手写数字识别

- Author = Stephen Cheung
- References = [Handwritten Digit Recognition Using PyTorch — Intro To Neural Networks]
- Dataset = MNIST
- Frameworks = PyTorch

Necessary Impots

Double-click (or enter) to edit

```
# Import necessary packages
%matplotlib inline
%config InlineBackend.figure_format = 'retina'

import numpy as np
import torch
import torchvision
import matplotlib.pyplot as plt
from time import time


import os
from google.colab import drive
```

Download The Dataset & Define The Transforms

```
### Run this cell

from torchvision import datasets, transforms

# Define a transform to normalize the data
transform = transforms.Compose([transforms.ToTensor(),
                              transforms.Normalize((0.5,), (0.5,)),
                              ])

# Download and load the training data
trainset = datasets.MNIST('drive/My Drive/mnist/MNIST_data/', download=True, train=True, transfo
valset = datasets.MNIST('drive/My Drive/mnist/MNIST_data/', download=True, train=False, transfor
trainloader = torch.utils.data.DataLoader(trainset, batch_size=64, shuffle=True)
valloader = torch.utils.data.DataLoader(valset, batch_size=64, shuffle=True)
```

```
0it [00:00, ?it/s]Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyt
9920512it [00:01, 8904696.49it/s]
Extracting drive/My Drive/mnist/MNIST_data/MNIST/raw/train-images-idx3-ubyte.gz to dr
  0%|          | 0/28881 [00:00<?, ?it/s]Downloading http://yann.lecun.com/exdb/mnist
32768it [00:00, 56038.75it/s]
  0%|          | 0/1648877 [00:00<?, ?it/s]Extracting drive/My Drive/mnist/MNIST_data
Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz to drive/My Dr
1654784it [00:02, 567551.81it/s]
0it [00:00, ?it/s]Extracting drive/My Drive/mnist/MNIST_data/MNIST/raw/t10k-images-ic
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz to drive/My Dr
8192it [00:00, 49533.48it/s]
Extracting drive/My Drive/mnist/MNIST_data/MNIST/raw/t10k-labels-idx1-ubyte.gz to dri
Processing...
Done!
```

Exploring The Data

```
dataiter = iter(trainloader)he Data
[4]
### Run this cell

from torchvision import datasets, transforms
dataiter = iter(trainloader)
images, labels = dataiter.next()
print(type(images))
print(images.shape)
print(labels.shape)
```

```
<class 'torch.Tensor'>
torch.Size([64, 1, 28, 28])
torch.Size([64])
```

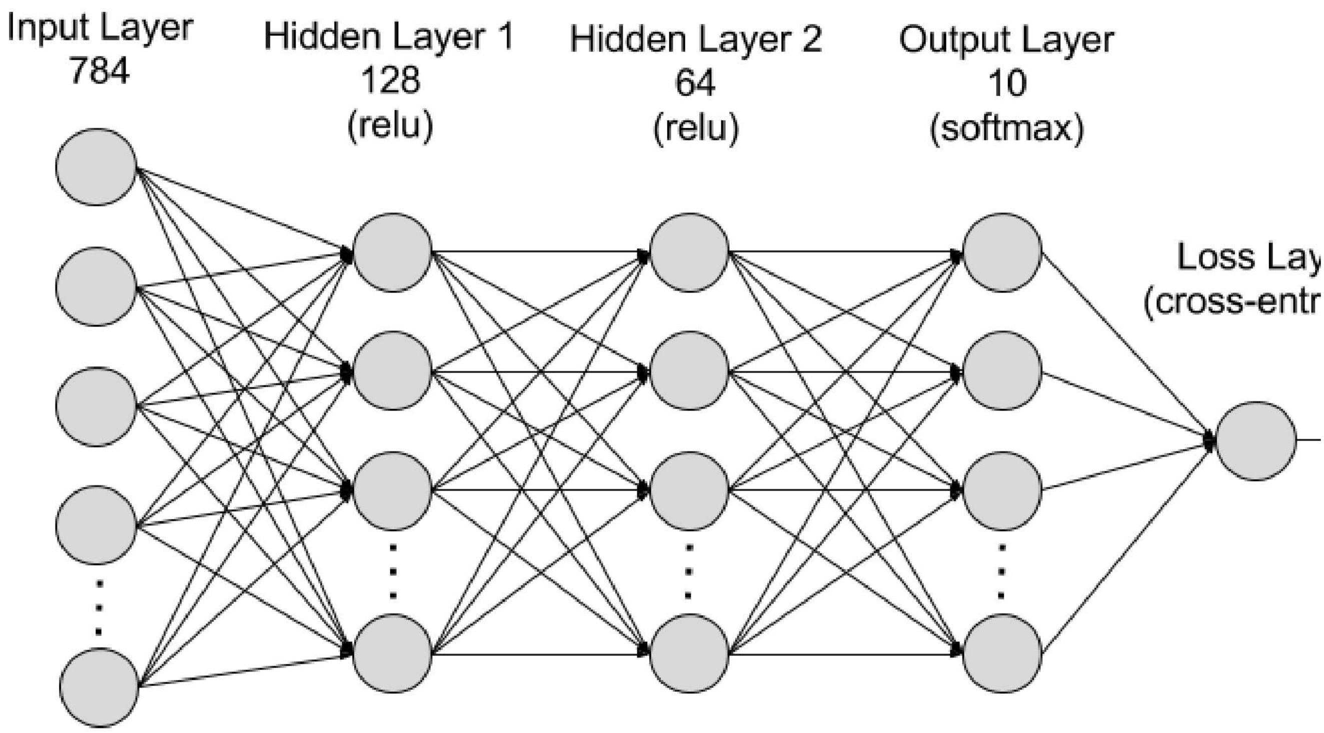
Show one training data

```
plt.imshow(images[0].numpy().squeeze(), cmap='gray_r');
```

```
figure = plt.figure()
num_of_images = 60
for index in range(1, num_of_images + 1):
    plt.subplot(6, 10, index)
```

```
    plt.axis('off')
    plt.imshow(images[index].numpy().squeeze(), cmap='gray_r')
```

Defining the Neural Network




```
from torch import nn

# Layer details for the neural network
input_size = 784
hidden_sizes = [128, 64]
output_size = 10

# Build a feed-forward network
model = nn.Sequential(nn.Linear(input_size, hidden_sizes[0]),
                      nn.ReLU(),
                      nn.Linear(hidden_sizes[0], hidden_sizes[1]),
                      nn.ReLU(),
                      nn.Linear(hidden_sizes[1], output_size),
                      nn.LogSoftmax(dim=1))
print(model)
```

```
criterion = nn.NLLLoss()
images, labels = next(iter(trainloader))
images = images.view(images.shape[0], -1)

logps = model(images)
loss = criterion(logps, labels)


print('Before backward pass: \n', model[0].weight.grad)

loss.backward()

print('After backward pass: \n', model[0].weight.grad)
```

```
from torch import optim

# Optimizers require the parameters to optimize and a learning rate
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.5)


print('Initial weights - ', model[0].weight)

images, labels = next(iter(trainloader))
images.resize_(64, 784)

# Clear the gradients, do this because gradients are accumulated
optimizer.zero_grad()

# Forward pass, then backward pass, then update weights
output = model(images)
loss = criterion(output, labels)
loss.backward()
print('Gradient -', model[0].weight.grad)
```

```
# Take an update step and few the new weights
optimizer.step()
print('Updated weights - ', model[0].weight)
```

Core Training Of Neural Network

```
optimizer = optim.SGD(model.parameters(), lr=0.003, momentum=0.9)
time0 = time()
epochs = 15
for e in range(epochs):
    running_loss = 0
    for images, labels in trainloader:
        # Flatten MNIST images into a 784 long vector
        images = images.view(images.shape[0], -1)

        # Training pass
        optimizer.zero_grad()

        output = model(images)
        loss = criterion(output, labels)

        #This is where the model learns by backpropagating
        loss.backward()

        #And optimizes its weights here
        optimizer.step()

        running_loss += loss.item()
    else:
        print("Epoch {} - Training loss: {}".format(e, running_loss/len(trainloader)))
print("\nTraining Time (in minutes) =",(time()-time0)/60)
```

```
def view_classify(img, ps):
    ''' Function for viewing an image and it's predicted classes.
    '''
    ps = ps.data.numpy().squeeze()

    fig, (ax1, ax2) = plt.subplots(figsize=(6,9), ncols=2)
    ax1.imshow(img.resize_(1, 28, 28).numpy().squeeze())
    ax1.axis('off')
    ax2.barh(np.arange(10), ps)
    ax2.set_aspect(0.1)
    ax2.set_yticks(np.arange(10))
    ax2.set_yticklabels(np.arange(10))
    ax2.set_title('Class Probability')
    ax2.set_xlim(0, 1.1)
    plt.tight_layout()
```

```
images, labels = next(iter(valloader))

img = images[0].view(1, 784)
# Turn off gradients to speed up this part
with torch.no_grad():
    logps = model(img)

# Output of the network are log-probabilities, need to take exponential for probabilities
ps = torch.exp(logps)
probab = list(ps.numpy()[0])
print("Predicted Digit =", probab.index(max(probab)))
view_classify(img.view(1, 28, 28), ps)
```

Model Evaluation

```
correct_count, all_count = 0, 0
for images,labels in valloader:
  for i in range(len(labels)):
    img = images[i].view(1, 784)
    # Turn off gradients to speed up this part
    with torch.no_grad():
        logps = model(img)

    # Output of the network are log-probabilities, need to take exponential for probabilities
    ps = torch.exp(logps)
```

```
    probab = list(ps.numpy()[0])
    pred_label = probab.index(max(probab))
    true_label = labels.numpy()[i]
    if(true_label == pred_label):
      correct_count += 1
    all_count += 1

print("Number Of Images Tested =", all_count)
print("\nModel Accuracy =", (correct_count/all_count))
```