Problem Statement

Build the linear regression model using scikit learn in boston data to predict 'Price' based on other dependent variable.

In [62]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import sklearn
%matplotlib inline
```

In [63]:
```
from sklearn.datasets import load_boston

boston = load_boston()
```

In [64]:
```
boston.keys()
```

Out[64]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

In [65]:
```
boston.feature_names
```

Out[65]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [66]:
```
print(boston.DESCR)
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is usually the target.

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1940
        - DIS      weighted distances to five Boston employment centres
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.
```

In [67]:
```
bos = pd.DataFrame(boston.data)
```

In [68]:
```
bos.head()
```

Out[68]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [69]:
```
bos.shape
```

Out[69]: (506, 13)

In [70]:
```
bos.columns = boston.feature_names
```

In [71]:
```
bos.head()
```

Out[71]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
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4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33

In [72]:
```
bos['Price'] = boston.target
```

In [73]:
```
bos.head()
```

Out[73]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Price
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2

In [76]:
```
bos.shape
```

Out[76]: (506, 14)

In [74]:
```
X = bos.iloc[:,:-1].values
```

In [77]:
```
X.shape
```

Out[77]: (506, 13)

In [78]:
```
y = bos.iloc[:,13].values
```

In [79]:
```
y.shape
```

Out[79]: (506,)

In [105]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

In [106]:
```
print('X_train: ', X_train.shape)
print('X_test: ', X_test.shape)
print('Y_train: ', y_train.shape)
print('Y_test: ', y_test.shape)
```

```
X_train:  (404, 13)
X_test:  (102, 13)
Y_train:  (404,)
Y_test:  (102,)
```

In [107]:
```
from sklearn.linear_model import LinearRegression

lm = LinearRegression()
lm.fit(X_train, y_train)
```

Out[107]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None,
         normalize=False)
```

In [108]:
```
y_pred = lm.predict(X_test)
```

In [134]:
```
ActualvsPred = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
```

In [135]:
```
print(ActualvsPred.head())
```

```
   Actual  Predicted
0    22.6  24.889638
1    50.0  23.721411
2    23.0  29.364999
3     8.3  12.122386
4    21.2  21.443823
```

In [139]:
```
print(ActualvsPred.tail())
```

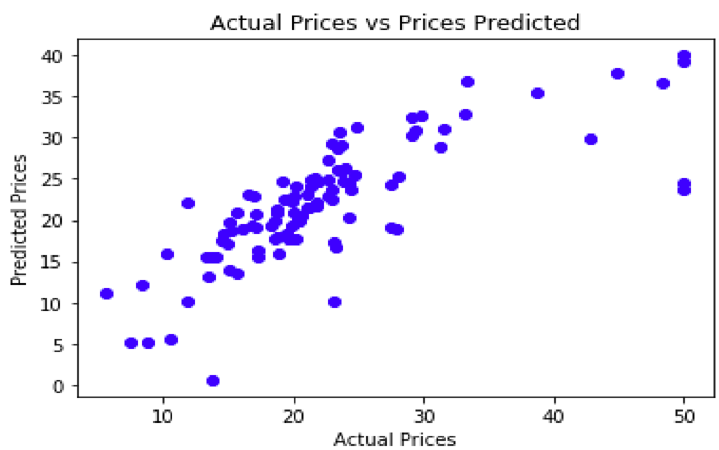
```
     Actual  Predicted
97     24.7  25.442171
98     14.1  15.571783
99     18.7  17.937195
100    28.1  25.305888
101    19.8  22.373233
```

In [138]:

```python
plt.scatter(y_test,y_pred, color = 'blue')
plt.xlabel('Actual Prices')
plt.ylabel('Predicted Prices')
plt.title('Actual Prices vs Prices Predicted')
plt.show
```

Out[138]:

```
<function matplotlib.pyplot.show(*args, **kw)>
```



In [125]:

```python
print(lm.coef_)
```

```
[-1.19443447e-01  4.47799511e-02  5.48526168e-03  2.34080361e+00
 -1.61236043e+01  3.70870901e+00 -3.12108178e-03 -1.38639737e+00
  2.44178327e-01 -1.09896366e-02 -1.04592119e+00  8.11010693e-03
 -4.92792725e-01]
```

In [140]:

```python
print(lm.intercept_)
```

```
38.091694926302004
```


In [140]:

```python
print(lm.intercept_)
```

```
38.091694926302004
```


In [141]:

```python
from sklearn.metrics import r2_score

score = r2_score(y_test,y_pred)
print('R Sqaured Score of the Test data is: ', score)
```

```
R Sqaured Score of the Test data is:  0.5892223849182534
```

In [143]:

```python
print('Mean Absolute Error (MAE) of Test data is: ',metrics.mean_absolute_error(y_test,y_pred))
print('Mean Squared Error (MSE) of Test data is: ',metrics.mean_squared_error(y_test,y_pred))
print('Root Mean Squared Error (RMSE) of Test data is: ',np.sqrt(metrics.mean_squared_error(y_test,y_pred)))
```

```
Mean Absolute Error (MAE) of Test data is:  3.8429092204444912
Mean Squared Error (MSE) of Test data is:  33.44897999767632
Root Mean Squared Error (RMSE) of Test data is:  5.783509315085117
```

In [144]:

```python
## The R2 Score of 0.58922 is Low, therefore our model is not very accurate at predicting the
## house prices based on the data provided.
```