Problem 2 Sample Code

This sample code is meant as a guide on how to use PyTorch and how to use the relevant model layers. This not a guide on how to design a network and the network in this example is intentionally designed to have poor performace.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

import torch
import torch.nn as nn
import torch.nn.functional as F
from torchvision import datasets, transforms
```

Loading MNIST

The `torchvision` module contains links to many standard datasets. We can load the MNIST dataset into a `Dataset` object as follows:

In [2]:
```
train_dataset = datasets.MNIST('./data', train=True, download=True,  # Downloads i
nto a directory ../data
                               transform=transforms.ToTensor())
test_dataset = datasets.MNIST('./data', train=False, download=False,  # No need to
download again
                              transform=transforms.ToTensor())
```

```
0.0%

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

100.1%

Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw

28.4%

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to ./dat
a/MNIST/raw/train-labels-idx1-ubyte.gz

0.5%5%

Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to ./data
/MNIST/raw/t10k-images-idx3-ubyte.gz

180.4%

Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to ./data
/MNIST/raw/t10k-labels-idx1-ubyte.gz
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
Processing...
Done!
```

The `Dataset` object is an iterable where each element is a tuple of (input `Tensor`, target):

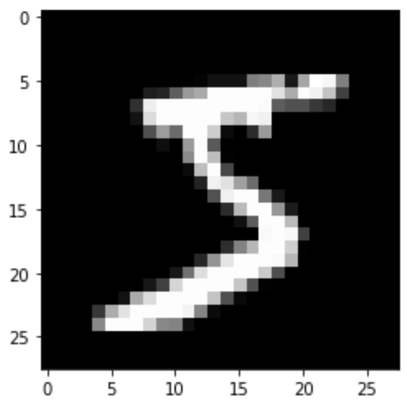
```
In [3]: print(len(train_dataset), type(train_dataset[0][0]), type(train_dataset[0][1]))
```

```
60000 <class 'torch.Tensor'> <class 'int'>
```

We can convert images to numpy arrays and plot them with matplotlib:

```
In [4]: plt.imshow(train_dataset[0][0][0].numpy(), cmap='gray')
```

```
Out[4]: <matplotlib.image.AxesImage at 0x10787c910>
```



Network Definition

Let's instantiate a model and take a look at the layers.

In [74]:
```
model = nn.Sequential(
    # In problem 2, we don't use the 2D structure of an image at all. Our network
    # takes in a flat vector of the pixel values as input.
    nn.Flatten(),
    nn.Linear(784, 500),
    nn.ReLU(),
    nn.Linear(500, 250),
    nn.ReLU(),
    nn.Linear(250, 150),
    nn.ReLU(),
    nn.Linear(150, 100),
    nn.ReLU(),
    nn.Linear(100, 10),
    nn.LogSoftmax(dim=1)
)
print(model)
```

```
Sequential(
  (0): Flatten()
  (1): Linear(in_features=784, out_features=500, bias=True)
  (2): ReLU()
  (3): Linear(in_features=500, out_features=250, bias=True)
  (4): ReLU()
  (5): Linear(in_features=250, out_features=150, bias=True)
  (6): ReLU()
  (7): Linear(in_features=150, out_features=100, bias=True)
  (8): ReLU()
  (9): Linear(in_features=100, out_features=10, bias=True)
  (10): LogSoftmax()
)
```

Training

We also choose an optimizer and a loss function.

In [75]:
```
optimizer = torch.optim.Adam(model.parameters(), lr=1e-3)
loss_fn = nn.CrossEntropyLoss()
```

We could write our training procedure manually and directly index the `Dataset` objects, but the `DataLoader` object conveniently creates an iterable for automatically creating random minibatches:

In [76]:
```
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=32, shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=32, shuffle=True)
```

We now write our backpropagation loop, training for 10 epochs.

In [79]:
```
# Some layers, such as Dropout, behave differently during training
model.train()

for epoch in range(30):
    for batch_idx, (data, target) in enumerate(train_loader):
        # Erase accumulated gradients
        optimizer.zero_grad()

        # Forward pass
        output = model(data)

        # Calculate loss
        loss = loss_fn(output, target)

        # Backward pass
        loss.backward()

        # Weight update
        optimizer.step()

    # Track loss each epoch
    print('Train Epoch: %d  Loss: %.4f' % (epoch + 1,  loss.item()))
```

```
Train Epoch: 1  Loss: 0.0016
Train Epoch: 2  Loss: 0.0074
Train Epoch: 3  Loss: 0.0018
Train Epoch: 4  Loss: 0.0002
Train Epoch: 5  Loss: 0.0000
Train Epoch: 6  Loss: 0.0000
Train Epoch: 7  Loss: 0.0002
Train Epoch: 8  Loss: 0.0663
Train Epoch: 9  Loss: 0.0002
Train Epoch: 10  Loss: 0.0637
Train Epoch: 11  Loss: 0.0004
Train Epoch: 12  Loss: 0.0003
Train Epoch: 13  Loss: 0.0049
Train Epoch: 14  Loss: 0.0010
Train Epoch: 15  Loss: 0.0000
Train Epoch: 16  Loss: 0.0004
Train Epoch: 17  Loss: 0.0000
Train Epoch: 18  Loss: 0.0001
Train Epoch: 19  Loss: 0.2435
Train Epoch: 20  Loss: 0.0000
Train Epoch: 21  Loss: 0.0081
Train Epoch: 22  Loss: 0.0000
Train Epoch: 23  Loss: 0.0071
Train Epoch: 24  Loss: 0.0100
Train Epoch: 25  Loss: 0.0000
Train Epoch: 26  Loss: 0.0002
Train Epoch: 27  Loss: 0.0000
Train Epoch: 28  Loss: 0.0000
Train Epoch: 29  Loss: 0.0000
Train Epoch: 30  Loss: 0.0000
```

Testing

We can perform forward passes through the network without saving gradients.

In [80]:
```
# Putting layers like Dropout into evaluation mode
model.eval()

test_loss = 0
correct = 0

# Turning off automatic differentiation
with torch.no_grad():
    for data, target in test_loader:
        output = model(data)
        test_loss += loss_fn(output, target).item()  # Sum up batch loss
        pred = output.argmax(dim=1, keepdim=True)  # Get the index of the max clas
s score
        correct += pred.eq(target.view_as(pred)).sum().item()

test_loss /= len(test_loader.dataset)

print('Test set: Average loss: %.4f, Accuracy: %d/%d (%.4f)' %
      (test_loss, correct, len(test_loader.dataset),
       100. * correct / len(test_loader.dataset)))
```

```
Test set: Average loss: 0.0074, Accuracy: 9840/10000 (98.4000)
```

In [ ]:

In [ ]: