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).

In [ ]:
```
import numpy as np
import torch
import torchvision
```

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

In [ ]:
```
a = np.random.rand(2,3)
b = torch.from_numpy(a)

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

```
contest of a:  [[0.816508   0.75597224 0.67269371]
 [0.38200301 0.06110529 0.70656539]]
contest of b:  tensor([[0.8165, 0.7560, 0.6727],
        [0.3820, 0.0611, 0.7066]], dtype=torch.float64)
```

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

In [ ]:
```
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([[0.9157],
        [1.3327]], grad_fn=<AddBackward0>)
tensor(2.2484, grad_fn=<SumBackward0>)
tensor([[0.7845],
        [1.7336]])
tensor([[0.1465],
        [0.9142]], 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.

In [ ]:
```
trainingdata = torchvision.datasets.FashionMNIST('./FashionMNIST/',train=True,download=True,transform
=torchvision.transforms.ToTensor())
testdata = torchvision.datasets.FashionMNIST('./FashionMNIST/',train=False,download=True,transform=to
rchvision.transforms.ToTensor())
```

```
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


Extracting ./FashionMNIST/FashionMNIST/raw/train-images-idx3-ubyte.gz to ./FashionMNIST/FashionMNIS
T/raw
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


Extracting ./FashionMNIST/FashionMNIST/raw/train-labels-idx1-ubyte.gz to ./FashionMNIST/FashionMNIS
T/raw
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


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


Extracting ./FashionMNIST/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to ./FashionMNIST/FashionMNIST/
raw
Processing...
Done!

/usr/local/lib/python3.6/dist-packages/torchvision/datasets/mnist.py:469: UserWarning: The given Num
Py array is not writeable, and PyTorch does not support non-writeable tensors. This means you can wr
ite to the underlying (supposedly non-writeable) NumPy array using the tensor. You may want to copy
the array to protect its data or make it writeable before converting it to a tensor. This type of wa
rning will be suppressed for the rest of this program. (Triggered internally at  /pytorch/torch/csr
c/utils/tensor_numpy.cpp:141.)
  return torch.from_numpy(parsed.astype(m[2], copy=False)).view(*s)
```

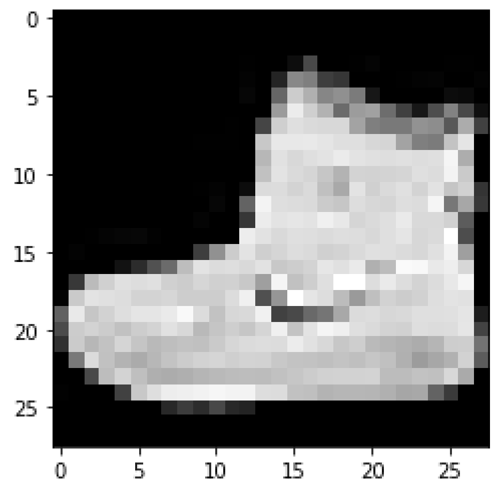
Let us examine the size of the dataset.

```
In [ ]: # Q4.2 How many training and testing data points are there in the dataset?
        # What is the number of features in each data point?

        # There are 60000 training data points and 10000 testing data points in the dataset
        # For each data point, we have the image data and the actual label for this image.
        # The data size of each image is 1*28*28
        # '1' means each pixel only has one channel, that's grayscale value
        #'28*28' means the width and height of each image are both 28 pixels,
        # that means each image has 28*28=784 pixels
        print("the number of traning data points: ", len(trainingdata))
        print("the number of testing data points: ", len(testdata))
        print("the size of each data point vector: ", len(trainingdata[0]))
        print("the size of each image data: ", trainingdata[0][0].size())
        print("label for each data is", type(trainingdata[0][1]))
```

```
the number of traning data points:  60000
the number of testing data points:  10000
the size of each data point vector:  2
the size of each image data:  torch.Size([1, 28, 28])
label for each data is <class 'int'>
```

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.

In [ ]:
```
import matplotlib.pyplot as plt
%matplotlib inline

image, label = trainingdata[0]
# Q4.3 Assuming each sample is an image of size 28x28, show it in matplotlib.
plt.figure()
plt.imshow(image[0], cmap='gray')
plt.show()
```



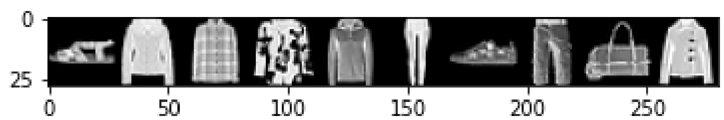
Let's try plotting several images. This is conveniently achieved in PyTorch using a *data loader*, which loads data in batches.

In [ ]:
```
trainDataLoader = torch.utils.data.DataLoader(trainingdata, batch_size=64, shuffle=True)
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([5, 4, 6, 6, 2, 1, 7, 1, 8, 4, 8, 8, 1, 6, 8, 8, 0, 8, 7, 4, 2,
9, 0, 7,
        2, 2, 1, 3, 8, 2, 2, 4, 0, 1, 4, 5, 3, 3, 2, 5, 5, 7, 3, 6, 4, 1, 5, 2,
        4, 7, 1, 0, 7, 1, 4, 6, 5, 0, 2, 6, 2, 7, 2, 6])
```

In [ ]:
```
# Q4.4 Visualize the first 10 images of the first minibatch
# returned by testDataLoader.

first_ten_images = images[:10, 0,...].numpy()
row = np.concatenate([first_ten_images[i] for i in range(10)], axis=1)
plt.figure()
print("Showing the 10 images in one row:")
plt.imshow(row, cmap='gray')
plt.show()
```

```
Showing the 10 images in one row:
```



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).

In [ ]:
```
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().cuda()
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.

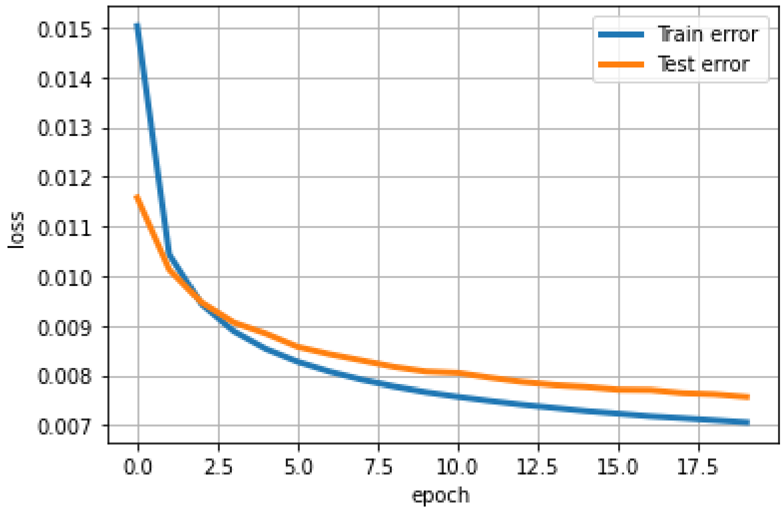
In [ ]:
```
train_loss_history = []
test_loss_history = []

# Q4.5 Write down a for-loop that trains this network for 20 minibatch iterations,
# 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.

#Initiate network
net = LinearReg().cuda()
Loss = torch.nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(net.parameters(), lr=0.01)

num_of_epochs = 20

for i in range(num_of_epochs):
  #shuffle training data
  trainDataLoader = torch.utils.data.DataLoader(trainingdata, batch_size=64, shuffle=True)

  #train the net with each minibatch
  epoch_train_loss = 0
  for images, labels in trainDataLoader:
    optimizer.zero_grad()
    # calculate train loss of the current minibatch
    preds = net(images.cuda())
    batch_images_loss = Loss(preds, labels.cuda())
    epoch_train_loss += batch_images_loss

    #optimize the network
    batch_images_loss.backward()
    optimizer.step()

  # calculate train loss for the epoch
  epoch_train_loss /= len(trainingdata)
  train_loss_history.append(epoch_train_loss)

  # test the net with each minibatch
  epoch_test_loss = 0
  for images, labels in testDataLoader:
    preds = net(images.cuda())
    batch_images_loss = Loss(preds, labels.cuda())
    epoch_test_loss += batch_images_loss
```

```
    # calculate test loss for the epoch
    epoch_test_loss /= len(testdata)
    test_loss_history.append(epoch_test_loss)

    print('Epoch: {}, Train Loss: {}, Test Loss: {}'.format(i, epoch_train_loss, epoch_test_loss))
```

```
Epoch: 0, Train Loss: 0.01502606924623251, Test Loss: 0.011578425765037537
Epoch: 1, Train Loss: 0.010432981885969639, Test Loss: 0.010125137865543365
Epoch: 2, Train Loss: 0.009428427554666996, Test Loss: 0.009466097690165043
Epoch: 3, Train Loss: 0.008885594084858894, Test Loss: 0.00906306505203247
Epoch: 4, Train Loss: 0.008530200459063053, Test Loss: 0.008839458227157593
Epoch: 5, Train Loss: 0.008271351456642151, Test Loss: 0.008571295067667961
Epoch: 6, Train Loss: 0.00807273667305708, Test Loss: 0.00842297449707985
Epoch: 7, Train Loss: 0.007911734282970428, Test Loss: 0.008297959342598915
Epoch: 8, Train Loss: 0.007779350504279137, Test Loss: 0.008169146254658699
Epoch: 9, Train Loss: 0.007666518911719322, Test Loss: 0.00807636696845293
Epoch: 10, Train Loss: 0.007574894465506077, Test Loss: 0.008048789575695992
Epoch: 11, Train Loss: 0.007492510136216879, Test Loss: 0.007952781394124031
Epoch: 12, Train Loss: 0.007416723761707544, Test Loss: 0.007868158631026745
Epoch: 13, Train Loss: 0.0073526217602193356, Test Loss: 0.0078074736520648
Epoch: 14, Train Loss: 0.007288788910955191, Test Loss: 0.007769959978759289
Epoch: 15, Train Loss: 0.007235296536237001, Test Loss: 0.007714950945228338
Epoch: 16, Train Loss: 0.0071831876412034035, Test Loss: 0.0077091665007174015
Epoch: 17, Train Loss: 0.007145352195948362, Test Loss: 0.007648747880011797
Epoch: 18, Train Loss: 0.007103899493813515, Test Loss: 0.007626079488545656
Epoch: 19, Train Loss: 0.007061449345201254, Test Loss: 0.007573876064270735
```

In [ ]:
```
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()
```

Out[ ]: <matplotlib.legend.Legend at 0x7f243392e710>



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)

In [ ]:
```
predicted_output = net(images.cuda())
print(torch.max(predicted_output, 1))
fit = Loss(predicted_output, labels.cuda())
print(labels)
```

```
torch.return_types.max(
values=tensor([ 6.1149,  2.9275,  8.9590,  7.8504,  6.6379,  6.2165, 10.2046,  4.3740,
         7.0905, 11.6778, 10.4770, 10.4350,  6.6251,  4.7262,  9.3121,  4.5606],
       device='cuda:0', grad_fn=<MaxBackward0>),
indices=tensor([3, 1, 7, 5, 8, 2, 5, 6, 8, 9, 1, 9, 1, 8, 1, 5], device='cuda:0'))
tensor([3, 2, 7, 5, 8, 4, 5, 6, 8, 9, 1, 9, 1, 8, 1, 5])
```

In [ ]:
```
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_pred = 0
  num_of_all_images = 0
  for images,labels in dataloader:
    predicted_output = net(images.cuda())
    _, predicted_labels = torch.max(predicted_output,1)
    preds_diff = labels - predicted_labels.cpu()
    correct_pred += int((preds_diff==0).sum())
    num_of_all_images += len(images)
  return correct_pred/num_of_all_images


print('Train acc = %0.2f, test acc = %0.2f' % (evaluate(trainDataLoader), evaluate(testDataLoader)))
```

```
Train acc = 0.85, test acc = 0.83
```