Univariate Linear Regression

Task 2: Load the Data and Libraries

In [1]:
```python
import matplotlib.pyplot as plt
plt.style.use('ggplot')
%matplotlib inline
```

In [4]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
plt.rcParams['figure.figsize'] = (12, 8)
```

In [5]:
```python
data = pd.read_csv('bike_sharing_data.txt')
data.head()
```

Out[5]:

	Population	Profit
0	6.1101	17.5920
1	5.5277	9.1302
2	8.5186	13.6620
3	7.0032	11.8540
4	5.8598	6.8233

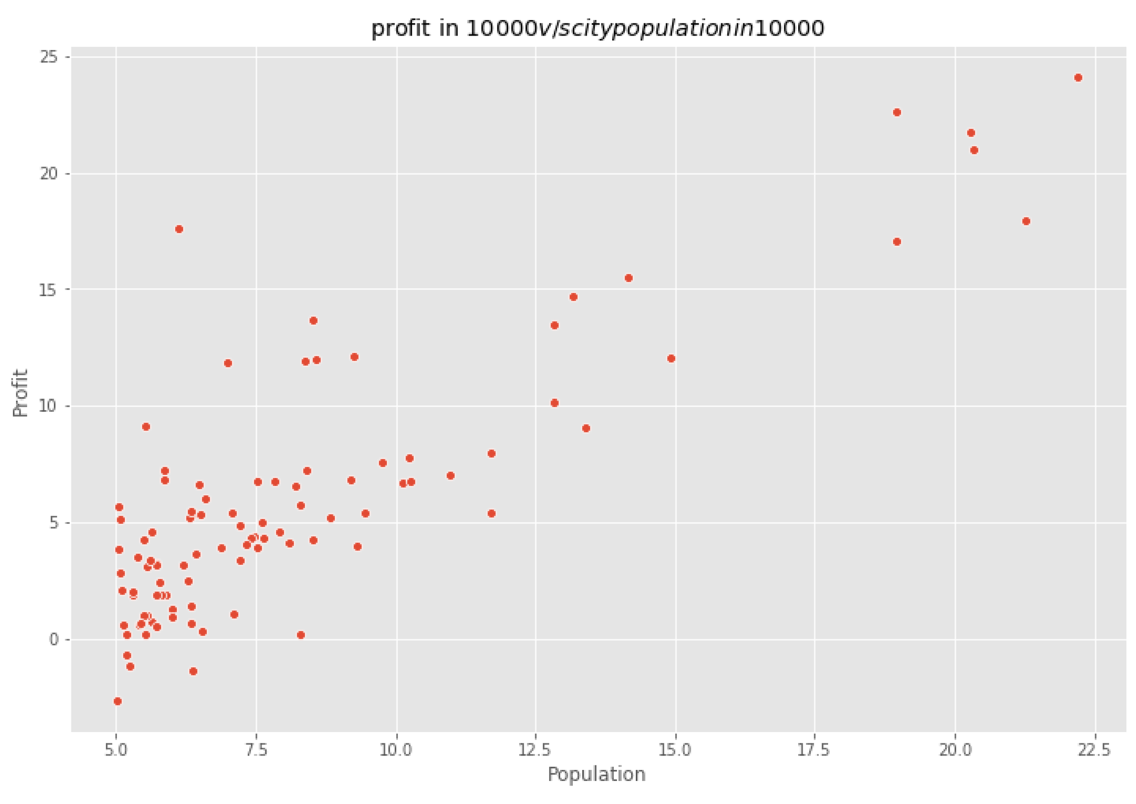
In [6]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 97 entries, 0 to 96
Data columns (total 2 columns):
Population    97 non-null float64
Profit        97 non-null float64
dtypes: float64(2)
memory usage: 1.6 KB
```

Task 3: Visualize the Data

In [8]:
```python
ax = sns.scatterplot(x='Population',y='Profit',data=data)
ax.set_title('profit in $10000 v/s city population in $10000')
```

Out[8]:
```
Text(0.5, 1.0, 'profit in $10000 v/s city population in $10000')
```



Task 4: Compute the Cost $J(\theta)$

The objective of linear regression is to minimize the cost function

$$J(\theta) = \frac{1}{2m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})^2$$

where $h_\theta(x)$ is the hypothesis and given by the linear model

$$h_\theta(x) = \theta^T x = \theta_0 + \theta_1 x_1$$

In [9]:
```python
def cost_fun(X, y, theta):
    m = len(y)
    y_pred = X.dot(theta)
    error = (y_pred - y)**2
    return 1/(2*m) * np.sum(error)
```

In [10]:
```python
m = data.Population.values.size
X = np.append(np.ones((m, 1)), data.Population.values.reshape(m, 1),axis = 1)
y = data.Profit.values.reshape(m, 1)
theta = np.zeros((2,1))
cost_fun(X,y,theta)
```

Out[10]:
```
32.072733877455676
```

Task 5: Gradient Descent

Minimize the cost function $J(\theta)$ by updating the below equation and repeat unitil convergence

$\theta_j := \theta_j - \alpha\frac{1}{m}\sum_{i=1}^{m}(h_\theta(x^{(i)}) - y^{(i)})x_j^{(i)}$ (simultaneously update θ_j for all j).

In [11]:
```python
def gradient(X,y,theta, alpha,iterations):
    m = len(y)
    costs = []
    for i in range(iterations):
        y_pred = X.dot(theta)
        error = np.dot(X.transpose(),(y_pred - y))
        theta-= alpha * 1/m *error
        costs.append(cost_fun(X,y,theta))
    return theta, costs
```

In [16]:
```python
theta , costs = gradient(X, y, theta, alpha = 0.01, iterations=2000)
print('h(x) = {} + {}x1'.format(str(round(theta[0,0],2)) ,
                                 str(round(theta[1,0,],2))))
```

```
h(x) = -3.9 + 1.19x1
```

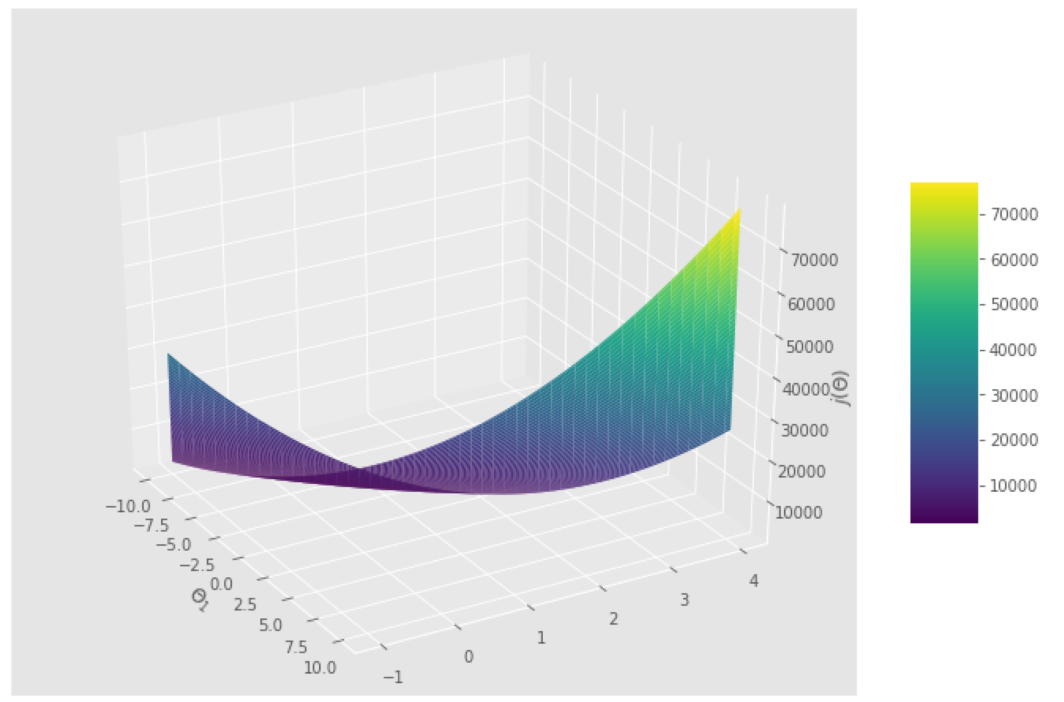
In [ ]:

Task 6: Visualising the Cost Function $J(\theta)$

In [17]:
```python
from mpl_toolkits.mplot3d import Axes3D
```

In [19]:
```python
theta_0 = np.linspace(-10,10,100)
theta_1 = np.linspace(-1,4,100)
cost_values = np.zeros((len(theta_0),len(theta_1)))
for i in range(len(theta_0)):
    for j in range(len(theta_1)):
        t = np.array([theta_0[i], theta_1[j]])
        cost_values[i,j] = cost_fun(X,y,t)
```

In [22]:
```python
fig = plt.figure(figsize = (12, 8))
ax = fig.gca(projection='3d')
surf = ax.plot_surface(theta_0, theta_1, cost_values, cmap = 'viridis')
fig.colorbar(surf, shrink=0.5, aspect=5)
plt.xlabel('$\Theta_0$')
plt.xlabel('$\Theta_1$')
ax.set_zlabel('$j(\Theta)$')
ax.view_init(30,330)
plt.show()
```



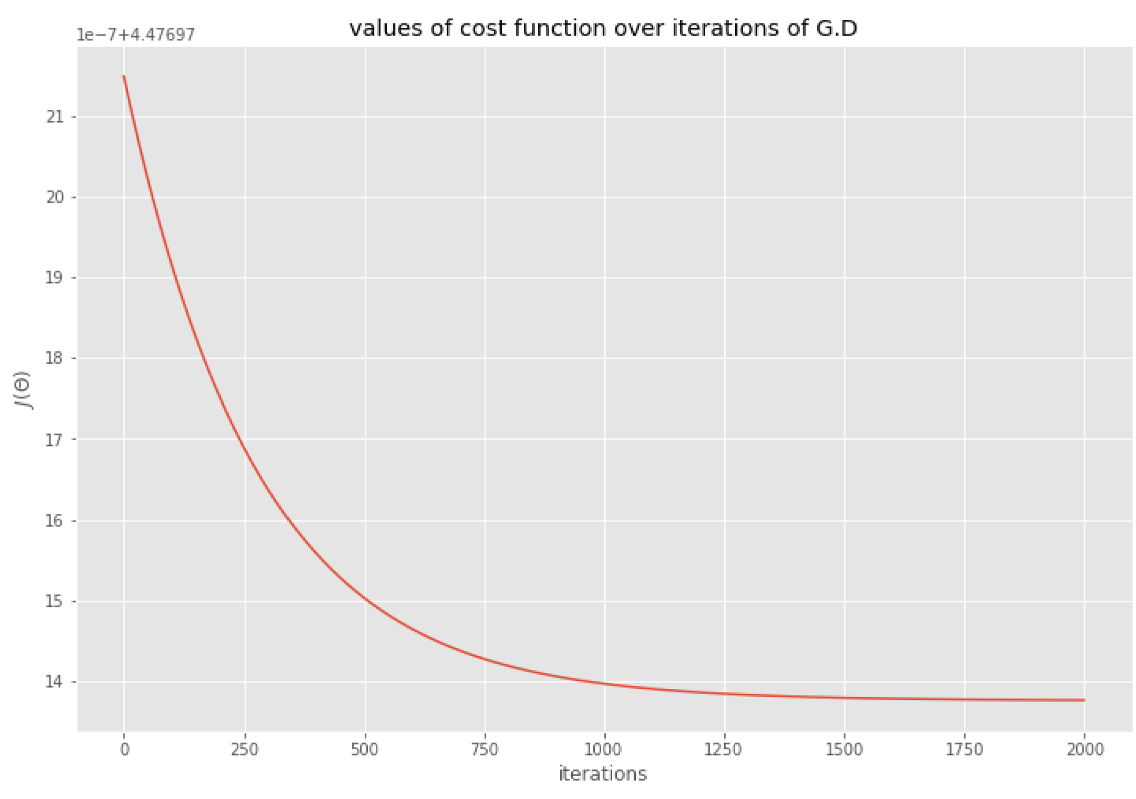
Task 7: Plotting the Convergence

Plot $J(\theta)$ against the number of iterations of gradient descent:

In [23]:
```python
plt.plot(costs)

plt.xlabel('iterations')
plt.ylabel('$J(\Theta)$')
plt.title('values of cost function over iterations of G.D')
```

Out[23]:
```
Text(0.5, 1.0, 'values of cost function over iterations of G.D')
```



Task 8: Training Data with Linear Regression Fit

In [24]:
```python
theta.shape
```

Out[24]:
```
(2, 1)
```

In [25]:
```python
theta
```

Out[25]:
```
array([[-3.89570181],
       [ 1.1930257 ]])
```

In [30]:
```python
theta = np.squeeze(theta)
sns.scatterplot(x='Population',y='Profit',data=data)
x_value = [x for x in range(5,25)]
y_value = [(x * theta[1] + theta[0]) for x in x_value]
sns.lineplot(x_value,y_value)
plt.xlabel("Population")
plt.ylabel("Profit")
plt.title("linear reg,. fit")
```

Out[30]:
```
Text(0.5, 1.0, 'linear reg,. fit')
```

Task 9: Inference using the optimized θ values

$h_\theta(x) = \theta^T x$

In [31]:
```python
def predict(x, theta):

    y_pred = np.dot(theta.transpose(),x)
    return y_pred
```

In [32]:
```python
y_pred1 = predict(np.array([1,4]), theta)*1000
print('for population of 40k people, the model predicts a profit of $'+ str(round(y_pred1, 0
)))
```

```
for population of 40k people, the model predicts a profit of $876.0
```

In [33]:
```python
y_pred2 = predict(np.array([1,8.3]), theta) *1000
print('for population of 83k people, the model predicts a profit of $'+ str(round(y_pred2, 0
)))
```

```
for population of 83k people, the model predicts a profit of $6006.0
```