Logistic Regression with PyTorch

About Logistic Regression

Logistic Regression Basics

Classification algorithm

- Example: Spam vs No Spam
  - Input: Bunch of words
  - Output: Probability spam or not

Basic Comparison

- **Linear regression**
  - Output: numeric value given inputs
- **Logistic regression**:
  - Output: probability [0, 1] given input belonging to a class

Input/Output Comparison

- **Linear regression: Multiplication**
    - Input: [1]
        - Output: 2
    - Input: [2]
        - Output: 4
    - Trying to model the relationship `y = 2x`
- **Logistic regression: Spam**
    - Input: "Sign up to get 1 million dollars by tonight"
        - Output: p = 0.8
    - Input: "This is a receipt for your recent purchase with Amazon"
        - Output: p = 0.3
    - **p: probability it is spam**

Problems of Linear Regression

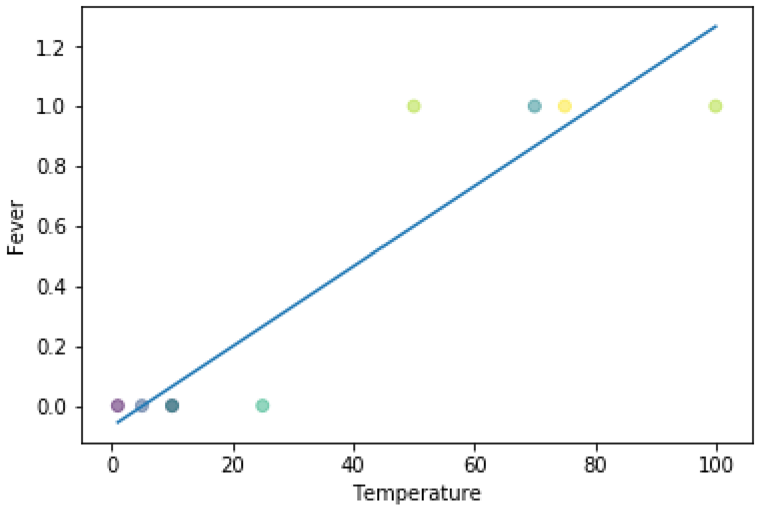
- Example
    - Fever
    - **Input**: temperature

- **Output**: fever or no fever
- Remember
    - **Linear regression**: minimize error between points and line

Linear Regression Problem 1: Fever value can go negative (below 0) and positive (above 1)

If you simply tried to do a simple linear regression on this fever problem, you would realize an apparent error. Fever can go beyond 1 and below 0 which does not make sense in this context.

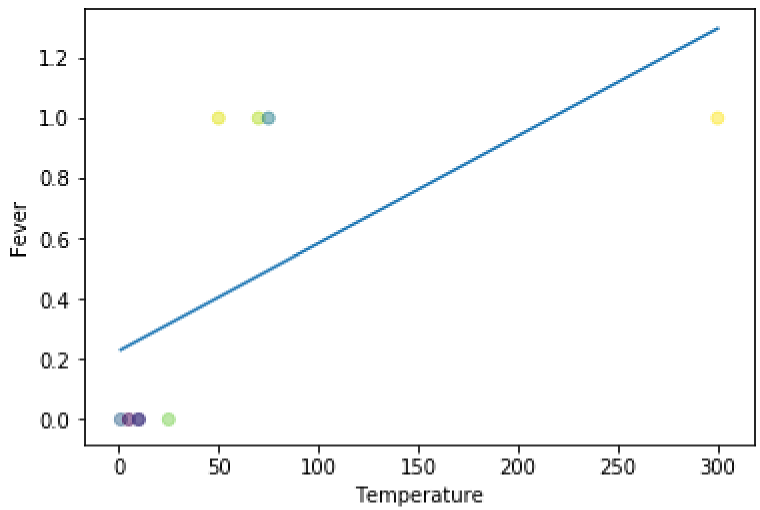
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

x = [1, 5, 10, 10, 25, 50, 70, 75, 100,]
y = [0, 0, 0, 0, 0, 1, 1, 1, 1]

colors = np.random.rand(len(x))
plt.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.unique(x)))
plt.ylabel("Fever")
plt.xlabel("Temperature")

plt.scatter(x, y, c=colors, alpha=0.5)
plt.show()
```



Linear Regression Problem 2: Fever points are not predicted with the presence of outliers

Previously at least some points could be properly predicted. However, with the presence of outliers, everything goes wonky for simple linear regression, having no predictive capacity at all.

```
import numpy as np
import matplotlib.pyplot as plt

x = [1, 5, 10, 10, 25, 50, 70, 75, 300]
y = [0, 0, 0, 0, 0, 1, 1, 1, 1]

colors = np.random.rand(len(x))
plt.plot(np.unique(x), np.poly1d(np.polyfit(x, y, 1))(np.unique(x)))
plt.ylabel("Fever")
plt.xlabel("Temperature")

plt.scatter(x, y, c=colors, alpha=0.5)
plt.show()
```

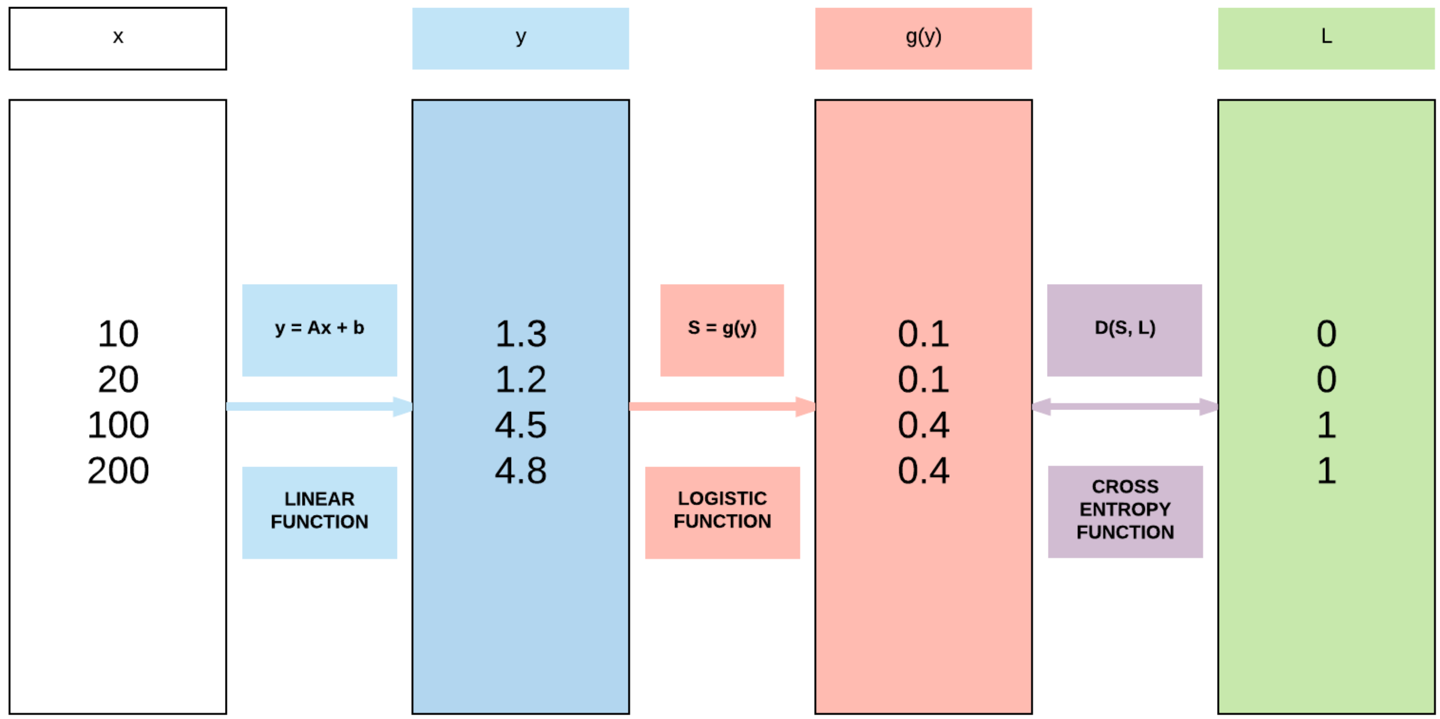


Logistic Regression In-Depth

Predicting Probability

- Linear regression doesn't work
- Instead of predicting direct values: **predict probability**

INPUT LOGITS SOFTMAX TRUE LABELS



Logistic Function g()

- Two-class logistic regression
- $y = Ax + b$

- $g(y) = Ax + b$
- $g(y) = \frac{1}{1+e^{-y}} = \frac{1}{1+e^{-(Ax+b)}}$
- $g(y)$ = Estimated probability that $y = 1$ given x

Softmax Function g()

- Multi-class logistic regression
- Generalization of logistic function

Cross Entropy Function D()

- $D(S, L) = LlogS - (1 - L)log(1 - S)$
    - If L = 0 (label)
        - $D(S, 0) = -log(1 - S)$
            - $-log(1 - S)$: less positive if $S \longrightarrow 0$
            - $-log(1 - S)$: more positive if $S \longrightarrow 1$ (BIGGER LOSS)
    - If L = 1 (label)
        - $D(S, 1) = logS$
            - $logS$: less negative if $S \longrightarrow 1$
            - $logS$: more negative if $S \longrightarrow 0$ (BIGGER LOSS)

> **Numerical example of bigger or small loss**

You get a small error of 1e-5 if your label = 0 and your S is closer to 0 (very correct prediction).

```
import math
print(-math.log(1 - 0.00001))
```

You get a large error of 11.51 if your label is 0 and S is near to 1 (very wrong prediction).

```
print(-math.log(1 - 0.99999))
```

You get a small error of -1e-5 if your label is 1 and S is near 1 (very correct prediction).

```
print(math.log(0.99999))
```

You get a big error of -11.51 if your label is 1 and S is near 0 (very wrong prediction).

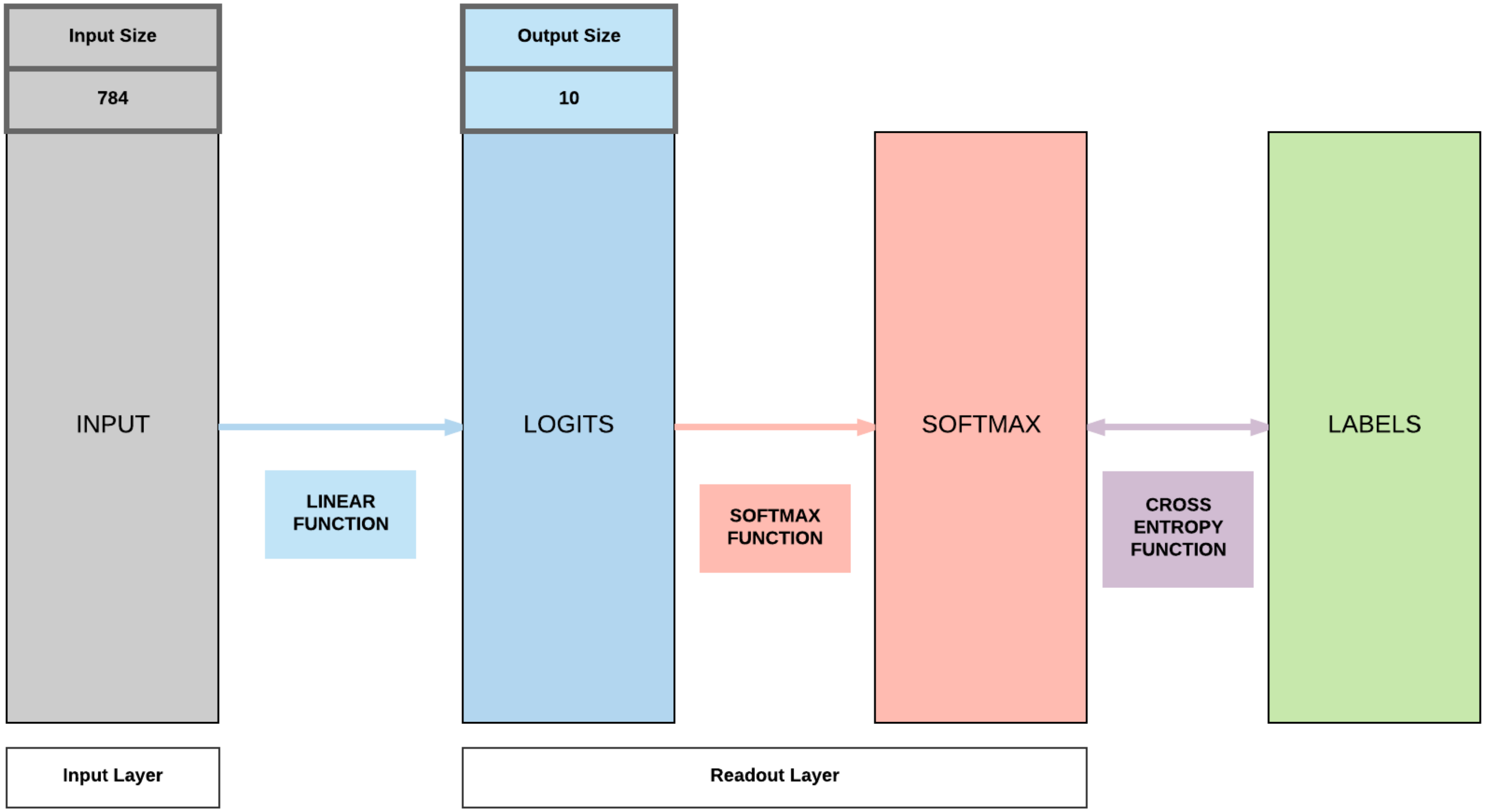
```
print(math.log(0.00001))
```

```
1.0000050000287824e-05
11.51292546497478
-1.0000050000287824e-05
-11.512925464970229
```

Cross Entropy Loss L

- Goal: Minimizing Cross Entropy Loss
- $L = \frac{1}{N} \sum_i D(g(Ax_i + b), L_i)$

Building a Logistic Regression Model with PyTorch



Steps

- Step 1: Load Dataset
- Step 2: Make Dataset Iterable
- Step 3: Create Model Class
- Step 4: Instantiate Model Class
- Step 5: Instantiate Loss Class
- Step 6: Instantiate Optimizer Class
- Step 7: Train Model

Step 1a: Loading MNIST Train Dataset

Images from 1 to 9

Inspect length of training dataset

You can easily load MNIST dataset with PyTorch. Here we inspect the training set, where our algorithms will learn from, and you will discover it is made up of 60,000 images.

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

```
train_dataset = dsets.MNIST(root='./data',
                            train=True,
                            transform=transforms.ToTensor(),
                            download=True)
```

```
len(train_dataset)
```

```
60000
```

Inspecting a single image

So this is how a single image is represented in numbers. It's actually a 28 pixel x 28 pixel image which is why you would end up with this 28x28 matrix of numbers.

```
train_dataset[0]
```

```
(tensor([[[ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
```

```
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0118,  0.0706,
            0.0706,  0.0706,  0.4941,  0.5333,  0.6863,  0.1020,  0.6510,
            1.0000,  0.9686,  0.4980,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.1176,  0.1412,  0.3686,  0.6039,  0.6667,  0.9922,
            0.9922,  0.9922,  0.9922,  0.9922,  0.8824,  0.6745,  0.9922,
            0.9490,  0.7647,  0.2510,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.1922,  0.9333,  0.9922,  0.9922,  0.9922,  0.9922,  0.9922,
            0.9922,  0.9922,  0.9922,  0.9843,  0.3647,  0.3216,  0.3216,
            0.2196,  0.1529,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0706,  0.8588,  0.9922,  0.9922,  0.9922,  0.9922,  0.9922,
            0.7765,  0.7137,  0.9686,  0.9451,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.3137,  0.6118,  0.4196,  0.9922,  0.9922,  0.8039,
            0.0431,  0.0000,  0.1686,  0.6039,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0549,  0.0039,  0.6039,  0.9922,  0.3529,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.5451,  0.9922,  0.7451,
            0.0078,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
            0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
          [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
```

```
          0.0000,  0.0000,  0.0000,  0.0000,  0.0431,  0.7451,  0.9922,
          0.2745,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.1373,  0.9451,
          0.8824,  0.6275,  0.4235,  0.0039,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.3176,
          0.9412,  0.9922,  0.9922,  0.4667,  0.0980,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.1765,  0.7294,  0.9922,  0.9922,  0.5882,  0.1059,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0627,  0.3647,  0.9882,  0.9922,  0.7333,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.9765,  0.9922,  0.9765,  0.2510,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.1804,  0.5098,  0.7176,  0.9922,  0.9922,  0.8118,  0.0078,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.1529,  0.5804,
          0.8980,  0.9922,  0.9922,  0.9922,  0.9804,  0.7137,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000],
        [ 0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,  0.0000,
          0.0000,  0.0000,  0.0000,  0.0941,  0.4471,  0.8667,  0.9922,
```

```
          0.9922, 0.9922, 0.9922, 0.7882, 0.3059, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [ 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0902, 0.2588, 0.8353, 0.9922, 0.9922, 0.9922,
          0.9922, 0.7765, 0.3176, 0.0078, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [ 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0706,
          0.6706, 0.8588, 0.9922, 0.9922, 0.9922, 0.9922, 0.7647,
          0.3137, 0.0353, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [ 0.0000, 0.0000, 0.0000, 0.0000, 0.2157, 0.6745, 0.8863,
          0.9922, 0.9922, 0.9922, 0.9922, 0.9569, 0.5216, 0.0431,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [ 0.0000, 0.0000, 0.0000, 0.0000, 0.5333, 0.9922, 0.9922,
          0.9922, 0.8314, 0.5294, 0.5176, 0.0627, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [ 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [ 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000],
        [ 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000,
          0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000]]]),
 tensor(5))
```

Inspecting a single data point in the training dataset

When you load MNIST dataset, each data point is actually a tuple containing the image matrix and the label.

```
type(train_dataset[0])
```

```
tuple
```

Inspecting training dataset first element of tuple

This means to access the image, you need to access the first element in the tuple.

```
# Input Matrix
train_dataset[0][0].size()
```

```
# A 28x28 sized image of a digit
torch.Size([1, 28, 28])
```

Inspecting training dataset second element of tuple

The second element actually represents the image's label. Meaning if the second element says 5, it means the 28x28 matrix of numbers represent a digit 5.

```
# Label
train_dataset[0][1]
```

```
tensor(5)
```

Displaying MNIST

Verifying shape of MNIST image

As mentioned, a single MNIST image is of the shape 28 pixel x 28 pixel.

```
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

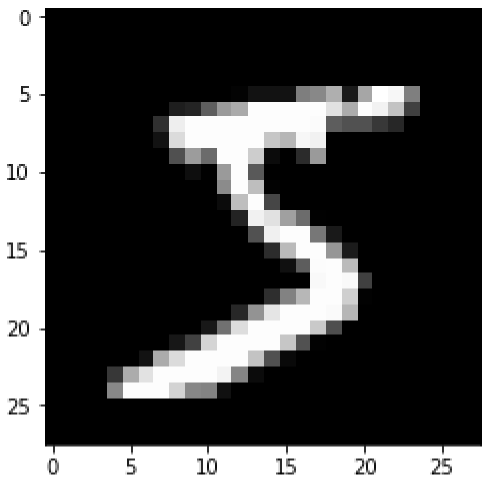
```
train_dataset[0][0].numpy().shape
```

```
(1, 28, 28)
```

Plot image of MNIST image

```
show_img = train_dataset[0][0].numpy().reshape(28, 28)
```

```
plt.imshow(show_img, cmap='gray')
```



Second element of tuple shows label

As you would expect, the label is 5.

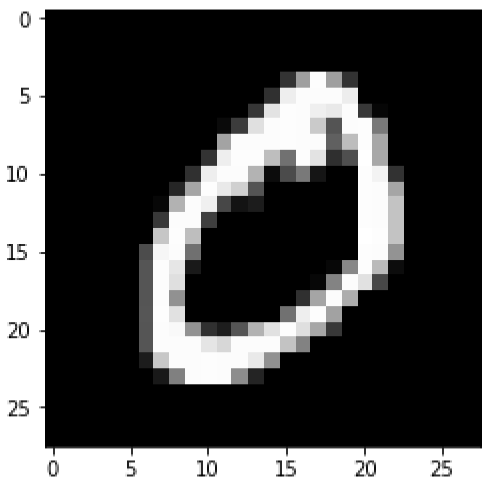
```
# Label
train_dataset[0][1]
```

```
tensor(5)
```

Plot second image of MNIST image

```
show_img = train_dataset[1][0].numpy().reshape(28, 28)
```

```
plt.imshow(show_img, cmap='gray')
```



Second element of tuple shows label

We should see 0 here as the label.

```
# Label
train_dataset[1][1]
```

```
tensor(0)
```

Step 1b: Loading MNIST Test Dataset

- Show our algorithm works beyond the data we have trained on.
- Out-of-sample

Load test dataset

Compared to the 60k images in the training set, the testing set where the model will not be trained on has 10k images to check for its out-of-sample performance.

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

```
len(test_dataset)
```

```
10000
```

Test dataset elements

Exactly like the training set, the testing set has 10k tuples containing the 28x28 matrices and their respective labels.

```
type(test_dataset[0])
```

```
tuple
```

Test dataset first element in tuple

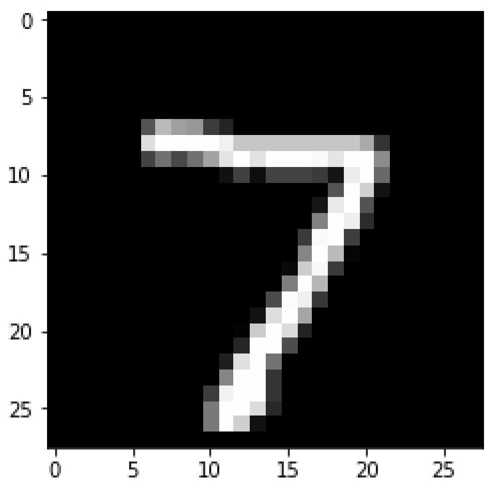
This contains the image matrix, similar to the training set.

```
# Image matrix
test_dataset[0][0].size()
```

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

Plot image sample from test dataset

```
show_img = test_dataset[0][0].numpy().reshape(28, 28)
plt.imshow(show_img, cmap='gray')
```



Test dataset second element in tuple

```
# Label
test_dataset[0][1]
```

```
tensor(7)
```

Step 2: Make Dataset Iterable

- Aim: make the dataset iterable
- **totaldata**: 60000
- **minibatch**: 100
    - Number of examples in 1 iteration
- **iterations**: 3000
    - 1 iteration: one mini-batch forward & backward pass
- **epochs**
    - 1 epoch: running through the whole dataset once
    - $epochs = iterations \div \frac{totaldata}{minibatch} = 3000 \div \frac{60000}{100} = 5 $

Recap training dataset

Remember training dataset has 60k images and testing dataset has 10k images.

```
len(train_dataset)
```

```
60000
```

Defining epochs

When the model goes through the whole 60k images once, learning how to classify 0-9, it's consider 1 epoch.

However, there's a concept of batch size where it means the model would look at 100 images before updating the model's weights, thereby learning. When the model updates its weights (parameters) after looking at all the images, this is considered 1 iteration.

```
batch_size = 100
```

We arbitrarily set 3000 iterations here which means the model would update 3000 times.

```
n_iters = 3000
```

One epoch consists of 60,000 / 100 = 600 iterations. Because we would like to go through 3000 iterations, this implies we would have 3000 / 600 = 5 epochs as each epoch has 600 iterations.

```
num_epochs = n_iters / (len(train_dataset) / batch_size)
num_epochs = int(num_epochs)
num_epochs
```

```
5
```

Create Iterable Object: Training Dataset

```
train_loader = torch.utils.data.DataLoader(dataset=train_dataset,
                                           batch_size=batch_size,
                                           shuffle=True)
```

Check Iterability

```
import collections
isinstance(train_loader, collections.Iterable)
```

```
True
```

Create Iterable Object: Testing Dataset

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

Check iterability of testing dataset

```
isinstance(test_loader, collections.Iterable)
```

```
True
```

Iterate through dataset

This is just a simplified example of what we're doing above where we're creating an iterable object `lst` to loop through so we can access all the images `img_1` and `img_2`.

Above, the equivalent of `lst` is `train_loader` and `test_loader`.

```
img_1 = np.ones((28, 28))
img_2 = np.ones((28, 28))
lst = [img_1, img_2]
```

```
# Need to iterate
# Think of numbers as the images
for i in lst:
    print(i.shape)
```

```
(28, 28)
(28, 28)
```

Step 3: Building Model

Create model class

```
# Same as linear regression!
class LogisticRegressionModel(nn.Module):
```

```
    def __init__(self, input_dim, output_dim):
        super(LogisticRegressionModel, self).__init__()
        self.linear = nn.Linear(input_dim, output_dim)

    def forward(self, x):
        out = self.linear(x)
        return out
```

Step 4: Instantiate Model Class

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

Check size of dataset

This should be 28x28.

```
# Size of images
train_dataset[0][0].size()
```

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

Instantiate model class based on input and out dimensions

As we're trying to classify digits 0-9 a total of 10 classes, our output dimension is 10.

And we're feeding the model with 28x28 images, hence our input dimension is 28x28.

```
input_dim = 28*28
output_dim = 10

model = LogisticRegressionModel(input_dim, output_dim)
```

Step 5: Instantiate Loss Class

- **Logistic Regression**: Cross Entropy Loss
    - *Linear Regression: MSE*

Create Cross Entry Loss Class

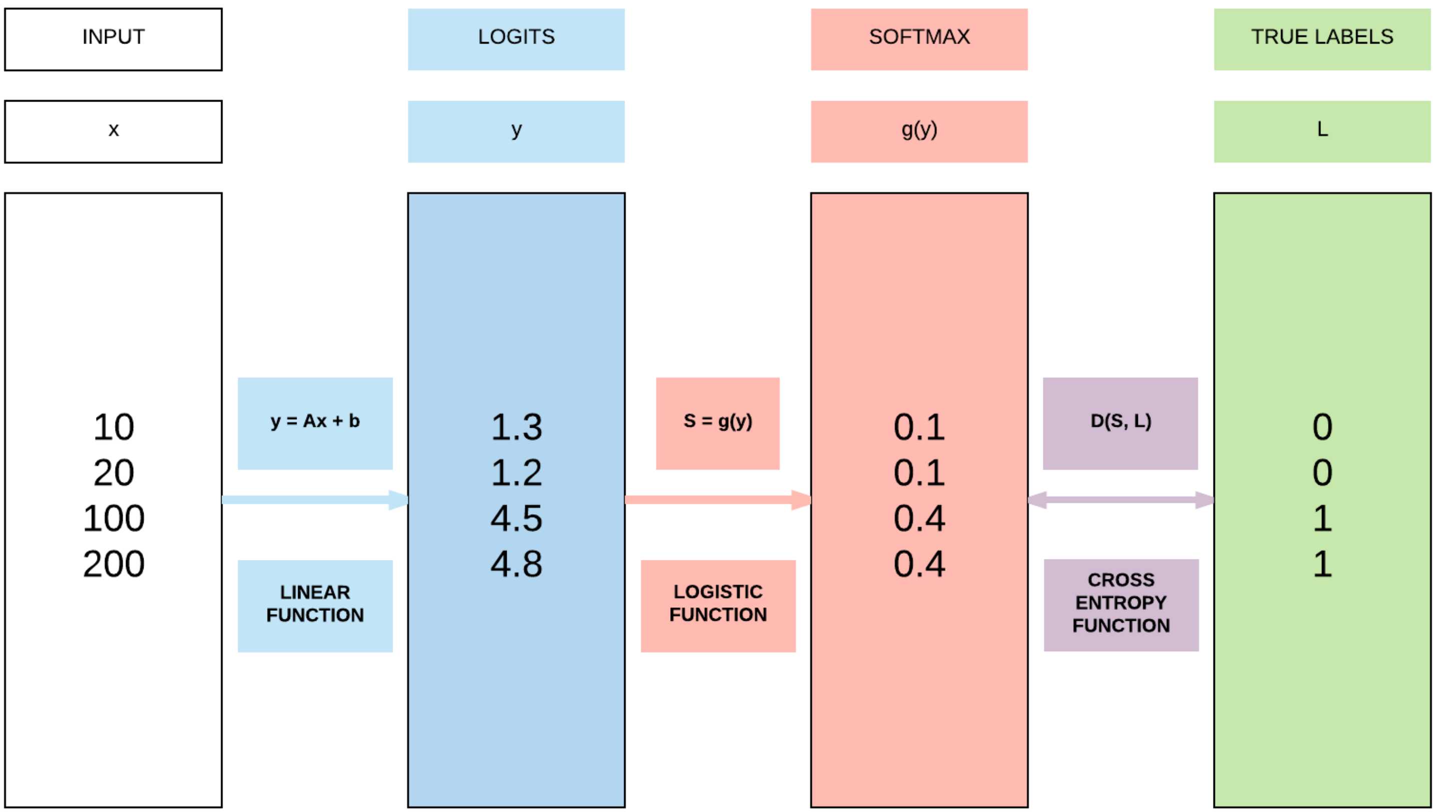
Unlike linear regression, we do not use MSE here, we need Cross Entry Loss to calculate our loss before we backpropagate and update our parameters.

```
criterion = nn.CrossEntropyLoss()
```

What happens in nn.CrossEntropyLoss()?

It does 2 things at the same time.

1. Computes softmax (logistic/softmax function)
2. Computes cross entropy



Step 6: Instantiate Optimizer Class

- Simplified equation
    - $\theta = \theta - \eta \cdot \nabla_\theta$
        - θ: parameters (our variables)
        - η: learning rate (how fast we want to learn)
        - ∇_θ: parameters' gradients
- Even simplier equation
    - `parameters = parameters - learning_rate * parameters_gradients`
    - **At every iteration, we update our model's parameters**

Create optimizer

Similar to what we've covered above, this calculates the parameters' gradients and update them subsequently.

```
learning_rate = 0.001

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

Parameters In-Depth

You'll realize we have 2 sets of parameters, 10x784 which is A and 10x1 which is b in the $y = AX + b$ equation where X is our input of size 784.

We'll go into details subsequently how these parameters interact with our input to produce our 10x1 output.

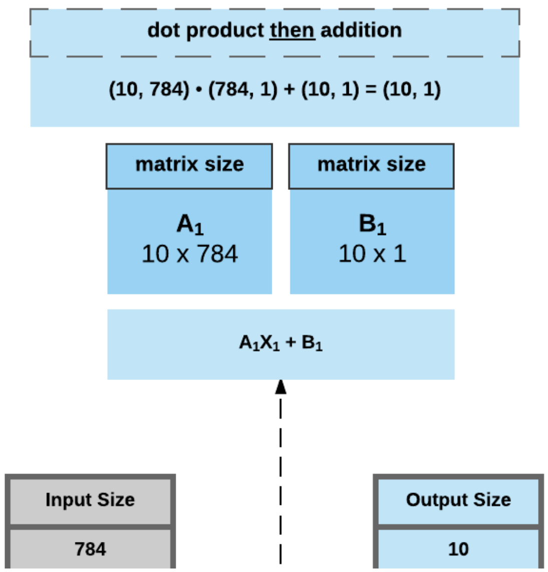
```
# Type of parameter object
print(model.parameters())

# Length of parameters
print(len(list(model.parameters())))

# FC 1 Parameters
print(list(model.parameters())[0].size())

# FC 1 Bias Parameters
print(list(model.parameters())[1].size())
```

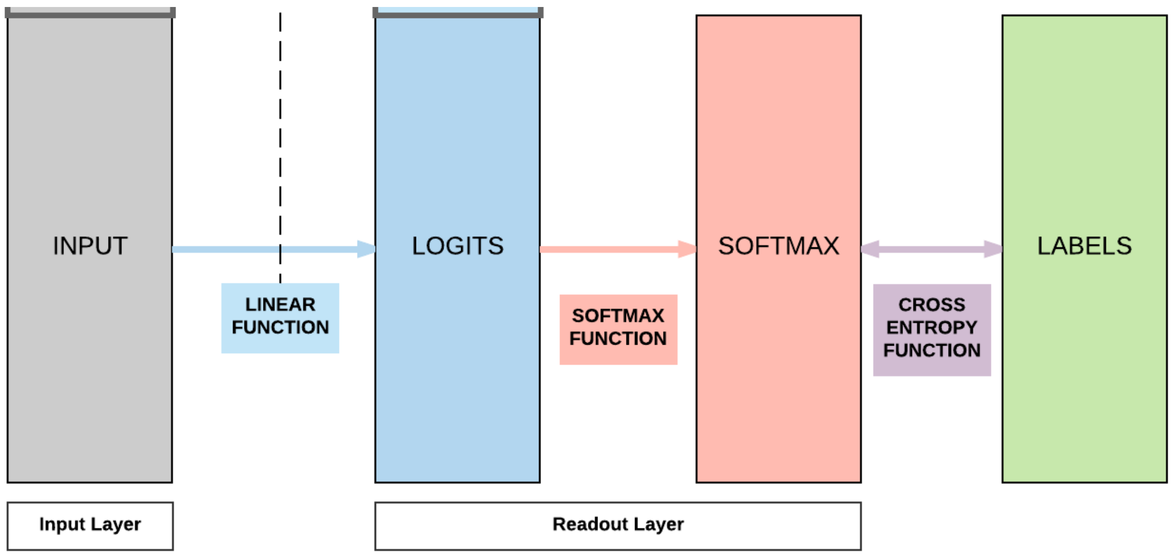
```
<generator object Module.parameters at 0x7ff7c884f830>
2
torch.Size([10, 784])
torch.Size([10])
```

Quick Dot Product Review

- Example 1: **dot product**
  - $A : (100, 10)$
  - $B : (10, 1)$

- $A \cdot B = (100, 10) \cdot (10, 1) = (100, 1)$
- Example 2: **dot product**
  - $A : (50, 5)$
  - $B : (5, 2)$
  - $A \cdot B = (50, 5) \cdot (5, 2) = (50, 2)$
- Example 3: **element-wise addition**
  - $A : (10, 1)$
  - $B : (10, 1)$
  - $A + B = (10, 1)$





Step 7: Train Model

7 step process for training models

- Process
  a. Convert inputs/labels to tensors with gradients
  b. Clear gradient buffets
  c. Get output given inputs
  d. Get loss
  e. Get gradients w.r.t. parameters
  f. Update parameters using gradients
     - `parameters = parameters - learning_rate * parameters_gradients`

g. REPEAT

```
iter = 0
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):
        # Load images as Variable
        images = images.view(-1, 28*28).requires_grad_()
        labels = labels

        # 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:
                # Load images to a Torch Variable
                images = images.view(-1, 28*28).requires_grad_()

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

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

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

            # Total correct predictions
            correct += (predicted == labels).sum()

        accuracy = 100 * correct / total

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

```
Iteration: 500. Loss: 1.8513233661651611. Accuracy: 70
Iteration: 1000. Loss: 1.5732524394989014. Accuracy: 77
Iteration: 1500. Loss: 1.3840199708938599. Accuracy: 79
Iteration: 2000. Loss: 1.1711134910583496. Accuracy: 81
Iteration: 2500. Loss: 1.1094708442687988. Accuracy: 82
Iteration: 3000. Loss: 1.002761721611023. Accuracy: 82
```

Break Down Accuracy Calculation

Printing outputs of our model

As we've trained our model, we can extract the accuracy calculation portion to understand what's happening without re-training the model.

This would print out the output of the model's predictions on your notebook.

```
iter_test = 0
for images, labels in test_loader:
    iter_test += 1
    images = images.view(-1, 28*28).requires_grad_()
    outputs = model(images)
    if iter_test == 1:
```

```
            print('OUTPUTS')
            print(outputs)
        _, predicted = torch.max(outputs.data, 1)
```

```
OUTPUTS
tensor([[-0.4181, -1.0784, -0.4840, -0.0985, -0.2394, -0.1801, -1.1639,
          2.9352, -0.1552,  0.8852],
        [ 0.5117, -0.1099,  1.5295,  0.8863, -1.8813,  0.5967,  1.3632,
         -1.8977,  0.4183, -1.4990],
        [-1.0126,  2.4112,  0.2373,  0.0857, -0.7007, -0.2015, -0.3428,
         -0.2548,  0.1659, -0.4703],
        [ 2.8072, -2.2973, -0.0984, -0.4313, -0.9619,  0.8670,  1.2201,
          0.3752, -0.2873, -0.3272],
        [-0.0343, -2.0043,  0.5081, -0.6452,  1.8647, -0.6924,  0.1435,
          0.4330,  0.2958,  1.0339],
        [-1.5392,  2.9070,  0.2297,  0.3139, -0.6863, -0.2734, -0.8377,
         -0.1238,  0.3285, -0.3004],
        [-1.2037, -1.3739, -0.5947,  0.3530,  1.4205,  0.0593, -0.7307,
          0.6642,  0.3937,  0.8004],
        [-1.4439, -0.3284, -0.7652, -0.0952,  0.9323,  0.3006,  0.0238,
         -0.0810,  0.0612,  1.3295],
        [ 0.5409, -0.5266,  0.9914, -1.2369,  0.6583,  0.0992,  0.8525,
         -1.0562,  0.2013,  0.0462],
        [-0.6548, -0.7253, -0.9825, -1.1663,  0.9076, -0.0694, -0.3708,
          1.8270,  0.2457,  1.5921],
        [ 3.2147, -1.7689,  0.8531,  1.2320, -0.8126,  1.1251, -0.2776,
         -1.4244,  0.5930, -1.6183],
        [ 0.7470, -0.5545,  1.0251,  0.0529,  0.4384, -0.5934,  0.7666,
         -1.0084,  0.5313, -0.3465],
        [-0.7916, -1.7064, -0.7805, -1.1588,  1.3284, -0.1708, -0.2092,
          0.9495,  0.1033,  2.0208],
```

```
        [ 3.0602, -2.3578, -0.2576, -0.2198, -0.2372,  0.9765, -0.1514,
         -0.5380,  0.7970,  0.1374],
        [-1.2613,  2.8594, -0.0874,  0.1974, -1.2018, -0.0064, -0.0923,
         -0.2142,  0.2575, -0.3218],
        [ 0.4348, -0.7216,  0.0021,  1.2864, -0.5062,  0.7761, -0.3236,
         -0.5667,  0.5431, -0.7781],
        [-0.2157, -2.0200,  0.1829, -0.6882,  1.3815, -0.7609, -0.0902,
          0.8647,  0.3679,  1.8843],
        [ 0.0950, -1.5009, -0.6347,  0.3662, -0.4679, -0.0359, -0.7671,
          2.7155, -0.3991,  0.5737],
        [-0.7005, -0.5366, -0.0434,  1.1289, -0.5873,  0.2555,  0.8187,
         -0.6557,  0.1241, -0.4297],
        [-1.0635, -1.5991, -0.4677, -0.1231,  2.0445,  0.1128, -0.1825,
          0.1075,  0.0348,  1.4317],
        [-1.0319, -0.1595, -1.3415,  0.1095,  0.5339,  0.1973, -1.3272,
          1.5765,  0.4784,  1.4176],
        [-0.4928, -1.5653, -0.0672,  0.3325,  0.5359,  0.5368,  2.1542,
         -1.4276,  0.3605,  0.0587],
        [-0.4761,  0.2958,  0.6597, -0.2658,  1.1279, -1.0676,  1.2506,
         -0.2059, -0.1489,  0.1051],
        [-0.0764, -0.9274, -0.6838,  0.3464, -0.2656,  1.4099,  0.4486,
         -0.9527,  0.5682,  0.0156],
        [-0.6900, -0.9611,  0.1395, -0.0079,  1.5424, -0.3208, -0.2682,
          0.3586, -0.2771,  1.0389],
        [ 4.3606, -2.8621,  0.6310, -0.9657, -0.2486,  1.2009,  1.1873,
         -0.8255, -0.2103, -1.2172],
        [-0.1000, -1.4268, -0.4627, -0.1041,  0.2959, -0.1392, -0.6855,
          1.8622, -0.2580,  1.1347],
        [-0.3625, -2.1323, -0.2224, -0.8754,  2.4684,  0.0295,  0.1161,
         -0.2660,  0.3037,  1.4570],
        [ 2.8688, -2.4517,  0.1782,  1.1149, -1.0898,  1.1062, -0.0681,
         -0.5697,  0.8888, -0.6965],
        [-1.0429,  1.4446, -0.3349,  0.1254, -0.5017,  0.2286,  0.2328,
```

```
         -0.3290,  0.3949, -0.2586],
        [-0.8476, -0.0004, -1.1003,  2.2806, -1.2226,  0.9251, -0.3165,
          0.4957,  0.0690,  0.0232],
        [-0.9108,  1.1355, -0.2715,  0.2233, -0.3681,  0.1442, -0.0001,
         -0.0174,  0.1454,  0.2286],
        [-1.0663, -0.8466, -0.7147,  2.5685, -0.2090,  1.2993, -0.3057,
         -0.8314,  0.7046, -0.0176],
        [ 1.7013, -1.8051,  0.7541, -1.5248,  0.8972,  0.1518,  1.4876,
         -0.8454, -0.2022, -0.2829],
        [-0.8179, -0.1239,  0.8630, -0.2137, -0.2275, -0.5411, -1.3448,
          1.7354,  0.7751,  0.6234],
        [ 0.6515, -1.0431,  2.7165,  0.1873, -1.0623,  0.1286,  0.3597,
         -0.2739,  0.3871, -1.6699],
        [-0.2828, -1.4663,  0.1182, -0.0896, -0.3640, -0.5129, -0.4905,
          2.2914, -0.2227,  0.9463],
        [-1.2596,  2.0468, -0.4405, -0.0411, -0.8073,  0.0490, -0.0604,
         -0.1206,  0.3504, -0.1059],
        [ 0.6089,  0.5885,  0.7898,  1.1318, -1.9008,  0.5875,  0.4227,
         -1.1815,  0.5652, -1.3590],
        [-1.4551,  2.9537, -0.2805,  0.2372, -1.4180,  0.0297, -0.1515,
         -0.6111,  0.6140, -0.3354],
        [-0.7182,  1.6778,  0.0553,  0.0461, -0.5446, -0.0338, -0.0215,
         -0.0881,  0.1506, -0.2107],
        [-0.8027, -0.7854, -0.1275, -0.3177, -0.1600, -0.1964, -0.6084,
          2.1285, -0.1815,  1.1911],
        [-2.0656, -0.4959, -0.1154, -0.1363,  2.2426, -0.7441, -0.8413,
          0.4675,  0.3269,  1.7279],
        [-0.3004,  1.0166,  1.1175, -0.0618, -0.0937, -0.4221,  0.1943,
         -1.1020,  0.3670, -0.4683],
        [-1.0720,  0.2252,  0.0175,  1.3644, -0.7409,  0.4655,  0.5439,
          0.0380,  0.1279, -0.2302],
        [ 0.2409, -1.2622, -0.6336,  1.8240, -0.5951,  1.3408,  0.2130,
         -1.3789,  0.8363, -0.2101],
```

```
        [-1.3849,  0.3773, -0.0585,  0.6896, -0.0998,  0.2804,  0.0696,
         -0.2529,  0.3143,  0.3409],
        [-0.9103, -0.1578,  1.6673, -0.4817,  0.4088, -0.5484,  0.6103,
         -0.2287, -0.0665,  0.0055],
        [-1.1692, -2.8531, -1.2499, -0.0257,  2.8580,  0.2616, -0.7122,
         -0.0551,  0.8112,  2.3233],
        [-0.2790, -1.9494,  0.6096, -0.5653,  2.2792, -1.0687,  0.1634,
          0.3122,  0.1053,  1.0884],
        [ 0.1267, -1.2297, -0.1315,  0.2428, -0.5436,  0.4123,  2.3060,
         -0.9278, -0.1528, -0.4224],
        [-0.0235, -0.9137, -0.1457,  1.6858, -0.7552,  0.7293,  0.2510,
         -0.3955, -0.2187, -0.1505],
        [ 0.5643, -1.2783, -1.4149,  0.0304,  0.8375,  1.5018,  0.0338,
         -0.3875, -0.0117,  0.5751],
        [ 0.2926, -0.7486, -0.3238,  1.0384,  0.0308,  0.6792, -0.0170,
         -0.5797,  0.2819, -0.3510],
        [ 0.1219, -0.5862,  1.5817, -0.1297,  0.4730, -0.9171,  0.7886,
         -0.7022, -0.0501, -0.2812],
        [ 1.7587, -2.4511, -0.7369,  0.4082, -0.6426,  1.1784,  0.6052,
         -0.7178,  1.6161, -0.2220],
        [-0.1267, -2.6719,  0.0505, -0.4972,  2.9027, -0.1461,  0.2807,
         -0.2921,  0.2231,  1.1327],
        [-0.9892,  2.4401,  0.1274,  0.2838, -0.7535, -0.1684, -0.6493,
         -0.1908,  0.2290, -0.2150],
        [-0.2071, -2.1351, -0.9191, -0.9309,  1.7747, -0.3046,  0.0183,
          1.0136, -0.1016,  2.1288],
        [-0.0103,  0.3280, -0.6974, -0.2504,  0.3187,  0.4390, -0.1879,
          0.3954,  0.2332, -0.1971],
        [-0.2280, -1.6754, -0.7438,  0.5078,  0.2544, -0.1020, -0.2503,
          2.0799, -0.5033,  0.5890],
        [ 0.3972, -0.9369,  1.2696, -1.6713, -0.4159, -0.0221,  0.6489,
         -0.4777,  1.2497,  0.3931],
        [-0.7566, -0.8230, -0.0785, -0.3083,  0.7821,  0.1880,  0.1037,
```

```
         -0.0956,  0.4219,  1.0798],
        [-1.0328, -0.1700,  1.3806,  0.5445, -0.2624, -0.0780, -0.3595,
         -0.6253,  0.4309,  0.1813],
        [-1.0360, -0.4704,  0.1948, -0.7066,  0.6600, -0.4633, -0.3602,
          1.7494,  0.1522,  0.6086],
        [-1.2032, -0.7903, -0.5754,  0.4722,  0.6068,  0.5752,  0.2151,
         -0.2495,  0.3420,  0.9278],
        [ 0.2247, -0.1361,  0.9374, -0.1543,  0.4921, -0.6553,  0.5885,
          0.2617, -0.2216, -0.3736],
        [-0.2867, -1.4486,  0.6658, -0.8755,  2.3195, -0.7627, -0.2132,
          0.2488,  0.3484,  1.0860],
        [-1.4031, -0.4518, -0.3181,  2.8268, -0.5371,  1.0154, -0.9247,
         -0.7385,  1.1031,  0.0422],
        [ 2.8604, -1.5413,  0.6241, -0.8017, -1.4104,  0.6314,  0.4614,
         -0.0218, -0.3411, -0.2609],
        [ 0.2113, -1.2348, -0.8535, -0.1041, -0.2703, -0.1294, -0.7057,
          2.7552, -0.4429,  0.4517],
        [ 4.5191, -2.7407,  1.1091,  0.3975, -0.9456,  1.2277,  0.3616,
         -1.6564,  0.5063, -1.4274],
        [ 1.4615, -1.0765,  1.8388,  1.5006, -1.2351,  0.2781,  0.2830,
         -0.8491,  0.2222, -1.7779],
        [-1.2160,  0.8502,  0.2413, -0.0798, -0.7880, -0.4286, -0.8060,
          0.7194,  1.2663,  0.6412],
        [-1.3318,  2.3388, -0.4003, -0.1094, -1.0285,  0.1021, -0.0388,
         -0.0497,  0.5137, -0.2507],
        [-1.7853,  0.5884, -0.6108, -0.5557,  0.8696, -0.6226, -0.7983,
          1.7169, -0.0145,  0.8231],
        [-0.1739,  0.1562, -0.2933,  2.3195, -0.9480,  1.2019, -0.4834,
         -1.0567,  0.5685, -0.6841],
        [-0.7920, -0.3339,  0.7452, -0.6529, -0.3307, -0.6092, -0.0950,
          1.7311, -0.3481,  0.3801],
        [-1.7810,  1.0676, -0.7611,  0.3658, -0.0431, -0.1012, -0.6048,
          0.3089,  0.9998,  0.7164],
```

```
        [-0.5856, -0.5261, -0.4859, -1.0551, -0.1838, -0.2144, -1.2599,
          3.3891,  0.4691,  0.7566],
        [-0.4984, -1.7770, -1.1998, -0.1075,  1.0882,  0.4539, -0.5651,
          1.4381, -0.5678,  1.7479],
        [ 0.2938, -1.8536,  0.4259, -0.5429,  0.0066,  0.4120,  2.3793,
         -0.3666, -0.2604,  0.0382],
        [-0.4080, -0.9851,  4.0264,  0.1099, -0.1766, -1.1557,  0.6419,
         -0.8147,  0.7535, -1.1452],
        [-0.4636, -1.7323, -0.6433, -0.0274,  0.7227, -0.1799, -0.9336,
          2.1881, -0.2073,  1.6522],
        [-0.9617, -0.0348, -0.3980, -0.4738,  0.7790,  0.4671, -0.6115,
         -0.7067,  1.3036,  0.4923],
        [-1.0151, -2.5385, -0.6072,  0.2902,  3.1570,  0.1062, -0.2169,
         -0.4491,  0.6326,  1.6829],
        [-1.8852,  0.6066, -0.2840, -0.4475, -0.1147, -0.7858, -1.1805,
          3.0723,  0.3960,  0.9720],
        [ 0.0344, -1.4878, -0.9675,  1.9649, -0.3146,  1.2183,  0.6730,
         -0.3650,  0.0646, -0.0898],
        [-0.2118, -2.0350,  0.9917, -0.8993,  1.2334, -0.6723,  2.5847,
         -0.0454, -0.4149,  0.3927],
        [-1.7365,  3.0447,  0.5115,  0.0786, -0.7544, -0.2158, -0.4876,
         -0.2891,  0.5089, -0.6719],
        [ 0.3652, -0.5457, -0.1167,  2.9056, -1.1622,  0.8192, -1.3245,
         -0.6414,  0.8097, -0.4958],
        [-0.8755, -0.6983,  0.2208, -0.6463,  0.5276,  0.1145,  2.7229,
         -1.0316,  0.1905,  0.2090],
        [-0.9702,  0.1265, -0.0007, -0.5106,  0.4970, -0.0804,  0.0017,
          0.0607,  0.6164,  0.4490],
        [-0.8271, -0.6822, -0.7434,  2.6457, -1.6143,  1.1486, -1.0705,
          0.5611,  0.6422,  0.1250],
        [-1.9979,  1.8175, -0.1658, -0.0343, -0.6292,  0.1774,  0.3150,
         -0.4633,  0.9266,  0.0252],
        [-0.9039, -0.6030, -0.2173, -1.1768,  2.3198, -0.5072,  0.3418,
```

```
         -0.1551,  0.1282,  1.4250],
        [-0.9891,  0.5212, -0.4518,  0.3267, -0.0759,  0.3826, -0.0341,
          0.0382,  0.2451,  0.3658],
        [-2.1217,  1.5102, -0.7828,  0.3554, -0.4192, -0.0772,  0.0578,
          0.8070,  0.1701,  0.5880],
        [ 1.0665, -1.3826,  0.6243, -0.8096, -0.4227,  0.5925,  1.8112,
         -0.9946,  0.2010, -0.7731],
        [-1.1263, -1.7484,  0.0041, -0.5439,  1.7242, -0.9475, -0.3835,
          0.8452,  0.3077,  2.2689]])
```

Printing output size

This produces a 100x10 matrix because each iteration has a batch size of 100 and each prediction across the 10 classes, with the largest number indicating the likely number it is predicting.

```
iter_test = 0
for images, labels in test_loader:
    iter_test += 1
    images = images.view(-1, 28*28).requires_grad_()
    outputs = model(images)
    if iter_test == 1:
        print('OUTPUTS')
        print(outputs.size())
    _, predicted = torch.max(outputs.data, 1)
```

```
OUTPUTS
torch.Size([100, 10])
```

Printing one output

This would be a 1x10 matrix where the largest number is what the model thinks the image is. Here we can see that in the tensor, position 7 has the largest number, indicating the model thinks the image is 7.

number 0: -0.4181
number 1: -1.0784
...
number 7: 2.9352

```
iter_test = 0
for images, labels in test_loader:
    iter_test += 1
    images = images.view(-1, 28*28).requires_grad_()
    outputs = model(images)
    if iter_test == 1:
        print('OUTPUTS')
        print(outputs[0, :])
    _, predicted = torch.max(outputs.data, 1)
```

```
OUTPUTS
tensor([-0.4181, -1.0784, -0.4840, -0.0985, -0.2394, -0.1801, -1.1639,
         2.9352, -0.1552,  0.8852])
```

Printing prediction output

Because our output is of size 100 (our batch size), our prediction size would also of the size 100.

```
iter_test = 0
for images, labels in test_loader:
    iter_test += 1
    images = images.view(-1, 28*28).requires_grad_()
    outputs = model(images)
    _, predicted = torch.max(outputs.data, 1)
```

```
    if iter_test == 1:
        print('PREDICTION')
        print(predicted.size())
```

```
PREDICTION
torch.Size([100])
```

Print prediction value

We are printing our prediction which as verified above, should be digit 7.

```
iter_test = 0
for images, labels in test_loader:
    iter_test += 1
    images = images.view(-1, 28*28).requires_grad_()
    outputs = model(images)
    _, predicted = torch.max(outputs.data, 1)
    if iter_test == 1:
        print('PREDICTION')
        print(predicted[0])
```

```
PREDICTION
tensor(7)
```

Print prediction, label and label size

We are trying to show what we are predicting and the actual values. In this case, we're predicting the right value 7!

```
iter_test = 0
for images, labels in test_loader:
    iter_test += 1
    images = images.view(-1, 28*28).requires_grad_()
    outputs = model(images)
    _, predicted = torch.max(outputs.data, 1)
    if iter_test == 1:
        print('PREDICTION')
        print(predicted[0])

        print('LABEL SIZE')
        print(labels.size())

        print('LABEL FOR IMAGE 0')
        print(labels[0])
```

```
PREDICTION
tensor(7)

LABEL SIZE
torch.Size([100])

LABEL FOR IMAGE 0
tensor(7)
```

Print second prediction and ground truth

Again, the prediction is correct. Naturally, as our model is quite competent in this simple task.

```
iter_test = 0
for images, labels in test_loader:
    iter_test += 1
    images = images.view(-1, 28*28).requires_grad_()
```

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

    if iter_test == 1:
        print('PREDICTION')
        print(predicted[1])

        print('LABEL SIZE')
        print(labels.size())

        print('LABEL FOR IMAGE 1')
        print(labels[1])
```

```
PREDICTION
tensor(2)

LABEL SIZE
torch.Size([100])

LABEL FOR IMAGE 1
tensor(2)
```

Print accuracy

Now we know what each object represents, we can understand how we arrived at our accuracy numbers.

One last thing to note is that `correct.item()` has this syntax is because `correct` is a PyTorch tensor and to get the value to compute with `total` which is an integer, we need to do this.

```
correct = 0
total = 0
iter_test = 0
for images, labels in test_loader:
```

```
    iter_test += 1
    images = images.view(-1, 28*28).requires_grad_()
    outputs = model(images)
    _, predicted = torch.max(outputs.data, 1)

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

    # Total correct predictions
    correct += (predicted == labels).sum()

accuracy = 100 * (correct.item() / total)

print(accuracy)
```

```
82.94
```

Explanation of Python's .sum() function

Python's .sum() function allows you to do a comparison between two matrices and sum the ones that return `True` or in our case, those predictions that match actual labels (correct predictions).

```
# Explaining .sum() python built-in function
# correct += (predicted == labels).sum()
import numpy as np
a = np.ones((10))
print(a)
b = np.ones((10))
print(b)

print(a == b)

print((a == b).sum())
```

```
# matrix a
[1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]

# matrix b
[1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]

# boolean array
[ True  True  True  True  True  True  True  True  True  True]

# number of elementswhere a matches b
10
```

Saving Model

Saving PyTorch model

This is how you save your model. Feel free to just change `save_model = True` to save your model

```
save_model = False
if save_model is True:
    # Saves only parameters
    torch.save(model.state_dict(), 'awesome_model.pkl')
```

Building a Logistic Regression Model with PyTorch (GPU)

CPU version

The usual 7-step process, getting repetitive by now which we like.

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

'''
STEP 1: LOADING DATASET
'''

train_dataset = dsets.MNIST(root='./data',
                            train=True,
                            transform=transforms.ToTensor(),
                            download=True)

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

'''
STEP 2: MAKING DATASET ITERABLE
'''

batch_size = 100
n_iters = 3000
num_epochs = n_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)

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

'''
STEP 3: CREATE MODEL CLASS
'''
```

```python
class LogisticRegressionModel(nn.Module):
    def __init__(self, input_size, num_classes):
        super(LogisticRegressionModel, self).__init__()
        self.linear = nn.Linear(input_dim, output_dim)

    def forward(self, x):
        out = self.linear(x)
        return out

'''
STEP 4: INSTANTIATE MODEL CLASS
'''
input_dim = 28*28
output_dim = 10

model = LogisticRegressionModel(input_dim, output_dim)

'''
STEP 5: INSTANTIATE LOSS CLASS
'''
criterion = nn.CrossEntropyLoss()


'''
STEP 6: INSTANTIATE OPTIMIZER CLASS
'''
learning_rate = 0.001

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

'''
STEP 7: TRAIN THE MODEL
'''
iter = 0
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):
        # Load images as Variable
        images = images.view(-1, 28*28).requires_grad_()
        labels = labels

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

```
        optimizer.zero_grad()

        # Forward pass to get output/logits
        # 100 x 10
        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:
                # Load images to a Torch Variable
                images = images.view(-1, 28*28).requires_grad_()

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

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

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

                # Total correct predictions
                correct += (predicted == labels).sum()

            accuracy = 100 * correct.item() / total
```

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

```
Iteration: 500. Loss: 1.876196026802063. Accuracy: 64.44
Iteration: 1000. Loss: 1.5153584480285645. Accuracy: 75.68
Iteration: 1500. Loss: 1.3521136045455933. Accuracy: 78.98
Iteration: 2000. Loss: 1.2136967182159424. Accuracy: 80.95
Iteration: 2500. Loss: 1.0934826135635376. Accuracy: 81.97
Iteration: 3000. Loss: 1.024120569229126. Accuracy: 82.49
```

GPU version

2 things must be on GPU
- `model`
- `variables`

Remember step 4 and 7 will be affected and this will be the same for all model building moving forward.

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

'''
STEP 1: LOADING DATASET
'''

train_dataset = dsets.MNIST(root='./data',
                            train=True,
                            transform=transforms.ToTensor(),
                            download=True)

test_dataset = dsets.MNIST(root='./data',
```

```
                           train=False,
                           transform=transforms.ToTensor())

'''
STEP 2: MAKING DATASET ITERABLE
'''

batch_size = 100
n_iters = 3000
num_epochs = n_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)

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

'''
STEP 3: CREATE MODEL CLASS
'''
class LogisticRegressionModel(nn.Module):
    def __init__(self, input_size, num_classes):
        super(LogisticRegressionModel, self).__init__()
        self.linear = nn.Linear(input_dim, output_dim)

    def forward(self, x):
        out = self.linear(x)
        return out

'''
STEP 4: INSTANTIATE MODEL CLASS
'''
input_dim = 28*28
output_dim = 10

model = LogisticRegressionModel(input_dim, output_dim)

#######################
```

```
#  USE GPU FOR MODEL  #
#######################

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
model.to(device)

'''
STEP 5: INSTANTIATE LOSS CLASS
'''
criterion = nn.CrossEntropyLoss()


'''
STEP 6: INSTANTIATE OPTIMIZER CLASS
'''
learning_rate = 0.001

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

'''
STEP 7: TRAIN THE MODEL
'''
iter = 0
for epoch in range(num_epochs):
    for i, (images, labels) in enumerate(train_loader):

        #######################
        #  USE GPU FOR MODEL  #
        #######################
        images = images.view(-1, 28*28).requires_grad_().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:
                #######################
                #  USE GPU FOR MODEL  #
                #######################
                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.data, 1)

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

                #######################
                #  USE GPU FOR MODEL  #
                #######################
                # 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: 1.8571407794952393. Accuracy: 68.99
Iteration: 1000. Loss: 1.5415704250335693. Accuracy: 75.86
Iteration: 1500. Loss: 1.2755383253097534. Accuracy: 78.92
Iteration: 2000. Loss: 1.2468739748001099. Accuracy: 80.72
Iteration: 2500. Loss: 1.0708973407745361. Accuracy: 81.73
Iteration: 3000. Loss: 1.0359245538711548. Accuracy: 82.74
```

Summary

We've learnt to...

Success

- [x] **Logistic regression** basics
- [x] **Problems** of **linear regression**
- [x] **In-depth** Logistic Regression
  - [x] Get logits
  - [x] Get softmax
  - [x] Get cross-entropy loss
- [x] **Aim**: reduce cross-entropy loss
- [x] Built a **logistic regression model** in **CPU and GPU**
  - [x] Step 1: Load Dataset
  - [x] Step 2: Make Dataset Iterable

- [x] Step 3: Create Model Class
- [x] Step 4: Instantiate Model Class
- [x] Step 5: Instantiate Loss Class
- [x] Step 6: Instantiate Optimizer Class
- [x] Step 7: Train Model
- [x] Important things to be on **GPU**
    - [x] `model`
    - [x] `tensors with gradients`

Comments