Name: Afroz Quraishi
Roll no.: 2018IMT-009
Course: Machine Learning
Course Code: ITIT 4107-2021
Assignment-4
Deadline: 18th Oct 2021

Problem:

Suppose you are the CEO of a restaurant franchise and are considering different cities for opening a new outlet. The chain already has trucks in various cities and you have data for profits and populations from the cities. You would like to use this data to help you select which city to expand to next. The file ex1data1.txt contains the dataset for our linear regression problem. The first column is the population of a city and the second column is the profit of a food truck in that city. A negative value for profit indicates a loss.

1. Use a scatter plot to visualize the data, since it has only two properties to plot (profit and population).
2. Consider a simple linear model with two parameters and one input variable and mean square error cost function to implement the gradient descent algorithm to find the intercepts. Assume a suitable terminating condition.
3. Plot the model alongside the scatterplot to show the fit model.
4. Perform steps 1,2,3 in batch mode for varying values of alpha, learning rate and plot the results.
5. For each of the experiments performed above in steps 1,2,3,4 with varying learning rates visualize the cost function as a contour plot as well as plot the values of parameters to visualize the stepwise traversion of the parameters on this contour plot.

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

```
df=pd.read_csv("https://raw.githubusercontent.com/AlfTang/Linear-Regression/master/
```

```
df.head()
```

	population	profit
0	6.1101	17.5920
1	5.5277	9.1302

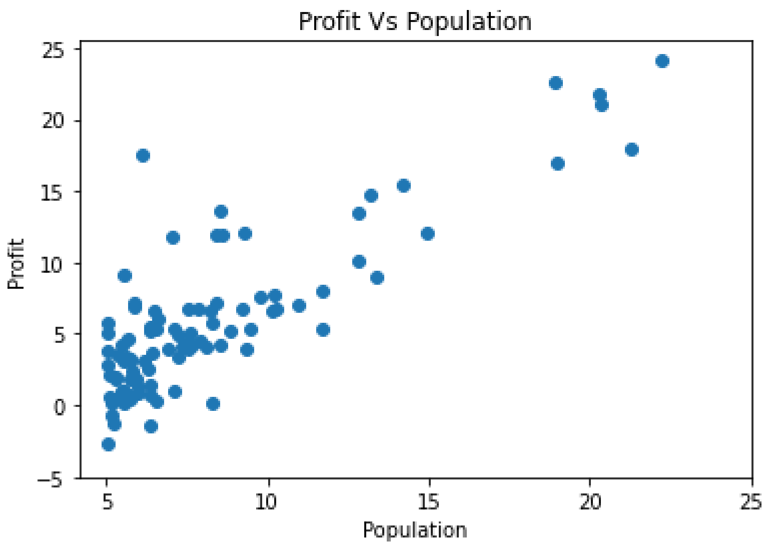
```
df.describe()
```

	population	profit
count	97.000000	97.000000
mean	8.159800	5.839135
std	3.869884	5.510262
min	5.026900	-2.680700
25%	5.707700	1.986900
50%	6.589400	4.562300
75%	8.578100	7.046700
max	22.203000	24.147000

Visualizing the Data

```
plt.scatter(df['population'],df['profit'])
plt.title("Profit Vs Population")
plt.xticks(np.arange(5,30,step=5))
plt.yticks(np.arange(-5,30,step=5))
plt.xlabel("Population")
plt.ylabel("Profit")
```

```
Text(0, 0.5, 'Profit')
```




```
def computeCost(X,y,theta):
    m=len(y)
    predictions=X.dot(theta)
```

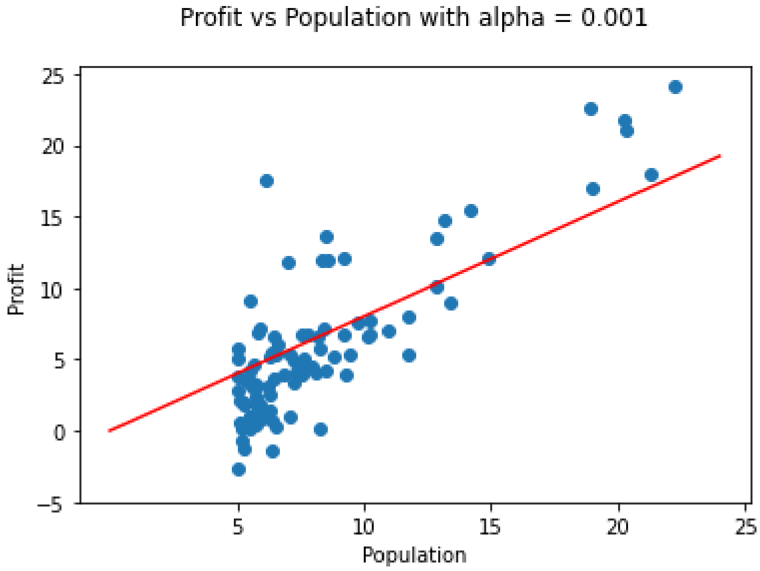
```
    square_err=(predictions - y)**2

    return 1/(2*m) * np.sum(square_err)


data_n=df.values
m=len(data_n[:,-1])
X=np.append(np.ones((m,1)),data_n[:,0].reshape(m,1),axis=1)
y=data_n[:,1].reshape(m,1)
theta=np.zeros((2,1))
computeCost(X,y,theta)
```

```
32.072733877455676
```

```
def gradientDescent(X,y,theta,alpha,num_iters):

    m=len(y)
    J_history=[]

    for i in range(num_iters):
        predictions = X.dot(theta)
        error = np.dot(X.transpose(),(predictions -y))
        descent=alpha * 1/m * error
        theta-=descent
        J_history.append(computeCost(X,y,theta))

    return theta, J_history


def plot_model_fit(alpha,theta):
    plt.scatter(df['population'],df['profit'])
    plt.title("Profit vs Population with alpha = {}\n".format(alpha))
    x_value=[x for x in range(25)]
    y_value=[y*theta[1]+theta[0] for y in x_value]
    plt.plot(x_value,y_value,color="r")
    plt.xticks(np.arange(5,30,step=5))
    plt.yticks(np.arange(-5,30,step=5))
    plt.xlabel("Population")
    plt.ylabel("Profit")

def func(i):
  theta=np.zeros((2,1))
  alpha = alpha_values[i]
  theta,J_history = gradientDescent(X,y,theta,alpha,100)
  print('The ALPHA value, learning_rate: {}'.format(alpha))
  print('The THETA value: {}'.format(theta))
  print('\nHypothesis Function:')
  print("h(x) ="+str(round(theta[0,0],2))+" + "+str(round(theta[1,0],2))+"x1")
  J_histories.append(J_history)
  plot_model_fit(alpha,theta)



alpha_values = np.arange(0.001, 0.02, 0.002)
J_histories =[]
```

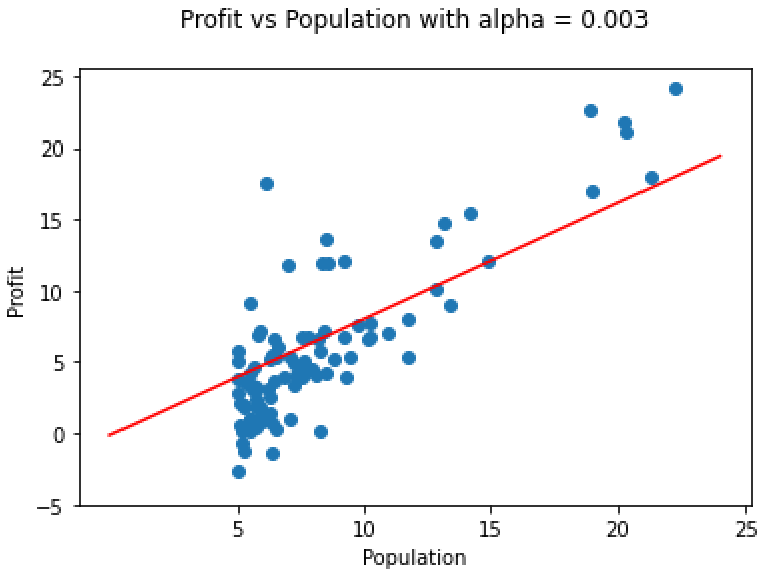
```
print("Alpha values: ({})".format(len(alpha_values)), alpha_values)
func(0)
```

```
Alpha values: (10) [0.001 0.003 0.005 0.007 0.009 0.011 0.013 0.015 0.017 0.0
The ALPHA value, learning_rate: 0.001
The THETA value: [[0.00868909]
 [0.80063674]]

Hypothesis Function:
h(x) =0.01 + 0.8x1
```



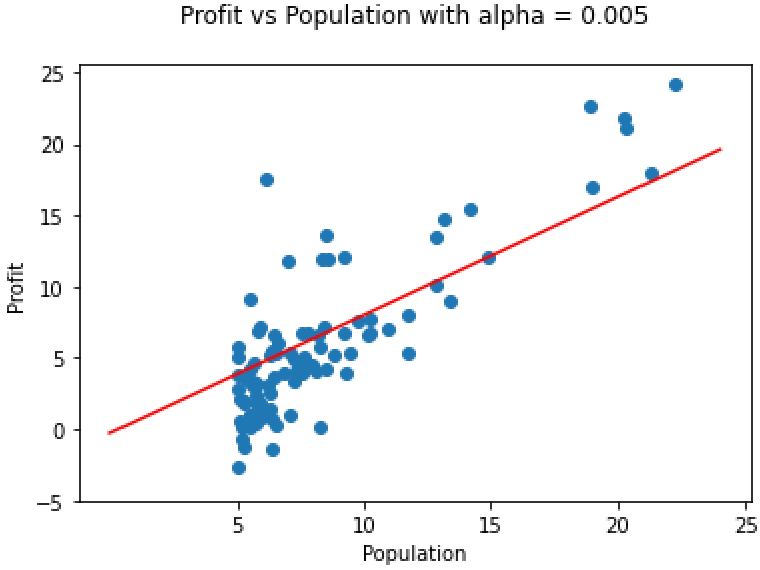

```
func(1)
```

```
The ALPHA value, learning_rate: 0.003
The THETA value: [[-0.12960188]
 [ 0.81468011]]

Hypothesis Function:
h(x) =-0.13 + 0.81x1
```



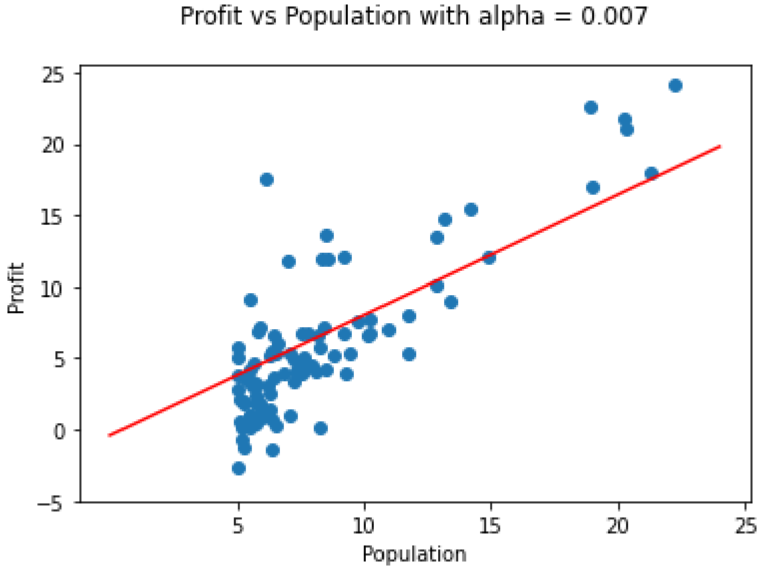

```
func(2)
```

```
The ALPHA value, learning_rate: 0.005
The THETA value: [[-0.26305598]
 [ 0.82808702]]

Hypothesis Function:
h(x) =-0.26 + 0.83x1
```



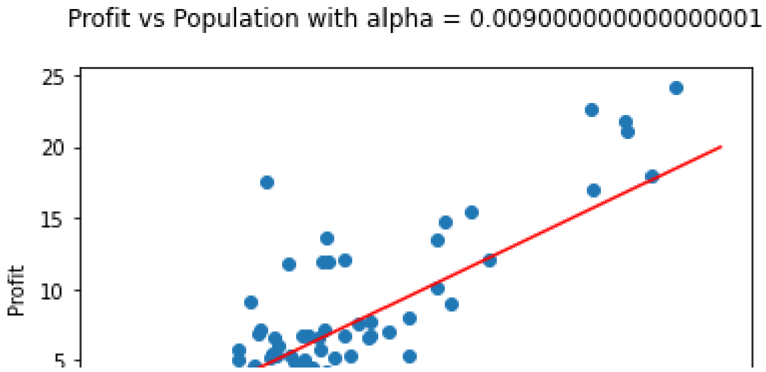

```
func(3)
```

```
The ALPHA value, learning_rate: 0.007
The THETA value: [[-0.39182677]
 [ 0.84102345]]

Hypothesis Function:
h(x) =-0.39 + 0.84x1
```



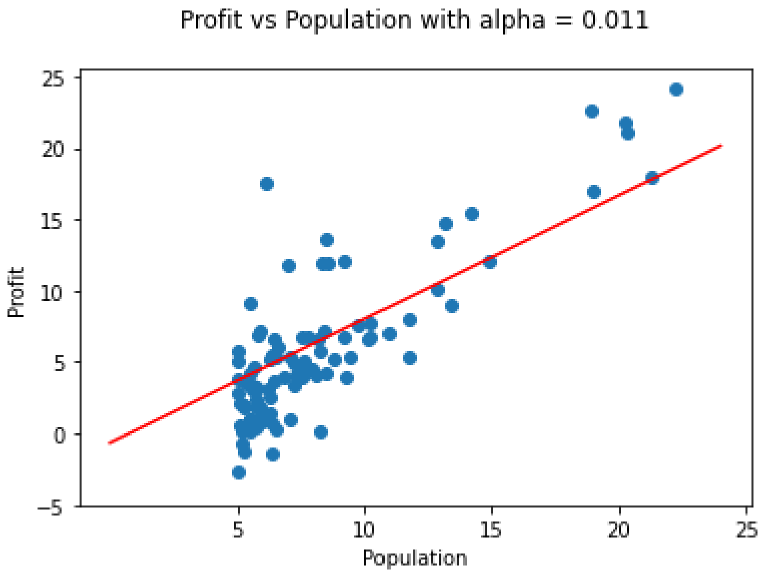

```
func(4)
```

```
The ALPHA value, learning_rate: 0.009000000000000001
The THETA value: [[-0.516077  ]
 [ 0.85350573]]

Hypothesis Function:
h(x) =-0.52 + 0.85x1
```



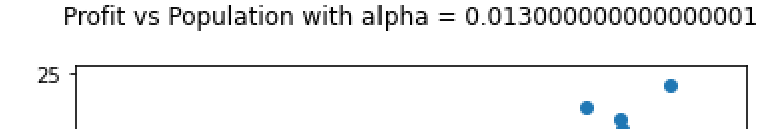

```
func(5)
```

```
The ALPHA value, learning_rate: 0.011
The THETA value: [[-0.63596383]
 [ 0.86554966]]

Hypothesis Function:
h(x) =-0.64 + 0.87x1
```



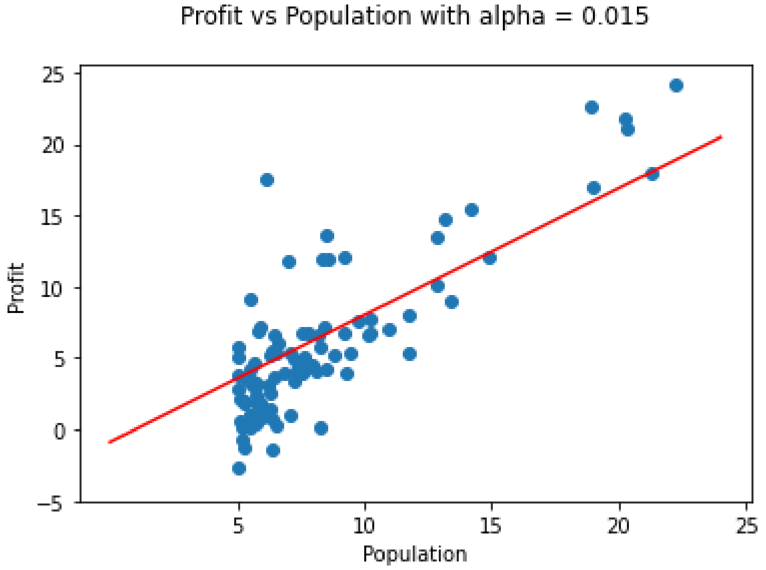

```
func(6)
```

```
The ALPHA value, learning_rate: 0.013000000000000001
The THETA value: [[-0.75163899]
 [ 0.87717049]]

Hypothesis Function:
h(x) =-0.75 + 0.88x1
```




```
func(7)
```

```
The ALPHA value, learning_rate: 0.015
The THETA value: [[-0.863249  ]
 [ 0.88838292]]

Hypothesis Function:
h(x) =-0.86 + 0.89x1
```

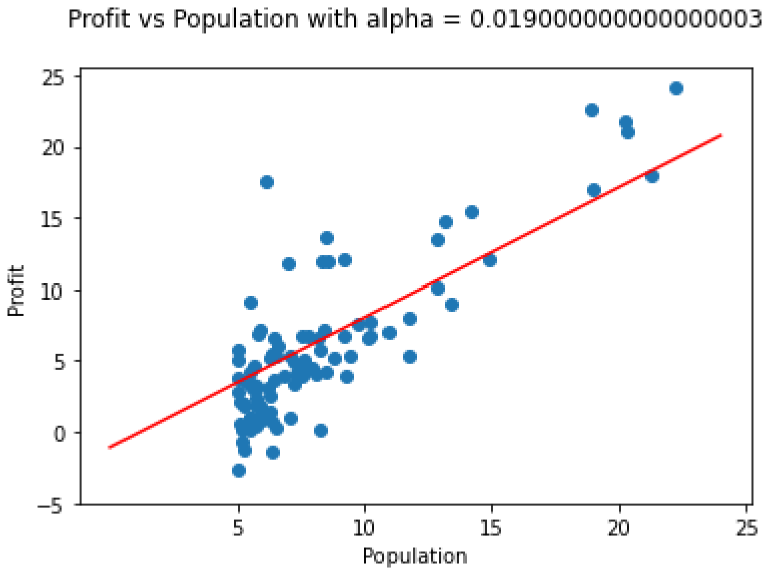



```
func(8)
```

```
The ALPHA value, learning_rate: 0.017
The THETA value: [[-0.97093532]
 [ 0.89920118]]
```

```
func(9)
```

```
The ALPHA value, learning_rate: 0.019000000000000003
The THETA value: [[-1.07483455]
 [ 0.90963899]]

Hypothesis Function:
h(x) =-1.07 + 0.91x1
```



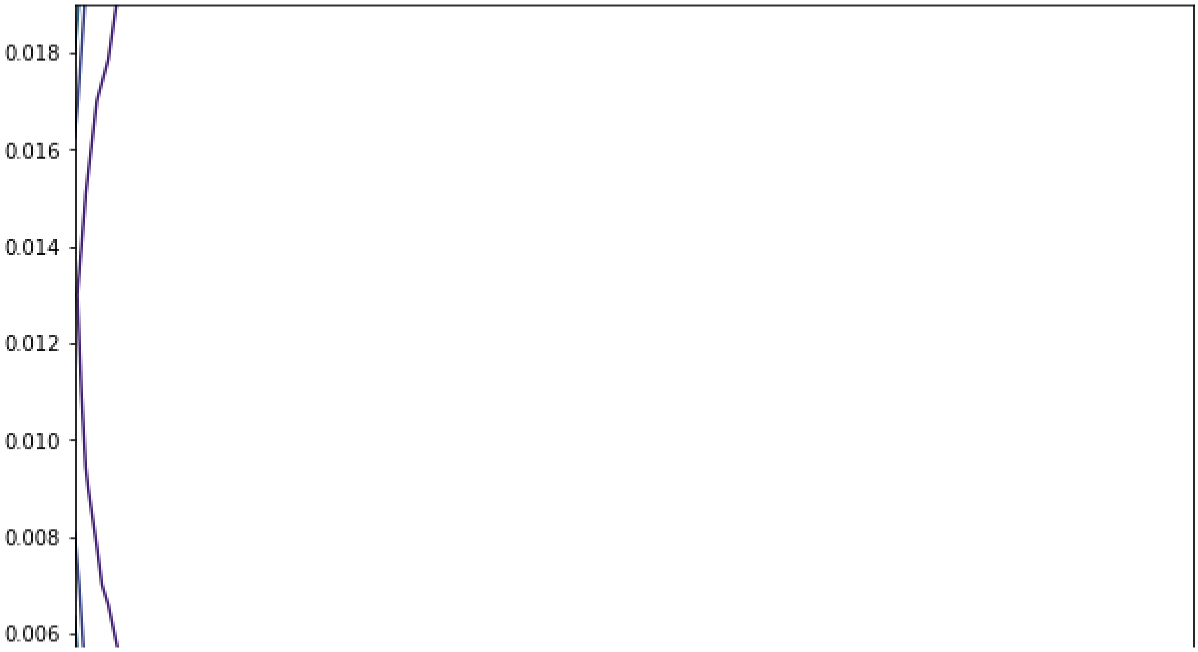

```
x = np.arange(1,125,1.25)
y = alpha_values
len(x)
```

```
100
```

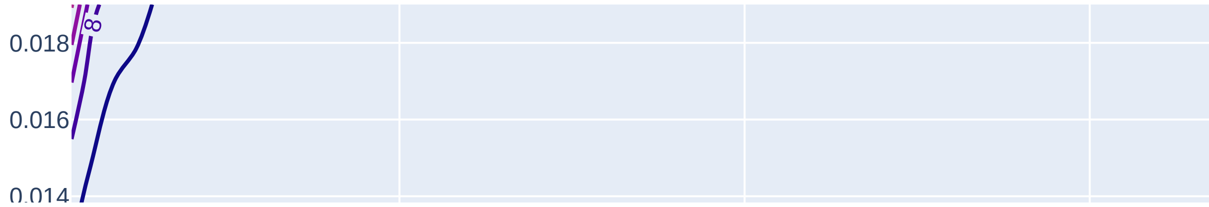
```
print(min(min(J_histories)))
max(max(J_histories))
```

```
5.376953190466999
27.94761974682486
```

```
z = J_histories
fig, ax = plt.subplots(1, 1,figsize=(10, 8))
ax.contour(x,y,z)
plt.show()
```




```
import plotly.graph_objects as go



fig = go.Figure(data=go.Contour(
  x=x, y=y, z=z,
  contours=dict(
    coloring='lines',
    showlabels=True,),
    line_width=2
))

fig.show()

# x -> Value of the cost function
# y -> Learning rates
# z -> The value of the cost function at a given learning rate alpha
```



Inference

If slope is +ve : θj = θj – (+ve value). Hence value of θj decreases.
If slope is -ve : θj = θj – (-ve value). Hence value of θj increases.
The choice of correct learning rate is very important as it ensures that Gradient Descent converges in a reasonable time:
- If we choose α to be very large, Gradient Descent can overshoot the minimum. It may fail to converge or even diverge.
- If we choose α to be very small, Gradient Descent will take small steps to reach local minima and will take a longer time to reach minima.

Code Link: https://github.com/afroz23/ITIT-4103-2021/tree/main/Assignment-4