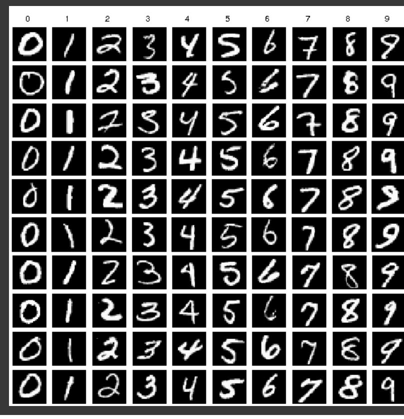
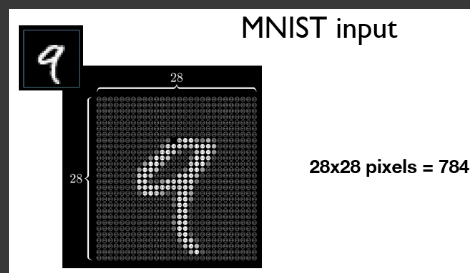
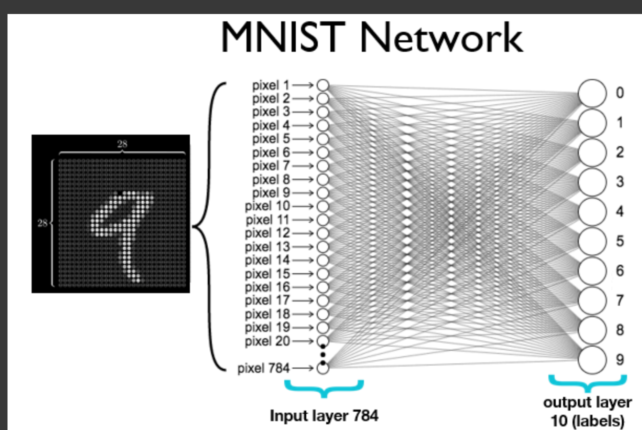
MNIST Digit Recognizer (Neural Network)





One Layer FNN with Sigmoid Activation

```
import torch
import torch.nn as nn
import torchvision.transforms as transforms
import torchvision.datasets as dsets
```



- Our input size is determined by the size of the image **(height x width) = (28X28)**. Hence the size of our input is **784 (28 x 28)**.
- When we pass an image to our model, it will try to predict if it's **0, 1, 2, 3, 4, 5, 6, 7, 8, or 9**. That is a total of 10 classes, hence we have an output size of 10.
- Determining the **hidden layer size** is one of the crutial part. The first layer prior to the non-linear layer. This can be any **real number**. A large number of hidden nodes denotes a **bigger model with more parameters**.
- The bigger model isn't **always the better model**. On the otner hand, bigger model requires **more training samples** to learn and converge to a good model.
- Actually a bigger model **requires more training samples** to learn and converge to a good model. Hence, it is wise to pick the model size for the problem at hand. Because it is a simple problem of recognizing digits, we typically would not need a big model to achieve good results.

- Moreover, too small of a hidden size would mean there would be **insufficient model capacity to predict competently**. Too small of a capacity denotes a **smaller brain capacity** so no matter how many training samples you provide, it has a maximum capacity boundary in terms of its **predictive power**.

- **Input dimension:**
  - Size of image: $28 \times 28 = 784$
- **Output dimension: 10**
  - 0, 1, 2, 3, 4, 5, 6, 7, 8, 9

```
# Hyperparameters

batch_size = 100
num_iters = 3000
input_dim = 28*28 # num_features = 784
num_hidden = 100 # num of hidden nodes
output_dim = 10

learning_rate = 0.1  # More power so we can learn faster! previously it was 0.001

# Device
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
```

Loading MNIST Dataset

```
'''
LOADING DATASET
'''
train_dataset = dsets.MNIST(root='./data',
                            train=True,
                            transform=transforms.ToTensor(),  # Normalize the image to [0-1] from [0-255]
                            download=True)

test_dataset = dsets.MNIST(root='./data',
                           train=False,
                           transform=transforms.ToTensor())

'''
MAKING DATASET ITERABLE
'''
num_epochs = num_iters / (len(train_dataset) / batch_size)
num_epochs = int(num_epochs)

train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_size,
                                           shuffle=True)   # It's better to shuffle the whole training dataset!

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                          batch_size=batch_size,
                                          shuffle=False)
```

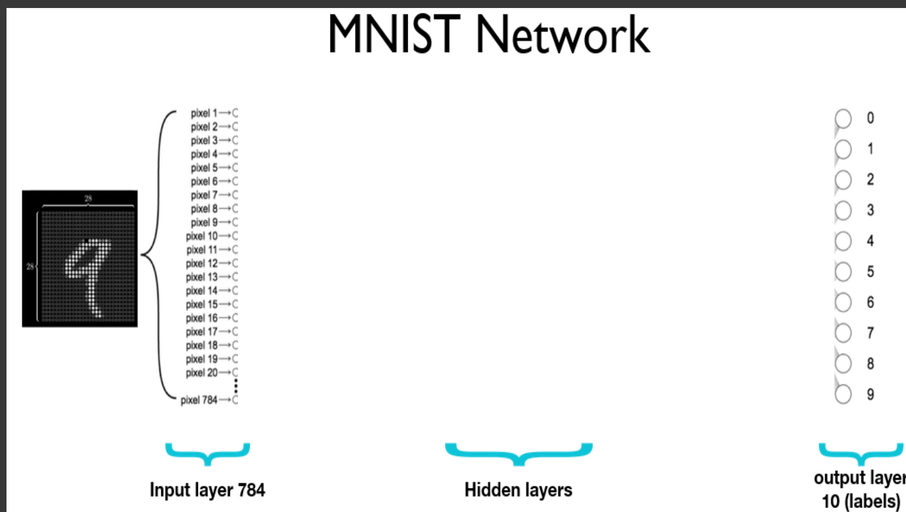
```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz to ./data/MNIST/raw/train-images-idx3-ubyte.gz
9920512/? [00:20<00:00, 1332586.75it/s]
Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw
Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz to ./data/MNIST/raw/train-labels-idx1-ubyte.gz
0% 0/28881 [00:00<?, ?it/s]
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
1654784/? [00:18<00:00, 1026194.01it/s]
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
0% 0/4542 [00:00<?, ?it/s]
Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/raw
Processing...
Done!
/pytorch/torch/csrc/utils/tensor_numpy.cpp:141: UserWarning: The given NumPy array is not writeable, and PyTorch does not support non-wr
```

```
print(len(train_dataset))
print(len(test_dataset))
```

```
60000
10000
```

```
# One Image Size
print(train_dataset[0][0].size())
print(train_dataset[0][0].numpy().shape)
# First Image Label
print(train_dataset[0][1])
```

```
torch.Size([1, 28, 28])
(1, 28, 28)
5
```



Step #1 : Design your model using class

```
class NeuralNetworkModel(nn.Module):
    def __init__(self, input_size, num_classes, num_hidden):
        super().__init__()
        ### 1st hidden layer
        self.linear_1 = nn.Linear(input_size, num_hidden)

        ### Non-linearity
        self.sigmoid = nn.Sigmoid()

        ### Output layer
        self.linear_out = nn.Linear(num_hidden, num_classes)

    def forward(self, x):
        # Linear layer
        out  = self.linear_1(x)
        # Non-linearity
        out = self.sigmoid(out)
        # Linear layer (output)
        logits  = self.linear_out(out)
        return logits
```

```
'''
INSTANTIATE MODEL CLASS
'''
model = NeuralNetworkModel(input_size = input_dim,
                           num_classes = output_dim,
                           num_hidden = num_hidden)
# To enable GPU
model.to(device)
```

```
NeuralNetworkModel(
  (linear_1): Linear(in_features=784, out_features=100, bias=True)
  (sigmoid): Sigmoid()
  (linear_out): Linear(in_features=100, out_features=10, bias=True)
)
```

Step #2 : Construct loss and optimizer

Unlike linear regression, we do not use MSE here, we need Cross Entropy Loss to calculate our loss before we backpropagate and update our parameters.

`criterion = nn.CrossEntropyLoss()`

It does 2 things at the same time.

1. Computes softmax ([Logistic or Sigmoid]/softmax function)
2. Computes Cross Entropy Loss

```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)
```

Step #3 : Training: forward, loss, backward, step

```
'''
TRAIN THE MODEL
'''
iter = 0
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):

        images = images.view(-1, 28*28).to(device)
        labels = labels.to(device)

        # Clear gradients w.r.t. parameters
        optimizer.zero_grad()

        # Forward pass to get output/logits
        outputs = model(images)

        # Calculate Loss: softmax --> cross entropy loss
        loss = criterion(outputs, labels)

        # Getting gradients w.r.t. parameters
        loss.backward()

        # Updating parameters
        optimizer.step()

        iter += 1

        if iter % 500 == 0:
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:

                images = images.view(-1, 28*28).to(device)

                # Forward pass only to get logits/output
                outputs = model(images)

                # Get predictions from the maximum value
                _, predicted = torch.max(outputs, 1)

                # Total number of labels
                total += labels.size(0)


                # Total correct predictions
                if torch.cuda.is_available():
                    correct += (predicted.cpu() == labels.cpu()).sum()
                else:
                    correct += (predicted == labels).sum()

            accuracy = 100 * correct.item() / total

            # Print Loss
            print('Iteration: {}. Loss: {}. Accuracy: {}'.format(iter, loss.item(), accuracy))
```

```
Iteration: 500. Loss: 0.6597447991371155. Accuracy: 86.5
Iteration: 1000. Loss: 0.41724541783332825. Accuracy: 89.48
Iteration: 1500. Loss: 0.4041314721107483. Accuracy: 90.35
Iteration: 2000. Loss: 0.3359662592411041. Accuracy: 90.97
Iteration: 2500. Loss: 0.22867584228515625. Accuracy: 91.64
Iteration: 3000. Loss: 0.24442128837108612. Accuracy: 91.95
```

Expanding Neural Network variants

2 ways to expand a neural network

- Different non-linear activation
- More hidden layers

One Layer FNN with Tanh Activation

```
import torch
import torch.nn as nn
import torchvision.transforms as transforms
import torchvision.datasets as dsets

# Hyperparameters
batch_size = 100
num_iters = 3000
input_dim = 28*28 # num_features = 784
num_hidden = 100
output_dim = 10

learning_rate = 0.1

# Device
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")


train_dataset = dsets.MNIST(root='./data',
                            train=True,
                            transform=transforms.ToTensor(),  # Normalize the image to [0-1] from [0-255]
                            download=True)

test_dataset = dsets.MNIST(root='./data',
                           train=False,
                           transform=transforms.ToTensor())


num_epochs = num_iters / (len(train_dataset) / batch_size)
num_epochs = int(num_epochs)

train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_size,
                                           shuffle=True)   # It's better to shuffle the whole training dataset!

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                          batch_size=batch_size,
                                          shuffle=False)

class NeuralNetworkModel(nn.Module):
    def __init__(self, input_size, num_classes, num_hidden):
        super().__init__()
        ### 1st hidden layer
        self.linear_1 = nn.Linear(input_size, num_hidden)

        ### Non-linearity
        self.tanh = nn.Tanh()

        ### Output layer
        self.linear_out = nn.Linear(num_hidden, num_classes)

    def forward(self, x):
        # Linear layer
        out  = self.linear_1(x)
        # Non-linearity
        out = self.tanh(out)
        # Linear layer (output)
        probas  = self.linear_out(out)
        return probas

model = NeuralNetworkModel(input_size = input_dim,
                           num_classes = output_dim,
                           num_hidden = num_hidden)
# To enable GPU
model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

iter = 0
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):

        images = images.view(-1, 28*28).to(device)
        labels = labels.to(device)

        # Clear gradients w.r.t. parameters
```

```
        optimizer.zero_grad()

        # Forward pass to get output/logits
        outputs = model(images)

        # Calculate Loss: softmax --> cross entropy loss
        loss = criterion(outputs, labels)

        # Getting gradients w.r.t. parameters
        loss.backward()

        # Updating parameters
        optimizer.step()

        iter += 1

        if iter % 500 == 0:
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:

                images = images.view(-1, 28*28).to(device)

                # Forward pass only to get logits/output
                outputs = model(images)

                # Get predictions from the maximum value
                _, predicted = torch.max(outputs, 1)

                # Total number of labels
                total += labels.size(0)


                # Total correct predictions
                if torch.cuda.is_available():
                    correct += (predicted.cpu() == labels.cpu()).sum()
                else:
                    correct += (predicted == labels).sum()

            accuracy = 100 * correct.item() / total

            # Print Loss
            print('Iteration: {}. Loss: {}. Accuracy: {}'.format(iter, loss.item(), accuracy))
```

```
Iteration: 500. Loss: 0.21413597464561462. Accuracy: 90.9
Iteration: 1000. Loss: 0.3538866341114044. Accuracy: 92.31
Iteration: 1500. Loss: 0.15589021146297455. Accuracy: 93.24
Iteration: 2000. Loss: 0.3556366264820099. Accuracy: 93.98
Iteration: 2500. Loss: 0.2028314620256424. Accuracy: 94.64
Iteration: 3000. Loss: 0.333248496055603. Accuracy: 95.05
```

One Layer FNN with ReLU Activation

```
import torch
import torch.nn as nn
import torchvision.transforms as transforms
import torchvision.datasets as dsets

# Hyperparameters
batch_size = 100
num_iters = 3000
input_dim = 28*28 # num_features = 784
num_hidden = 100
output_dim = 10

learning_rate = 0.1

# Device
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")


train_dataset = dsets.MNIST(root='./data',
                            train=True,
                            transform=transforms.ToTensor(),  # Normalize the image to [0-1] from [0-255]
                            download=True)

test_dataset = dsets.MNIST(root='./data',
                           train=False,
                           transform=transforms.ToTensor())


num_epochs = num_iters / (len(train_dataset) / batch_size)
num_epochs = int(num_epochs)

train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_size,
                                           shuffle=True)   # It's better to shuffle the whole training dataset!

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                          batch_size=batch_size,
                                          shuffle=False)

class NeuralNetworkModel(nn.Module):
    def __init__(self, input_size, num_classes, num_hidden):
        super().__init__()
        ### 1st hidden layer
        self.linear_1 = nn.Linear(input_size, num_hidden)

        ### Non-linearity
        self.relu = nn.ReLU()

        ### Output layer
        self.linear_out = nn.Linear(num_hidden, num_classes)

    def forward(self, x):
        # Linear layer
        out  = self.linear_1(x)
        # Non-linearity
        out = self.relu(out)
        # Linear layer (output)
        probas  = self.linear_out(out)
        return probas

model = NeuralNetworkModel(input_size = input_dim,
                           num_classes = output_dim,
                           num_hidden = num_hidden)
# To enable GPU
model.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

iter = 0
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):

        images = images.view(-1, 28*28).to(device)
        labels = labels.to(device)

        # Clear gradients w.r.t. parameters
```

```
        optimizer.zero_grad()

        # Forward pass to get output/logits
        outputs = model(images)

        # Calculate Loss: softmax --> cross entropy loss
        loss = criterion(outputs, labels)

        # Getting gradients w.r.t. parameters
        loss.backward()

        # Updating parameters
        optimizer.step()

        iter += 1

        if iter % 500 == 0:
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:

                images = images.view(-1, 28*28).to(device)

                # Forward pass only to get logits/output
                outputs = model(images)

                # Get predictions from the maximum value
                _, predicted = torch.max(outputs, 1)

                # Total number of labels
                total += labels.size(0)


                # Total correct predictions
                if torch.cuda.is_available():
                    correct += (predicted.cpu() == labels.cpu()).sum()
                else:
                    correct += (predicted == labels).sum()

            accuracy = 100 * correct.item() / total

            # Print Loss
            print('Iteration: {}. Loss: {}. Accuracy: {}'.format(iter, loss.item(), accuracy))
```

```
Iteration: 500. Loss: 0.18737341463565826. Accuracy: 91.48
Iteration: 1000. Loss: 0.3523785471916199. Accuracy: 93.14
Iteration: 1500. Loss: 0.22952955961227417. Accuracy: 93.83
Iteration: 2000. Loss: 0.09236818552017212. Accuracy: 94.86
Iteration: 2500. Loss: 0.262081503868103. Accuracy: 95.21
Iteration: 3000. Loss: 0.14769437909126282. Accuracy: 95.89
```

Two Layer FNN with ReLU Activation

```
import torch
import torch.nn as nn
import torchvision.transforms as transforms
import torchvision.datasets as dsets

# Hyperparameters
batch_size = 100
num_iters = 3000
input_dim = 28*28 # num_features = 784
num_hidden = 100
output_dim = 10

learning_rate = 0.1

# Device
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")


train_dataset = dsets.MNIST(root='./data',
                            train=True,
                            transform=transforms.ToTensor(),  # Normalize the image to [0-1] from [0-255]
                            download=True)

test_dataset = dsets.MNIST(root='./data',
                           train=False,
                           transform=transforms.ToTensor())


num_epochs = num_iters / (len(train_dataset) / batch_size)
num_epochs = int(num_epochs)

train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_size,
                                           shuffle=True)   # It's better to shuffle the whole training dataset!

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                          batch_size=batch_size,
                                          shuffle=False)

class DeepNeuralNetworkModel(nn.Module):
    def __init__(self, input_size, num_classes, num_hidden):
        super().__init__()
        ### 1st hidden layer: 784 --> 100
        self.linear_1 = nn.Linear(input_size, num_hidden)
        ### Non-linearity in 1st hidden layer
        self.relu_1 = nn.ReLU()

        ### 2nd hidden layer: 100 --> 100
        self.linear_2 = nn.Linear(num_hidden, num_hidden)
        ### Non-linearity in 2nd hidden layer
        self.relu_2 = nn.ReLU()

        ### Output layer: 100 --> 10
        self.linear_out = nn.Linear(num_hidden, num_classes)

    def forward(self, x):
        ### 1st hidden layer
        out  = self.linear_1(x)
        ### Non-linearity in 1st hidden layer
        out = self.relu_1(out)

        ### 2nd hidden layer
        out  = self.linear_2(out)
        ### Non-linearity in 2nd hidden layer
        out = self.relu_2(out)

        # Linear layer (output)
        probas  = self.linear_out(out)
        return probas

# INSTANTIATE MODEL CLASS

model = DeepNeuralNetworkModel(input_size = input_dim,
                               num_classes = output_dim,
                               num_hidden = num_hidden)
# To enable GPU
model.to(device)
```

```
# INSTANTIATE LOSS & OPTIMIZER CLASS

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

iter = 0
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):

        images = images.view(-1, 28*28).to(device)
        labels = labels.to(device)

        # Clear gradients w.r.t. parameters
        optimizer.zero_grad()

        # Forward pass to get output/logits
        outputs = model(images)

        # Calculate Loss: softmax --> cross entropy loss
        loss = criterion(outputs, labels)

        # Getting gradients w.r.t. parameters
        loss.backward()

        # Updating parameters
        optimizer.step()

        iter += 1

        if iter % 500 == 0:
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:

                images = images.view(-1, 28*28).to(device)

                # Forward pass only to get logits/output
                outputs = model(images)

                # Get predictions from the maximum value
                _, predicted = torch.max(outputs, 1)

                # Total number of labels
                total += labels.size(0)


                # Total correct predictions
                if torch.cuda.is_available():
                    correct += (predicted.cpu() == labels.cpu()).sum()
                else:
                    correct += (predicted == labels).sum()

            accuracy = 100 * correct.item() / total

            # Print Loss
            print('Iteration: {}. Loss: {}. Accuracy: {}'.format(iter, loss.item(), accuracy))
```

```
Iteration: 500. Loss: 0.38067626953125. Accuracy: 91.27
Iteration: 1000. Loss: 0.1768297553062439. Accuracy: 93.35
Iteration: 1500. Loss: 0.10338889807462692. Accuracy: 95.04
Iteration: 2000. Loss: 0.1981402188539505. Accuracy: 95.89
Iteration: 2500. Loss: 0.05458816513419151. Accuracy: 96.15
Iteration: 3000. Loss: 0.14130154252052307. Accuracy: 96.5
```

Three Layer FNN with ReLU Activation

```
import torch
import torch.nn as nn
import torchvision.transforms as transforms
import torchvision.datasets as dsets

# Hyperparameters
batch_size = 100
num_iters = 3000
input_dim = 28*28 #num_features = 784
num_hidden = 100
output_dim = 10

learning_rate = 0.1

# Device
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")


train_dataset = dsets.MNIST(root='./data',
                            train=True,
                            transform=transforms.ToTensor(),  # Normalize the image to [0-1] from [0-255]
                            download=True)

test_dataset = dsets.MNIST(root='./data',
                           train=False,
                           transform=transforms.ToTensor())


num_epochs = num_iters / (len(train_dataset) / batch_size)
num_epochs = int(num_epochs)

train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_size,
                                           shuffle=True)   # It's better to shuffle the whole training dataset

test_loader = torch.utils.data.DataLoader(dataset=test_dataset,
                                          batch_size=batch_size,
                                          shuffle=False)

class DeepNeuralNetworkModel(nn.Module):
    def __init__(self, input_size, num_classes, num_hidden):
        super().__init__()
        ### 1st hidden layer: 784 --> 100
        self.linear_1 = nn.Linear(input_size, num_hidden)
        ### Non-linearity in 1st hidden layer
        self.relu_1 = nn.ReLU()

        ### 2nd hidden layer: 100 --> 100
        self.linear_2 = nn.Linear(num_hidden, num_hidden)
        ### Non-linearity in 2nd hidden layer
        self.relu_2 = nn.ReLU()

        ### 3rd hidden layer: 100 --> 100
        self.linear_3 = nn.Linear(num_hidden, num_hidden)
        ### Non-linearity in 3rd hidden layer
        self.relu_3 = nn.ReLU()

        ### Output layer: 100 --> 10
        self.linear_out = nn.Linear(num_hidden, num_classes)

    def forward(self, x):
        ### 1st hidden layer
        out  = self.linear_1(x)
        ### Non-linearity in 1st hidden layer
        out = self.relu_1(out)

        ### 2nd hidden layer
        out  = self.linear_2(out)
        ### Non-linearity in 2nd hidden layer
        out = self.relu_2(out)

        ### 3rd hidden layer
        out  = self.linear_3(out)
        ### Non-linearity in 3rd hidden layer
        out = self.relu_3(out)

        # Linear layer (output)
```

```
        probas  = self.linear_out(out)
        return probas

# INSTANTIATE MODEL CLASS

model = DeepNeuralNetworkModel(input_size = input_dim,
                               num_classes = output_dim,
                               num_hidden = num_hidden)
# To enable GPU
model.to(device)

# INSTANTIATE LOSS & OPTIMIZER CLASS
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(model.parameters(), lr=learning_rate)

iter = 0
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):

        images = images.view(-1, 28*28).to(device)
        labels = labels.to(device)

        # Clear gradients w.r.t. parameters
        optimizer.zero_grad()

        # Forward pass to get output/logits
        outputs = model(images)

        # Calculate Loss: softmax --> cross entropy loss
        loss = criterion(outputs, labels)

        # Getting gradients w.r.t. parameters
        loss.backward()

        # Updating parameters
        optimizer.step()

        iter += 1

        if iter % 500 == 0:
            # Calculate Accuracy
            correct = 0
            total = 0
            # Iterate through test dataset
            for images, labels in test_loader:

                images = images.view(-1, 28*28).to(device)

                # Forward pass only to get logits/output
```