hw1_q3

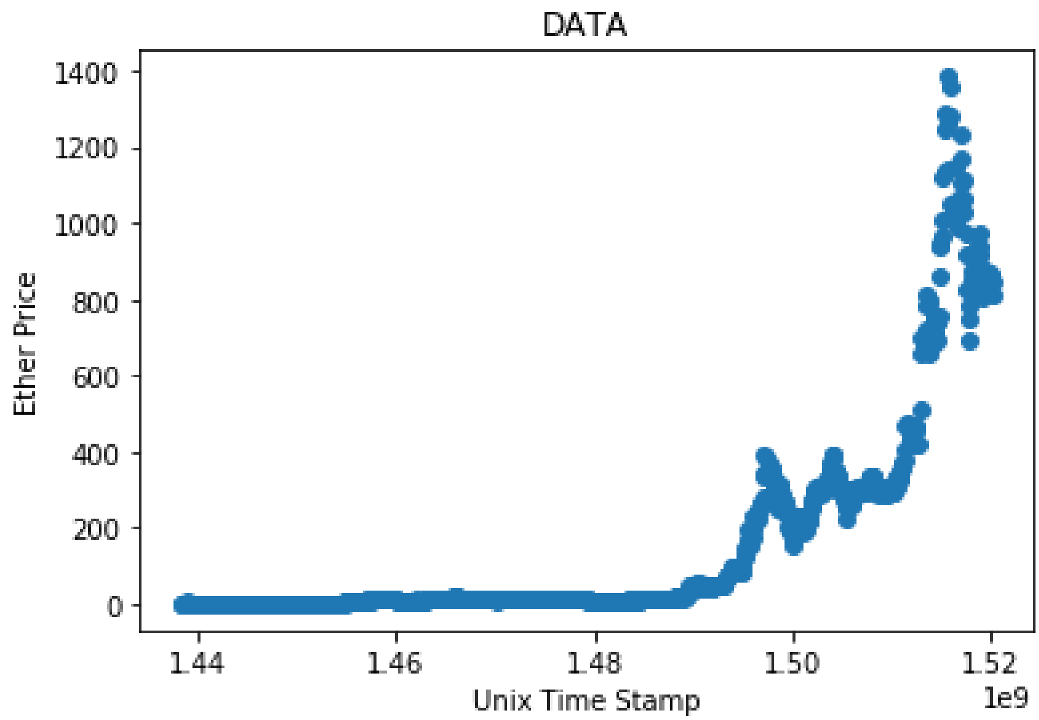
March 18, 2018

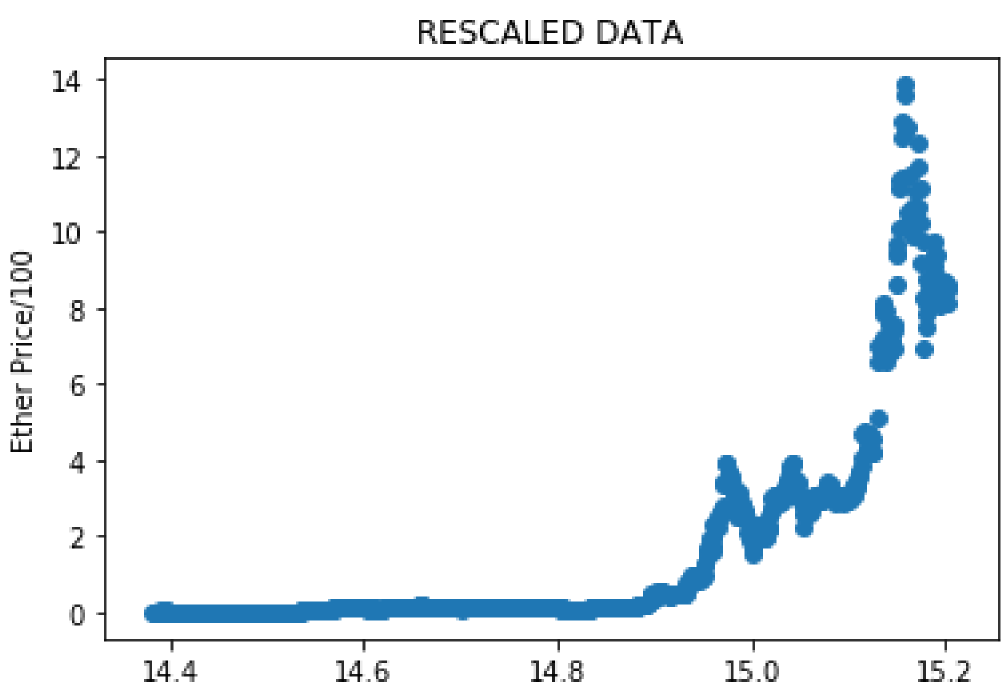
1 HW1 Q3. Linear Regression for Bitcoin/Ethereum Price

1.0.1 (a) Develop a linear regression model to predict Ethereum price. Print the last 10 values of {step, cost, W, b}

In [1]:
```
# import packages
import tensorflow as tf
import numpy as np
import os
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
import matplotlib.pyplot as plt
```

In [2]:
```
# load data
file_path = os.path.join('hw1data/bitcoin', 'export-EtherPrice.csv')
load_data = pd.read_csv(file_path, sep=',')
dataset = load_data.values[:, 1:]

plt.scatter(dataset[:,0], dataset[:,1])
plt.title('DATA')
plt.xlabel('Unix Time Stamp')
plt.ylabel('Ether Price')
plt.show()

x_train = dataset[:, 0]
y_train = dataset[:, 1]

# too big numbers to put it in float64
# need to be rescaled
x_train = x_train/100000000.0
y_train = y_train/100.0

plt.scatter(x_train, y_train)
plt.title('RESCALED DATA')
plt.xlabel('Unix Time Stamp/(10^8)')
plt.ylabel('Ether Price/100')
plt.show()
```


DATA
1400
1200
1000
800
600
400
200
0
Ether Price
1.44
1.46
1.48
1.50
1.52
1e9
Unix Time Stamp


RESCALED DATA
14
12
10
8
6
4
2
0
Ether Price/100
14.4
14.6
14.8
15.0
15.2
Unix Time Stamp/(10^8)

```
In [3]: learning_rate = 15**(-2)
        epochs = 8000001
        #epochs = 500000
        g1 = tf.Graph()
        with g1.as_default():
            X = tf.placeholder(tf.float64, shape = [None])
            Y = tf.placeholder(tf.float64, shape = [None])

            W = tf.Variable(tf.random_normal([1], dtype=tf.float64), name='weight')
            b = tf.Variable(tf.random_normal([1], dtype=tf.float64), name='bias')

            hypothesis = tf.add(tf.multiply(X, W), b)

            cost = tf.reduce_mean(tf.square(tf.subtract(hypothesis, Y)))

            optimizer = tf.train.GradientDescentOptimizer(learning_rate = learning_rate)
            train = optimizer.minimize(cost)

        with tf.Session(graph=g1) as sess:
            print("step | cost | W | b")
            sess.run(tf.global_variables_initializer())

            for step in range(epochs):
                cost_val, W_val, b_val, _ = \
                    sess.run([cost, W, b, train],
                             feed_dict={X: x_train, Y: y_train})
                if step > (epochs-11):
                #if step % 50000 == 0:
                    print(step, cost_val, W_val, b_val)

            predict_price = sess.run(hypothesis, feed_dict={X: [(1520294400+13.0*86400.0)/(10.0*
```

```
step | cost | W | b
7999991 3.4177773855676197 [8.42342213] [-123.04942481]
7999992 3.4177773855676192 [8.42342213] [-123.04942481]
7999993 3.4177773855676192 [8.42342213] [-123.04942481]
7999994 3.4177773855676197 [8.42342213] [-123.04942481]
7999995 3.417777385567621 [8.42342213] [-123.04942481]
7999996 3.41777738556762 [8.42342213] [-123.04942481]
7999997 3.417777385567621 [8.42342213] [-123.04942481]
7999998 3.4177773855676192 [8.42342213] [-123.04942481]
7999999 3.41777738556762 [8.42342213] [-123.04942481]
8000000 3.417777385567621 [8.42342213] [-123.04942481]
```

1.0.2 (b) Predict the price on March 19th?

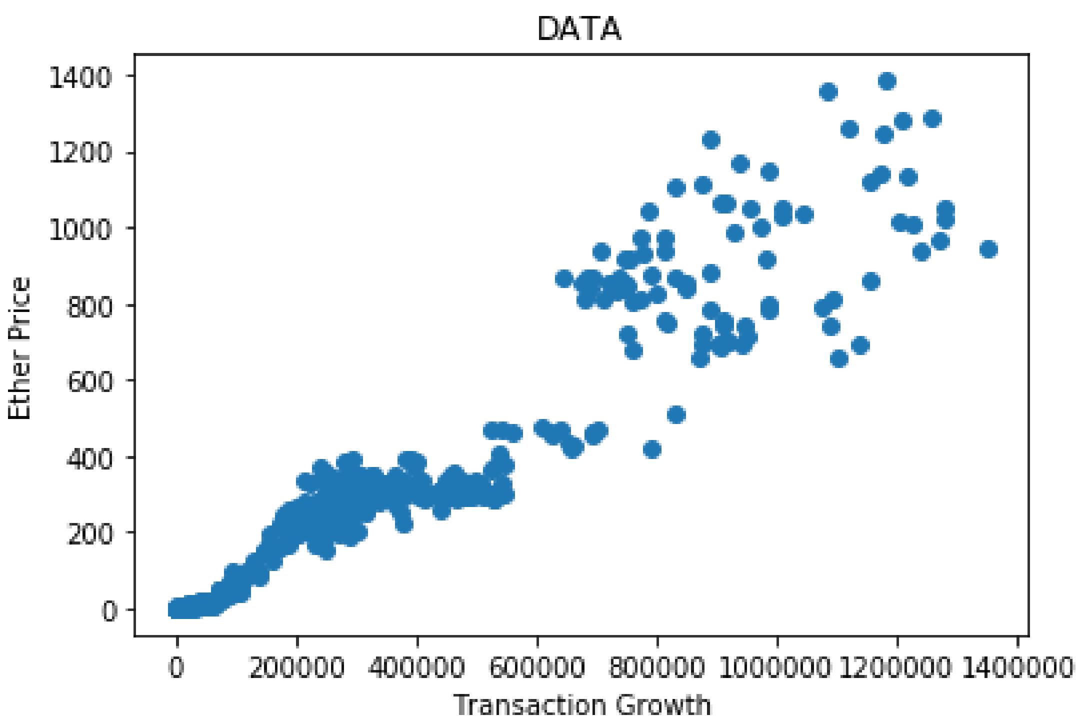
```
In [4]: print("The Ether Price on March 19th : ", predict_price*100.0)
```

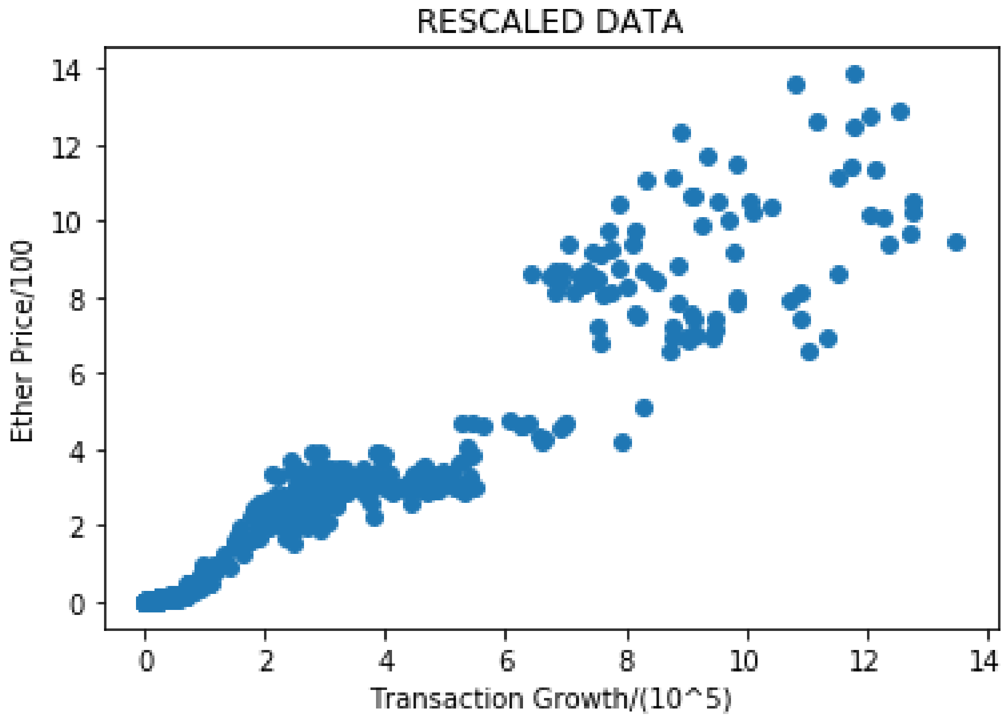
```
The Ether Price on March 19th :  [510.60020448]
```

1.0.3 Use transaction growth "export-TxGrowth.csv" as a feature to predict the Ethereum price.

1.0.4 (c) Develop a linear regression model and print the last 10 values of {step, cost, W, b}.

```
In [5]: # load data
        file_path = os.path.join('hw1data/bitcoin', 'export-TxGrowth.csv')
        load_data = pd.read_csv(file_path, sep=',')
        tx_growth = load_data.values[:, 2]
        #print(tx_growth)

        plt.scatter(tx_growth, y_train*100.0)
        plt.title('DATA')
        plt.xlabel('Transaction Growth')
        plt.ylabel('Ether Price')
        plt.show()

        tx_growth = tx_growth/100000.0

        plt.scatter(tx_growth, y_train)
        plt.title('RESCALED DATA')
        plt.xlabel('Transaction Growth/(10^5)')
        plt.ylabel('Ether Price/100')
        plt.show()
```






```
In [6]: learning_rate = 10**(-3)
        epochs = 25001

        g2 = tf.Graph()
        with g2.as_default():
            X = tf.placeholder(tf.float64, shape = [None])
            Y = tf.placeholder(tf.float64, shape = [None])

            W = tf.Variable(tf.random_normal([1], dtype=tf.float64), name='weight')
            b = tf.Variable(tf.random_normal([1], dtype=tf.float64), name='bias')

            hypothesis = tf.add(tf.multiply(X, W), b)

            cost = tf.reduce_mean(tf.square(tf.subtract(hypothesis, Y)))

            optimizer = tf.train.GradientDescentOptimizer(learning_rate = learning_rate)
            train = optimizer.minimize(cost)

        with tf.Session(graph=g2) as sess:
            print("step | cost | W | b")
            sess.run(tf.global_variables_initializer())
```

```
        for step in range(epochs):
            cost_val, W_val, b_val, _ = \
                sess.run([cost, W, b, train],
                         feed_dict={X: tx_growth, Y: y_train})
            if step > (epochs-11):
            #if step % 5000 == 0:
                print(step, cost_val, W_val, b_val)
```

```
step | cost | W | b
24991 0.509867178494975 [0.94034854] [-0.19450488]
24992 0.509867178494975 [0.94034854] [-0.19450488]
24993 0.509867178494975 [0.94034854] [-0.19450488]
24994 0.509867178494975 [0.94034854] [-0.19450488]
24995 0.509867178494975 [0.94034854] [-0.19450488]
24996 0.509867178494975 [0.94034854] [-0.19450488]
24997 0.509867178494975 [0.94034854] [-0.19450488]
24998 0.509867178494975 [0.94034854] [-0.19450488]
24999 0.509867178494975 [0.94034854] [-0.19450488]
25000 0.509867178494975 [0.94034854] [-0.19450488]
```

1.0.5 (e) Any correlations between transaction growth and price?

According to the plots, the price proportionally increases as the transaction growth increases even though high values of the transation growth are scattered. ### Now, use price to predict the transaction growth. ### (f) Develop a linear regression model and print the last 10 values of {step, cost, W, b}

```
In [7]: learning_rate = 10**(-3)
        epochs = 25001

        g3 = tf.Graph()
        with g3.as_default():
            X = tf.placeholder(tf.float64, shape = [None])
            Y = tf.placeholder(tf.float64, shape = [None])

            W = tf.Variable(tf.random_normal([1], dtype=tf.float64), name='weight')
            b = tf.Variable(tf.random_normal([1], dtype=tf.float64), name='bias')

            hypothesis = tf.add(tf.multiply(X, W), b)

            cost = tf.reduce_mean(tf.square(tf.subtract(hypothesis, Y)))

            optimizer = tf.train.GradientDescentOptimizer(learning_rate = learning_rate)
            train = optimizer.minimize(cost)

        with tf.Session(graph=g3) as sess:
```

```
print("step | cost | W | b")
sess.run(tf.global_variables_initializer())

for step in range(epochs):
    cost_val, W_val, b_val, _ = \
        sess.run([cost, W, b, train],
                 feed_dict={X: y_train, Y: tx_growth})
    if step > (epochs-11):
    #if step % 5000 == 0:
        print(step, cost_val, W_val, b_val)
```

```
step | cost | W | b
24991 0.536861598587961 [0.99013438] [0.32012889]
24992 0.536861598587961 [0.99013438] [0.32012889]
24993 0.536861598587961 [0.99013438] [0.32012889]
24994 0.536861598587961 [0.99013438] [0.32012889]
24995 0.536861598587961 [0.99013438] [0.32012889]
24996 0.536861598587961 [0.99013438] [0.32012889]
24997 0.536861598587961 [0.99013438] [0.32012889]
24998 0.536861598587961 [0.99013438] [0.32012889]
24999 0.536861598587961 [0.99013438] [0.32012889]
25000 0.536861598587961 [0.99013438] [0.32012889]
```

```
In [ ]:
```