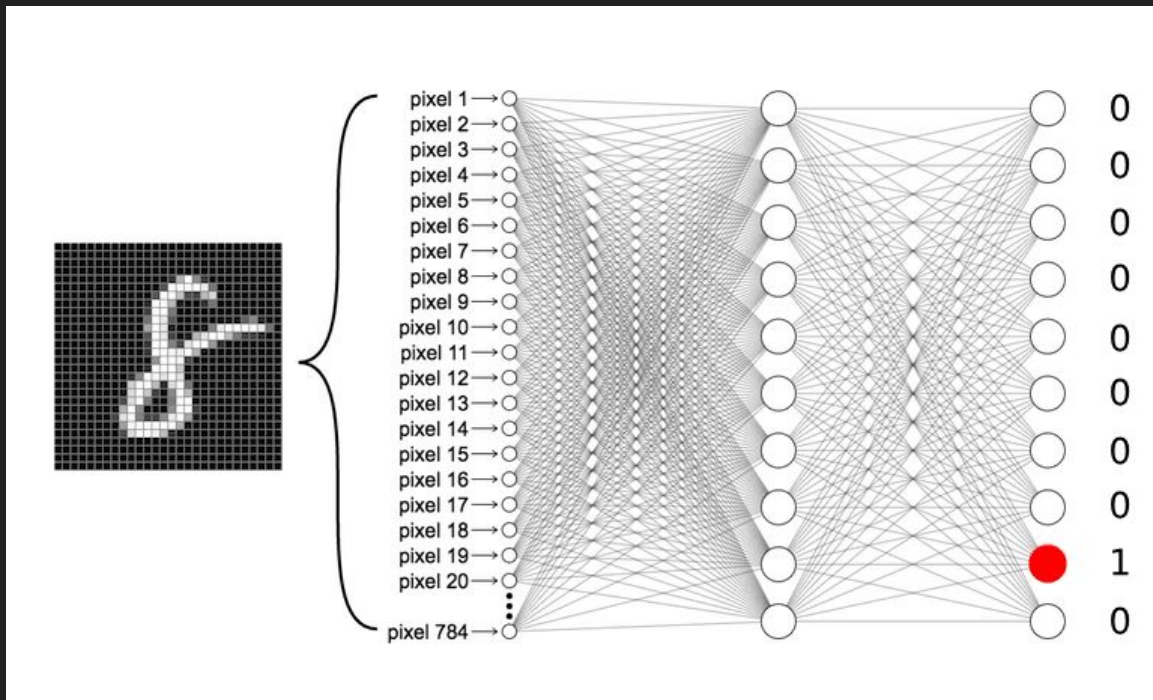


Intro to Tensorflow part 2

Classifying MNIST using fully connected NN



Importing libraries and loading mnist data

```
import tensorflow as tf
```

```
# Useful for n-dimensional array operations
```

```
import numpy as np
```

```
# Useful for plotting graphs/images
```

```
import matplotlib.pyplot as plt
```

```
# Helper class for importing MNIST dataset
```

```
from tensorflow.examples.tutorials.mnist import input_data
```

```
# Loads MNIST dataset with one-hot encoding
```

```
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
```

```
pip install tensorflow
```

```
pip install numpy
```

```
pip install matplotlib
```

Setting up hyperparameters

Define number of input neurons in the network (image_size * image_size = 784 neurons)

image_size = 28

Define number of output neurons in the network (output goes from 0 - 9, 10 neurons)

num_labels = 10

No. of neurons in the first hidden layer

num_neurons_hidden_layer1 = 10

Controls the rate of change of weights in neurons

learning_rate = 0.05

No. of times the network has to see the same data during training

num_iterations = 1000

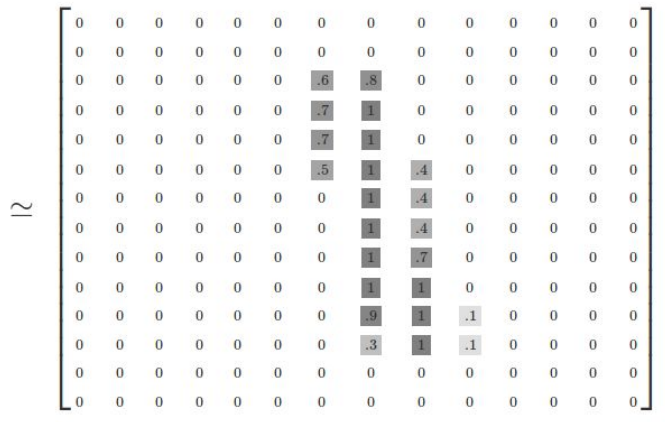
For batch-wise training, each batch will have 100 images

batch_size = 100

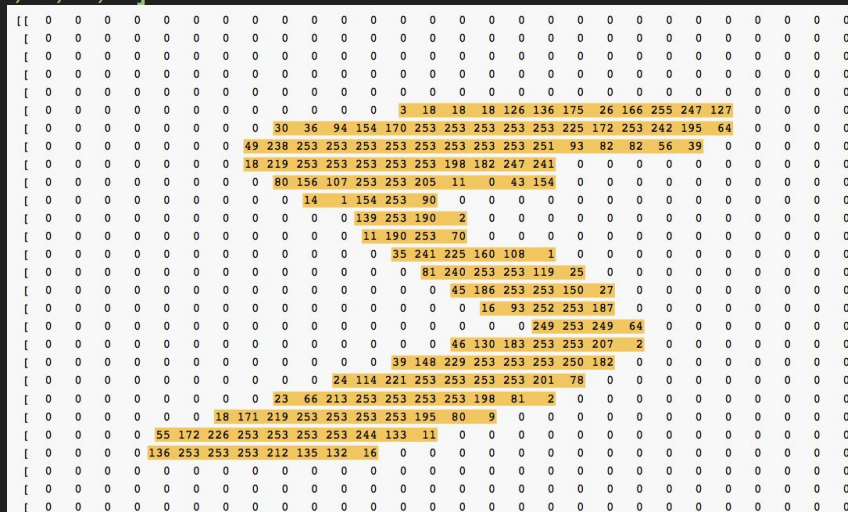
A closer look at the data

```
# Get random 100 images (batch_size=100) and their corresponding ground-truth from the training set
input_batch, labels_batch = mnist.train.next_batch(batch_size)
```

```
# print a 1D array with pixel value (for eg [0, 1, 0, 0, 1, 1, 1, 0, 1, 0,...])
print(input_batch[5])
```



Pixel values are between 0 and 1



Usually the range is 0 - 255

Data Preprocessing

MNIST dataset is already normalized

Data Normalization

$\text{pixel_value} = \text{pixel_value} / 255$

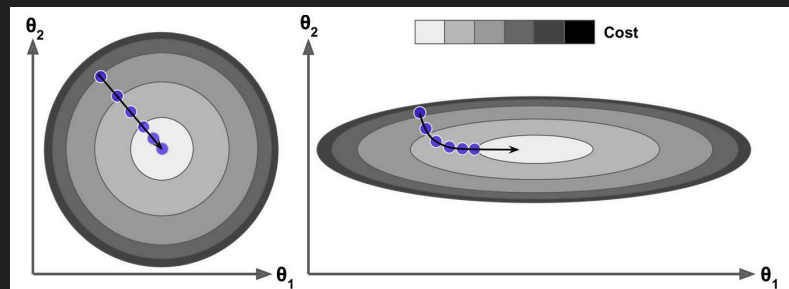
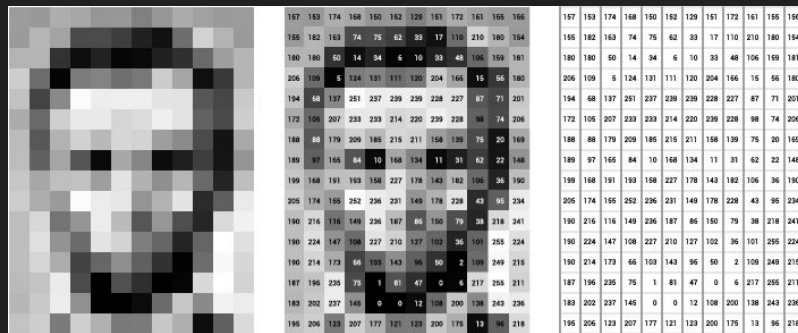
We can do the same operation on a numpy array of images

$\text{image_array} = \text{image_array} / 255$

Why we need data normalized?

1) To standardize the input by bringing it to the same scale

2) Gradient descent (our optimizer) will converge faster



A closer look at the data

```
# Get random 100 images (batch_size=100) and their corresponding ground-truth from the training set
input_batch, labels_batch = mnist.train.next_batch(batch_size)
```

```
# print a 1D array with pixel value (for eg [0, 1, 0, 0, 1, 1, 1, 0, 1, 0,...])
print(input_batch[5])
```

```
# To plot the image we need to reshape the 1D array to 2D array of shape 28x28
plt.imshow(np.reshape(input_batch[5], [28, 28]), cmap='gray')
print('Sample Input')
plt.show()
```

```
print('Sample output (one hot encoding)')
print(labels_batch[5])
```

Build the graph

```
# Define placeholders
```

```
# placeholder to store batch training data per iteration. Shape = [None, 784]  
training_data = tf.placeholder(tf.float32, [None, image_size*image_size])
```

```
# placeholder to store batch labels per iteration. Shape = [None, 10]  
labels = tf.placeholder(tf.float32, [None, num_labels])
```


Build the graph

Variables to be tuned. These are the learned parameters.

We initialize the weights with random values from a normal distribution using tf.truncated_normal()
While training, our optimizer will update the weight values for us

Weights and bias for the hidden layer. Shape = [784, 10]

W1 = tf.Variable(tf.truncated_normal([image_size*image_size, num_neurons_hidden_layer1], stddev=0.1))

Shape = [10]

b1 = tf.Variable(tf.constant(0.1, shape=[num_neurons_hidden_layer1]))

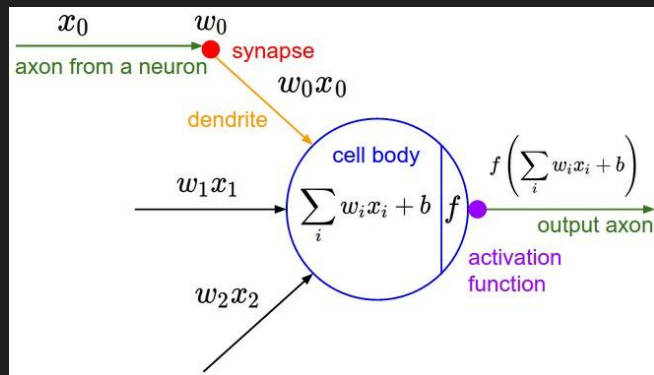
Weights and bias for the output layer. Shape = [10, 10]

W2 = tf.Variable(tf.truncated_normal([num_neurons_hidden_layer1, num_labels], stddev=0.1))

Shape = [10]

b2 = tf.Variable(tf.constant(0.1, shape=[num_labels]))

Build the Neural Network



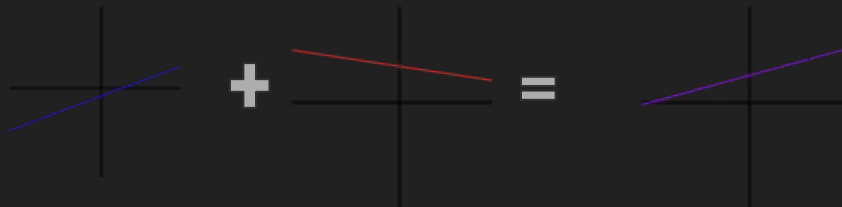
Two functions in the neuron

1) Linear Function: $Wx + b$

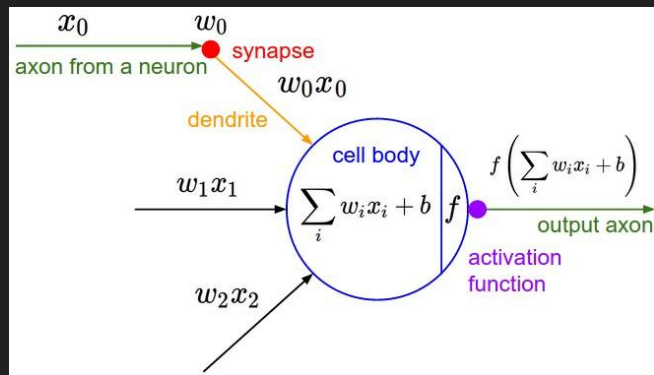
$Wx + b$ is basically $y = Mx + c$, equation of a straight line, where M is the slope/gradient and c is the y-intercept

$Wx + b$ is preferred because:

- It's easier to work with
- Straight lines are useful to model decision boundaries



Build the Neural Network

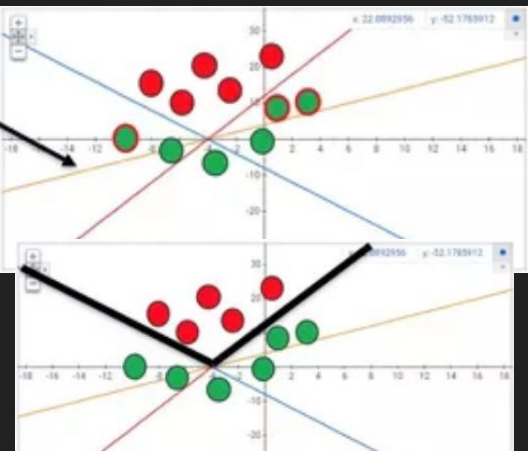


Two functions in the neuron

2) Activation function: $\sigma(Wx + b)$

σ activates neuron based on the output of the linear function

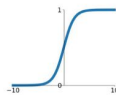
Creates non-linearity in the network



Activation Functions

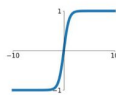
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



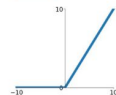
tanh

$$\tanh(x)$$



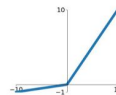
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

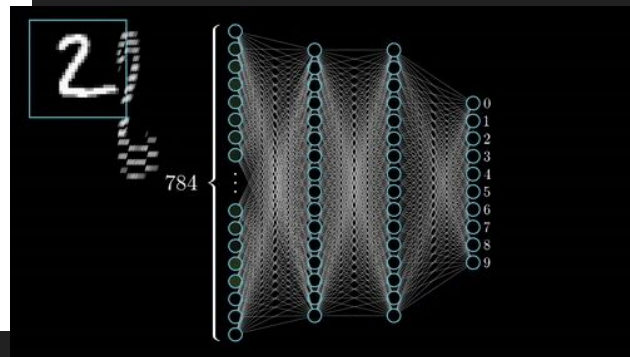
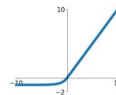


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



Build the Neural Network

Neural Network

$Wx + b$

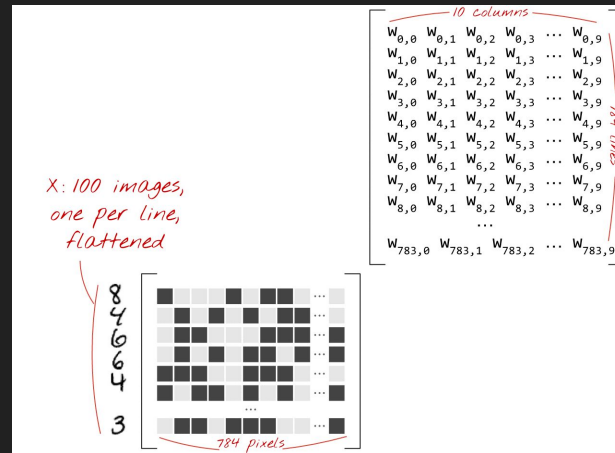
`hidden_layer1 = tf.matmul(training_data, W1) + b1`

Activation function ReLU is applied

`hidden_layer1 = tf.nn.relu(hidden_layer1)`

$Wx + b$

`output_layer = tf.matmul(hidden_layer1, W2) + b2`



TF Layers

```
# Weights and bias for the hidden layer. Shape = [784, 10]
W1 = tf.Variable(tf.truncated_normal([image_size*image_size, num_neurons_hidden_layer1],
stddev=0.1))
# Shape = [10]
b1 = tf.Variable(tf.constant(0.1, shape=[num_neurons_hidden_layer1]))

# Weights and bias for the output layer. Shape = [10, 10]
W2 = tf.Variable(tf.truncated_normal([num_neurons_hidden_layer1, num_labels], stddev=0.1))
# Shape = [10]
b1 = tf.Variable(tf.constant(0.1, shape=[num_labels]))

# Neural Network

# Wx + b
hidden_layer1 = tf.matmul(training_data, W1) + b1

# Activation function ReLU is applied
hidden_layer1 = tf.nn.relu(hidden_layer1)

# Wx + b
output_layer = tf.matmul(hidden_layer1, W2) + b2
```

```
hidden_layer1 = tf.layers.dense(training_data, num_neurons_hidden_layer1,
tf.nn.relu)
```

```
output_layer = tf.layers.dense(hidden_layer1, num_labels, activation=None)
```

Loss Function

Define the loss function

```
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits_v2(labels=labels, logits=output))
```

Loss function usually is a distance functions. How far away is the output produced by the network from the ground-truth?

Softmax converts the output from the network to probabilities (in this case it also acts as an activation function)

Cross-entropy measures the distance between probability distributions (output from softmax vs one-hot encoded ground-truth)

Softmax is only used when we want the output as a multi-class probability distribution

Other loss functions are L1 Loss, L2 Loss, GAN Loss

Optimizer

Define optimizer

Most commonly used optimizer is gradient descent

Goal of the optimizer is to find the optimal weights where the loss is minimum

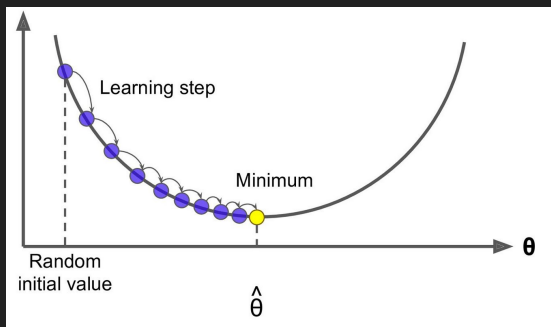
```
optimizer = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)
```

Evaluate accuracy

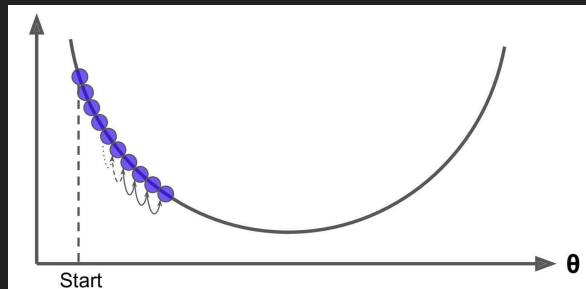
```
correct_prediction = tf.equal(tf.argmax(output, 1), tf.argmax(labels, 1))
```

```
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
```

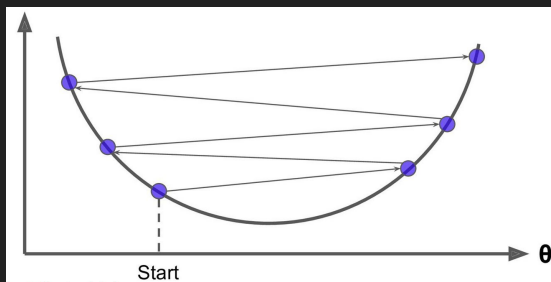
Learning Rate



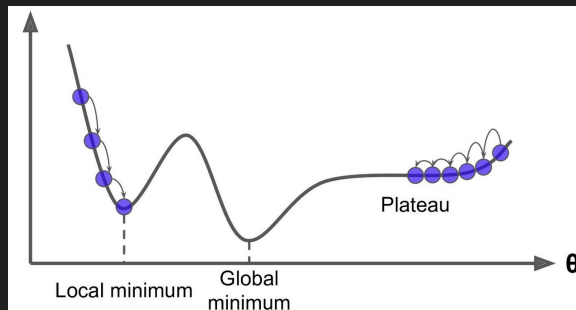
Ideal Learning Rate



Small Learning Rate



High Learning Rate



Real World Scenario

Tensorflow Session

```
# Run the training
sess = tf.Session()
sess.run(tf.global_variables_initializer())

for i in range(num_iterations):
    # Get the next batch
    input_batch, labels_batch = mnist.train.next_batch(batch_size)

    # Run the optimizer, feeding the current input batch and corresponding labels
    sess.run(optimizer, feed_dict={training_data: input_batch, labels: labels_batch})

    if i%100 == 0:
        train_accuracy = sess.run(accuracy, feed_dict={training_data: input_batch, labels: labels_batch})
        print("Iteration %d, training batch accuracy %g %%"%(i, train_accuracy*100))

# Evaluate on the test set
test_accuracy = sess.run(accuracy, feed_dict={training_data: mnist.test.images, labels: mnist.test.labels})
print("Test accuracy: %g %%"%(test_accuracy*100))
```

Converting fully connected MNIST to CNN

```
hidden_layer1 = tf.layers.dense(training_data, num_neurons_hidden_layer1, tf.nn.relu)
output_layer = tf.layers.dense(hidden_layer1, num_labels, activation=None)
```

```
training_data_reshaped = tf.reshape(training_data, shape=[-1, 28, 28, 1])
hidden_layer1 = tf.layers.conv2d(training_data_reshaped, 32, 3, activation=tf.nn.relu)
output_layer = tf.layers.conv2d(hidden_layer1, 32, 3, activation=tf.nn.relu)
output_layer = tf.layers.flatten(output_layer)
output_layer = tf.layers.dense(output_layer, num_labels)
```

CNN

```
# Convert 1D array to a 2D array. Shape = [num_of_images, width, height, channel]
# If num_of_images is unknown when building the graph put -1
# Since MNIST image are grayscale, channel = 1. If we have RGB image then channel = 3

training_data_reshaped = tf.reshape(training_data, shape=[-1, 28, 28, 1])

hidden_layer1 = tf.layers.conv2d(training_data_reshaped, filters=32, kernel_size=3, activation=tf.nn.relu)

output_layer = tf.layers.conv2d(hidden_layer1, filters=32, kernel_size=3, activation=tf.nn.relu)

# Convert 2D array to 1D array for the last layer
output_layer = tf.layers.flatten(output_layer)

# Last layer is fully connected layer
output_layer = tf.layers.dense(output_layer, num_labels)
```