NeuralNetwork-ANN

June 24, 2018

```
In [18]: import tensorflow as tf
         import numpy as np
```

```
In [36]: # utility function - print('\n') is too lazy to me :P
         def line():
             print('\n')
```

0.1 Operations (Basic)

```
In [19]: # review on using palceholders, etc.
         # step : w * x (tf.matmul) + (tf.add) b , pass to activation function
         np.random.seed(101)
         tf.set_random_seed(101)
```

```
In [20]: rand_a = np.random.uniform(0, 100, (5, 5)) # from 0 to 100, shape = (5, 5)
         rand_a
```

```
Out[20]: array([[51.63986277, 57.06675869,  2.84742265, 17.15216562, 68.52769817],
                [83.38968626, 30.69662197, 89.36130797, 72.15438618, 18.99389542],
                [55.42275911, 35.2131954 , 18.18924027, 78.56017619, 96.54832224],
                [23.23536618,  8.35614337, 60.35484223, 72.89927573, 27.62388285],
                [68.53063288, 51.78674742,  4.84845374, 13.78692376, 18.69674261]])
```

```
In [22]: rand_b = np.random.uniform(0, 100, (5, 1)) # from 0 to 100, shape = (5, 1)
         rand_b
```

```
Out[22]: array([[91.31535577],
                [80.7920151 ],
                [40.29978307],
                [35.72243428],
                [95.28767147]])
```

```
In [23]: # placeholders
         a = tf.placeholder(dtype=tf.float32)
         b = tf.placeholder(dtype=tf.float32)
```

```
In [26]: # tensorflow can understand operatons like a + b
         add_op = a + b
         mul_op = a * b
```

```
In [32]: # so that you don't have to close it
         with tf.Session() as sess:
             add_result = sess.run(add_op, feed_dict={a: rand_a, b:rand_b})
             # feed_dict : keys are placeholders
             mult_result = sess.run(mul_op, feed_dict={a: rand_a, b:rand_b})
```

```
In [35]: print(add_result)
         line()
         print(mult_result)
```

```
[[142.95522  148.38211   94.16277  108.46752  159.84305 ]
 [164.1817   111.48864  170.15332  152.94641   99.78591 ]
 [ 95.72254   75.51298   58.48902  118.859955 136.84811 ]
 [ 58.9578    44.07858   96.07728  108.62171   63.346317]
 [163.8183   147.07442  100.13612  109.0746   113.98442 ]]


[[4715.512   5211.0713   260.0134  1566.2561  6257.631  ]
 [6737.2207  2480.042   7219.6797  5829.4985  1534.555  ]
 [2233.5251  1419.0841   733.0224  3165.9578  3890.8765 ]
 [ 830.02386  298.50177 2156.022   2604.1396   986.79236]
 [6530.1245  4934.6387   461.99786 1313.7239  1781.5691 ]]
```

0.2 Example Neural Network (ANN)

```
In [37]: n_features = 10
         n_dense_neurons = 3
```

```
In [40]: W = tf.Variable(tf.random_normal([n_features, n_dense_neurons]))
         x = tf.placeholder(dtype=tf.float32, shape = (None, n_features))
         b = tf.Variable(tf.ones(shape = (n_dense_neurons)))
```

```
In [42]: # operations
         xW = tf.matmul(x, W)
         z = tf.add(xW, b) # z = wx + b
```

```
In [49]: sigmoid_op = tf.sigmoid(z)
```

```
In [47]: init = tf.global_variables_initializer()
```

```
In [50]: with tf.Session() as sess:
             sess.run(init)
             layer_out = sess.run(sigmoid_op, feed_dict={x: np.random.random([1, n_features])})
```

```
In [52]: layer_out # all values are from 0 to 1, as it's sigmoid
```

```
Out[52]: array([[0.29178154, 0.14873713, 0.7982155 ]], dtype=float32)
```

Now let's try to adjust the values of W and b. Then we'll move on to Backpropagation.

0.3 Simple Regression Example

```
In [56]: # this is going to be complete example with usage of optimizing.
         x_data = np.linspace(0, 10, 10) + np.random.uniform(-1.5, 1.5, 10) # add noise using
         # 10 points (linearly spaces) between (0, 10)
```

```
In [57]: x_data
```

```
Out[57]: array([-0.8725155 ,  1.59088467,  2.31109242,  4.07889444,  3.22571501,
                 6.40912111,  7.22839278,  8.36301327,  8.87948845, 11.42608338])
```

```
In [55]: y_label = np.linspace(0, 10, 10) + np.random.uniform(-1.5, 1.5, 10)
```

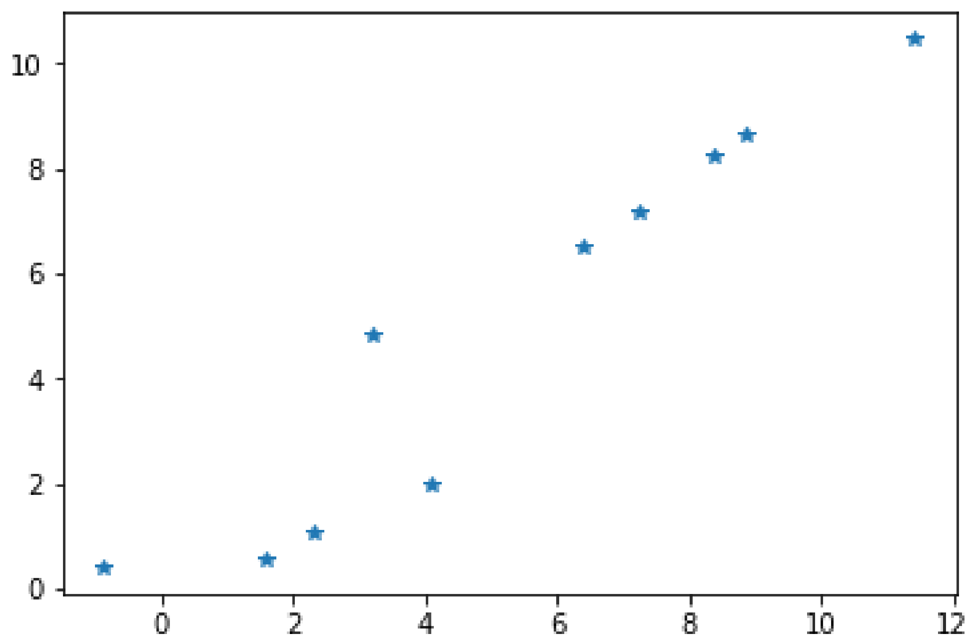
```
In [58]: y_label
```

```
Out[58]: array([ 0.41186709,  0.5849351 ,  1.0749565 ,  1.98663632,  4.8574204 ,
                 6.49235324,  7.17744793,  8.23308089,  8.66259572, 10.46978601])
```

```
In [59]: import matplotlib.pyplot as plt
         %matplotlib inline
```

```
In [61]: plt.plot(x_data, y_label, '*')
```

```
Out[61]: [<matplotlib.lines.Line2D at 0x7faee1587eb8>]
```



$y = mx + b$

```
In [66]: rand_list = np.random.rand(2) # 2 random variables , m and b to be random
         rand_list
```

Out[66]: array([0.37794193, 0.01324101])

In [67]:
```
m = tf.Variable(rand_list[0])
b = tf.Variable(rand_list[1])
```

In [72]:
```
error = 0

for x, y in zip(x_data, y_label):
    y_hat = m*x + b
    error += (y - y_hat) ** 2 # we square it to punish for higher errors
```

In [73]:
```
optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.001)
train = optimizer.minimize(error)
```

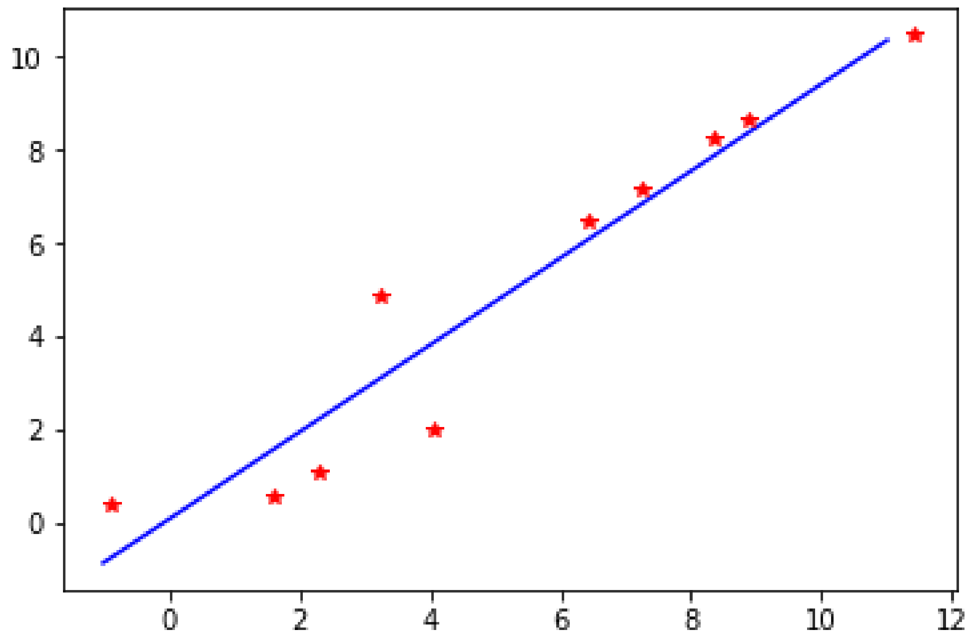
In [74]:
```
init = tf.global_variables_initializer()
```

In [107]:
```
with tf.Session() as sess:
    sess.run(init)
    training_steps = 10000

    for i in range(training_steps):
        sess.run(train)

    final_slope, final_intercept = sess.run([m, b])

print(final_slope, final_intercept)
```

```
0.9354856851745995 0.07069536869078673
```

In [108]:
```
x_test = np.linspace(-1, 11, 10)
y_predict_plot = final_slope * x_test + final_intercept

plt.plot(x_test, y_predict_plot, c = 'blue')
plt.plot(x_data, y_label, '*', c = 'red')
```

Out[108]: [<matplotlib.lines.Line2D at 0x7faee0a1dba8>]



0.4 Tensorflow (Estimator API) for Regression and Classification Techniques

Purpose of tf is to try and solve problems which ML algorithms can not solve. For example, image recognition, classification, RNN - text detection etc.

API used: tf.estimator

```
In [110]: import numpy as np
          import tensorflow as tf
          import pandas as pd
          import matplotlib.pyplot as plt
          %matplotlib inline
```

```
In [131]: plt.style.use('fivethirtyeight')
```

```
In [117]: x_data = np.linspace(0, 10.0, 1000000)
```

```
In [118]: x_data
```

```
Out[118]: array([0.000000e+00, 1.000001e-05, 2.000002e-05, ..., 9.999980e+00,
                 9.999990e+00, 1.000000e+01])
```

```
In [119]: noise = np.random.randn((len(x_data)))
```

y = mx + b
(m = 0.5 and b = 5) -- initial params

```
In [121]: y_true = (0.5 * x_data + 5) + noise
```

In [122]:
```
x_df = pd.DataFrame(data = x_data, columns=['X_Data'])
y_df = pd.DataFrame(data = y_true, columns=['Y'])
```

In [125]:
```
x_df.head(2)
# y_df.head(2)
```

Out[125]:

	X_Data
0	0.00000
1	0.00001

In [126]:
```
data = pd.concat([x_df, y_df], axis = 1) # axis = 1 means along the column
```

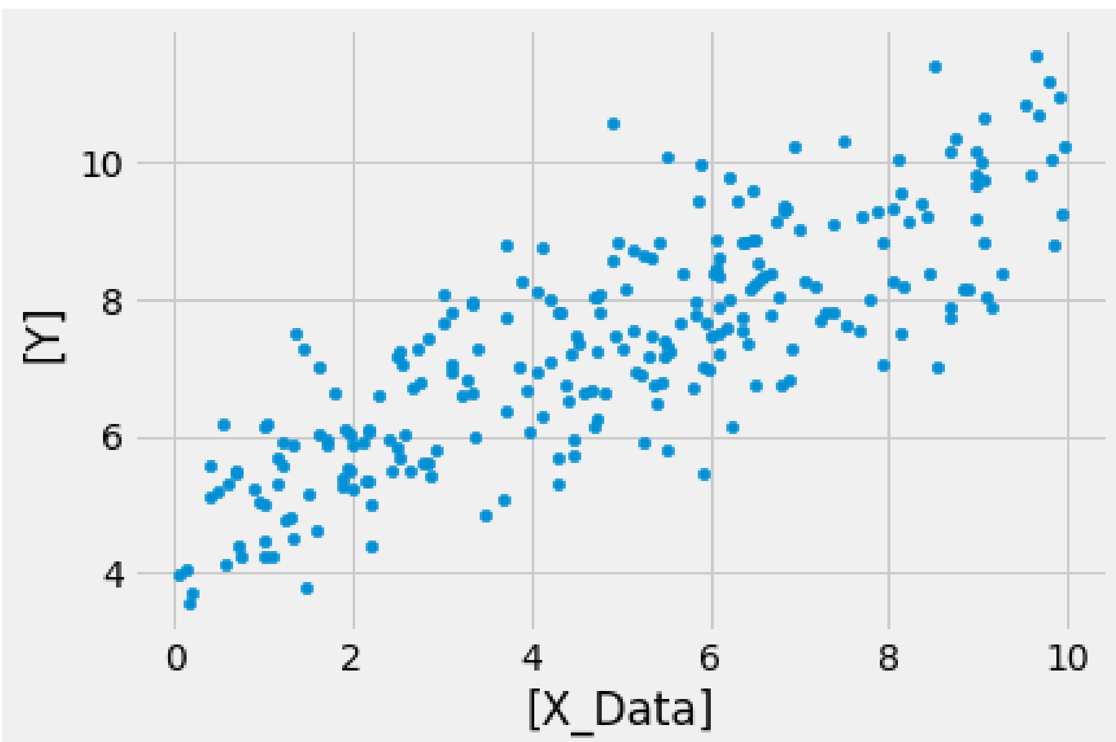
In [128]:
```
data.head(5)
```

Out[128]:

	X_Data	Y
0	0.00000	4.917151
1	0.00001	6.078071
2	0.00002	4.091082
3	0.00003	4.219464
4	0.00004	4.739096

In [132]:
```
# get a few samples from the data, and plot
data.sample(n = 250).plot(kind = 'scatter', x = ['X_Data'], \
                                              y = ['Y'])
```

Out[132]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7faee0bfb828>
```



We train batch by batch because 1 million data to input to a NN may increase the computational time. That's why called, batch-wise training.

```
In [133]: batch_size = 8 # 8 points at a time
```

```
In [139]: rand_list = np.random.randn(2)
          rand_list
```

```
Out[139]: array([-0.09140809, -0.03826566])
```

```
In [141]: m = tf.Variable(-0.091)
          b = tf.Variable(-0.038)
```

```
In [142]: xph = tf.placeholder(tf.float32, [batch_size])
          yph = tf.placeholder(tf.float32, [batch_size])
```

```
In [145]: # define our graph - next step
          y_model = m * xph + b
```

```
In [146]: error = tf.reduce_sum(tf.square(yph - y_model)) # loss function
          # tf.square for pow
```

```
In [147]: optimizer = tf.train.GradientDescentOptimizer(learning_rate=0.001)
          train = optimizer.minimize(error) # minimize the error function
```

```
In [149]: init = tf.global_variables_initializer()
```

```
In [153]: with tf.Session() as sess:
              sess.run(init) # initializes the variables
              # decide number of batches to run through this
              train_numbers = 10000 # total batches = 8000
              for i in range(train_numbers):
                  # choose random 8 data points
                  rand_ind = np.random.randint(len(x_data), size=batch_size)
                  feed = {xph: x_data[rand_ind], yph:y_true[rand_ind]}
                  sess.run(train, feed_dict = feed)

              model_m, model_b = sess.run([m, b])
```

```
In [155]: model_m, model_b
```

```
Out[155]: (0.5023327, 5.062884)
```

```
In [156]: y_hat = model_m * x_data + model_b
```

```
In [159]: data.sample(250).plot(kind = 'scatter', x = 'X_Data', y = 'Y')
          plt.plot(x_data, y_hat, 'r')
```

Out[159]: [<matplotlib.lines.Line2D at 0x7faed45c3e10>]