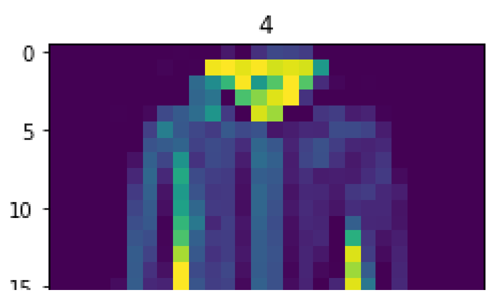

1


1









Now we are ready to define our linear model. Here is some boilerplate PyTorch code that implements the forward model for a single layer network for logistic regression (similar to the one discussed in class notes).

```
class LinearReg(torch.nn.Module):
  def __init__(self):
    super(LinearReg, self).__init__()
    self.linear = torch.nn.Linear(28*28,10)

  def forward(self, x):
```

```
        x = x.view(-1,28*28)
        transformed_x = self.linear(x)
        return transformed_x

net = LinearReg()
Loss = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(net.parameters(), lr=0.01)
```

Cool! Now we have set everything up. Let's try to train the network.

```
train_loss_history = []
test_loss_history = []

# Q4.5 Write down a for-loop that trains this network for 20 epochs,
# and print the train/test losses.
# Save them in the variables above. If done correctly, you should be able to
# execute the next code block.
x_train, y_train = iter(trainDataLoader).next()
x_test, y_test = iter(testDataLoader).next()

for epoch in range(20):
  for i,data in enumerate(trainDataLoader,0):
      X_train, Y_train = data
      optimizer.zero_grad()
      output = net(X_train)
      loss = Loss(output,Y_train)
      loss.backward()
      optimizer.step()

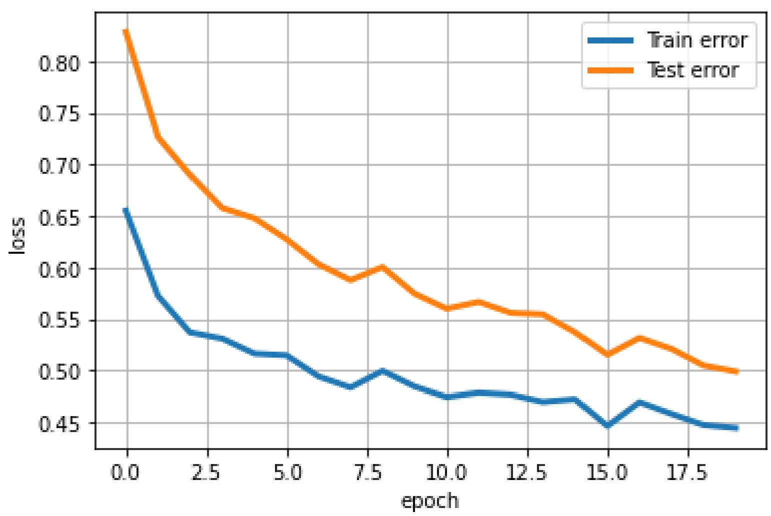
  train_loss = Loss(net(x_train),y_train)
  train_loss_history.append(train_loss)
  test_loss = Loss(net(x_test),y_test)
  test_loss_history.append(test_loss)
  print('Training Loss =',train_loss,'Testing Loss =',test_loss)
```

```
Training Loss = tensor(0.6553, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.5727, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.5369, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.5308, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.5163, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.5147, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4942, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4836, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4996, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4846, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4743, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4787, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4767, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4697, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4724, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4465, grad_fn=<NllLossBackward>) Testing Loss = tensor(
```

```
Training Loss = tensor(0.4695, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4581, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4474, grad_fn=<NllLossBackward>) Testing Loss = tensor(
Training Loss = tensor(0.4446, grad_fn=<NllLossBackward>) Testing Loss = tensor(
```

```
plt.plot(range(20),train_loss_history,'-',linewidth=3,label='Train error')
plt.plot(range(20),test_loss_history,'-',linewidth=3,label='Test error')
plt.xlabel('epoch')
plt.ylabel('loss')
plt.grid(True)
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f26943bd198>
```



Neat! Now let's evaluate our model accuracy on the entire dataset. The predicted class label for a given input image can computed by looking at the output of the neural network model and computing the index corresponding to the maximum activation. Something like

predicted_output = net(images) _, predicted_labels = torch.max(predicted_output,1)

```
predicted_output = net(images)
print(torch.max(predicted_output, 1))
fit = Loss(predicted_output, labels)
print(labels)
```

```
torch.return_types.max(
values=tensor([ 6.3237,  9.2878, 12.3574, 11.2712,  4.0627,  8.7971,  5.8120,  5
         2.3723,  6.8020,  5.5309,  4.4548,  4.8034,  7.6182,  8.0388,  8.1988,
         4.7154,  5.1468,  5.6541,  9.9059,  4.4855,  5.8125,  9.8484,  6.5423,
        11.3322,  3.7887,  7.2196,  6.7671,  7.8740,  4.8908, 10.3487,  5.0584,
         5.1107,  6.9286,  6.7489,  4.9269,  7.7297,  4.1808,  8.5116, 10.3495,
         8.7489, 12.2093,  4.7805,  8.7050,  8.2103,  3.8250,  6.5184,  8.4097,
         4.1752,  6.6815,  6.7731,  3.5929,  2.6959,  6.4896,  4.5608,  7.0841,
         8.3861,  6.3503,  7.4553,  4.8277,  8.3544,  7.9292,  7.8718,  4.6105],
       grad_fn=<MaxBackward0>),
indices=tensor([9, 2, 1, 1, 6, 1, 4, 6, 5, 7, 4, 5, 5, 3, 4, 1, 2, 6, 8, 0, 6, 7
```

```
            1, 2, 6, 0, 9, 3, 8, 8, 3, 3, 8, 0, 7, 5, 7, 9, 0, 1, 3, 9, 6, 7, 2, 1,
            2, 6, 6, 2, 5, 6, 2, 2, 8, 4, 8, 0, 7, 7, 8, 5]))
    tensor([9, 2, 1, 1, 6, 1, 4, 6, 5, 7, 4, 5, 7, 3, 4, 1, 2, 4, 8, 0, 2, 5, 7, 9,
            1, 4, 6, 0, 9, 3, 8, 8, 3, 3, 8, 0, 7, 5, 7, 9, 6, 1, 3, 7, 6, 7, 2, 1,
            2, 2, 4, 4, 5, 8, 2, 2, 8, 4, 8, 0, 7, 7, 8, 5])
```

```
def evaluate(dataloader):
  # Q4.6 Implement a function here that evaluates training and testing accuracy.
  # Here, accuracy is measured by probability of successful classification.
  # ...
  # ...
  correct = 0
  total = 0

  with torch.no_grad():
        for data in dataloader:
            images, labels = data

            outputs = net(images)
            _, predicted = torch.max(outputs.data, 1)

            total += labels.size(0)
            correct += (predicted == labels).sum().item()

  return 100 * correct / total

print('Train Accuracy = %0.2f, Test Accuracy = %0.2f' % (evaluate(trainDataLoader), ev
```

```
    Train Accuracy = 84.92, Test Accuracy = 83.28
```