rhyme

Univariate Linear Regression

Task 2: Load the Data and Libraries

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

In [2]:
```
import numpy as np
import pandas as pd
import seaborn as sns
plt.rcParams['figure.figsize'] = (12, 8)
```

In [3]:
```
data = pd.read_csv('bike_sharing_data.txt')
data.head()
```

	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

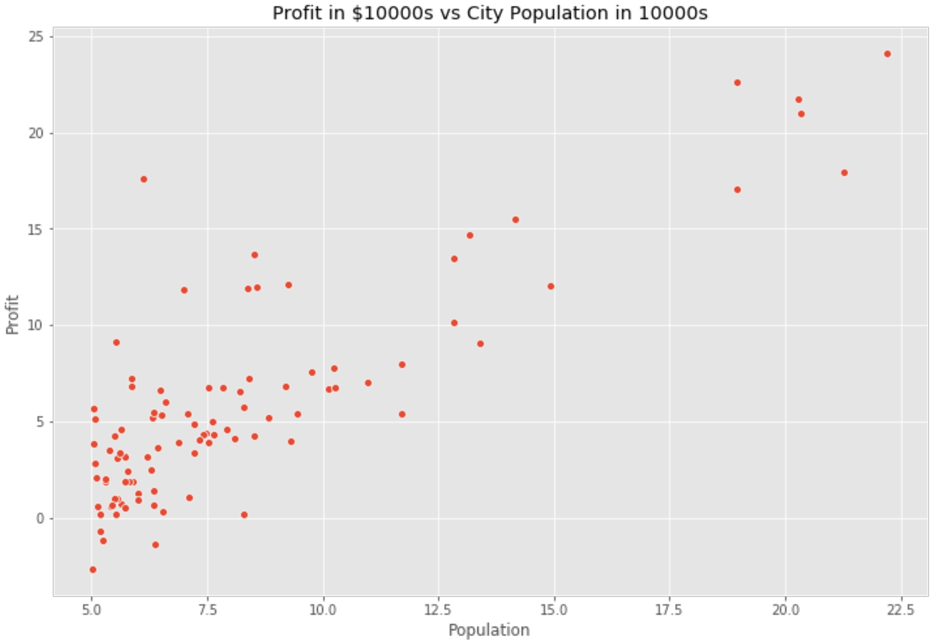
In [4]:
```
data.info()
```

```
<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 [5]:
```
ax = sns.scatterplot(x="Population", y="Profit", data=data)
ax.set_title("Profit in $10000s vs City Population in 10000s")
```

```
Text(0.5, 1.0, 'Profit in $10000s vs City Population in 10000s')
```



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 [6]:
```
def cost_function(X, y, theta):
    m = len(y)
    y_pred = X.dot(theta)
    error = (y_pred - y) ** 2

    return 1/(2*m) * np.sum(error)
```

In [9]:
```
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_function(X, y, theta)
```

```
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 [10]:
```
def gradient_descent(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_function(X, y, theta))
    return theta, costs
```

In [11]:
```
theta, costs = gradient_descent(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))))
```

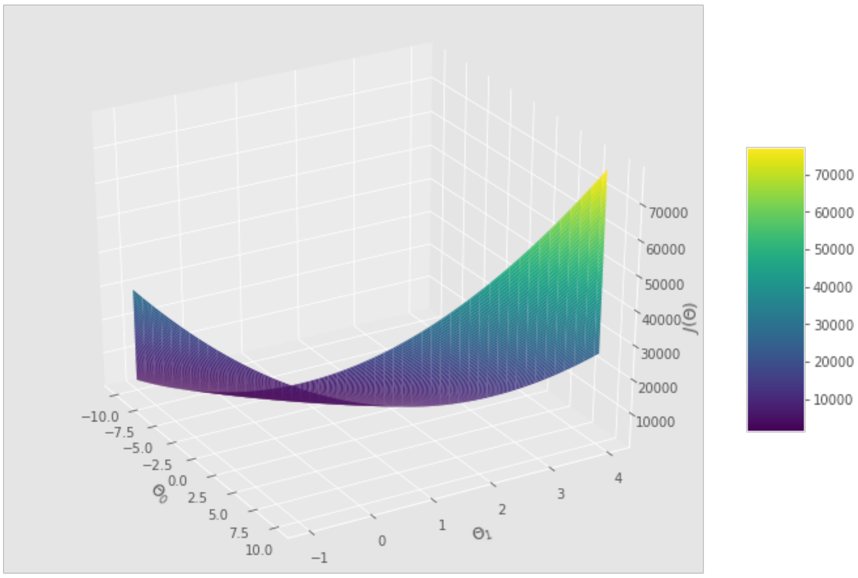
```
h(x) = -3.79 + 1.18x1
```

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

In [12]:
```
from mpl_toolkits.mplot3d import Axes3D
```

In [15]:
```
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_function(X, y, t)
```

In [16]:
```
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.ylabel("$\Theta_1$")
ax.set_zlabel("$J(\Theta)$")
ax.view_init(30,330)

plt.show()
```

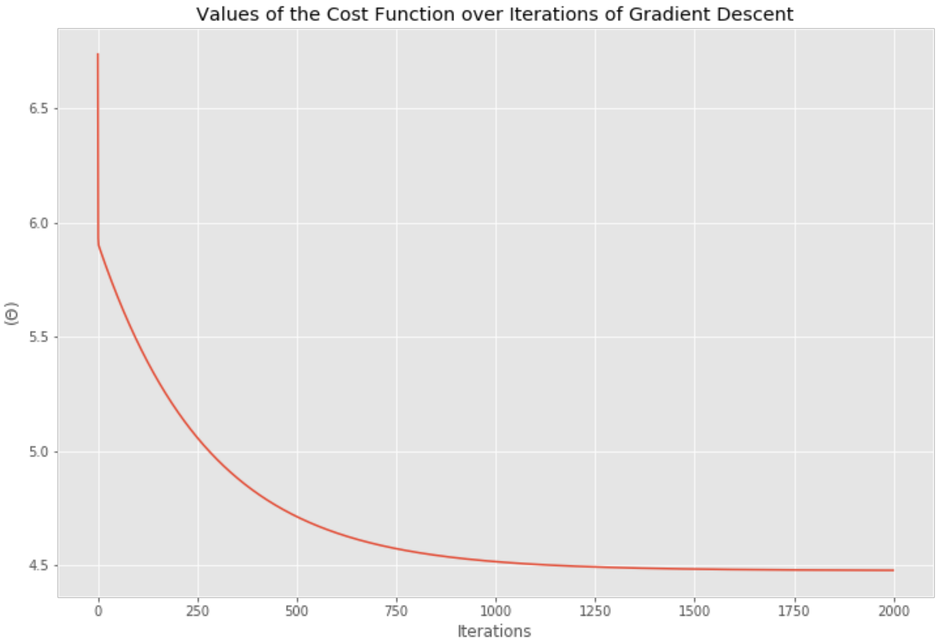


Task 7: Plotting the Convergence

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

In [17]:
```
plt.plot(costs)
plt.xlabel("Iterations")
plt.ylabel("$(\Theta)$")
plt.title("Values of the Cost Function over Iterations of Gradient Descent")
```

```
Text(0.5, 1.0, 'Values of the Cost Function over Iterations of Gradient Descent')
```



Task 8: Training Data with Linear Regression Fit

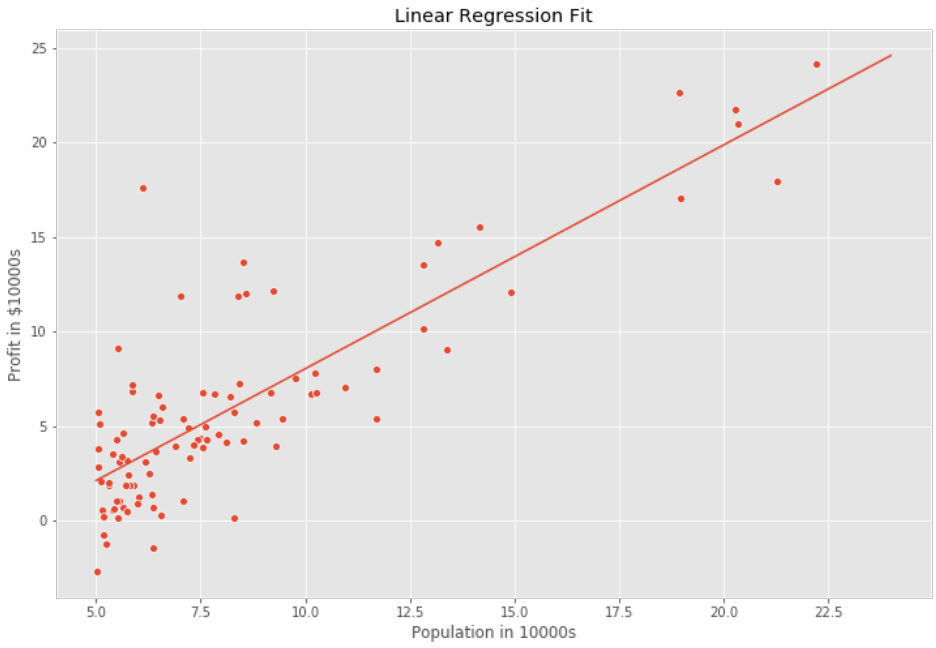
In [18]:
```
theta.shape
```

```
(2, 1)
```

In [19]:
```
theta
```

```
array([[-3.78806857],
       [ 1.18221277]])
```

In [22]:
```
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 in 10000s")
plt.ylabel("Profit in $10000s")
plt.title("Linear Regression Fit");
```



Task 9: Inference using the optimized θ values

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

In [23]:
```
def predict (x, theta):
    y_pred = np.dot(theta.transpose(), x)
    return y_pred
```

In [25]:
```
y_pred_1 = predict(np.array([1,4]), theta) * 10000
print("For a population of 40,000 people, the model predicts a profit of $" + str(round
(y_pred_1, 0)))
```

```
For a population of 40,000 people, the model predicts a profit of $9408.0
```

In [26]:
```
y_pred_2 = predict(np.array([1, 8.3]), theta) * 10000
print("For a population of 83,000 people, the model predicts a profit of $" + str(round
(y_pred_2, 0)))
```

```
For a population of 83,000 people, the model predicts a profit of $60243.0
```