# Boston_linear_reg

May 11, 2022

Create a Linear Regression Model using Python/R to predict home prices using Boston Housing Dataset (https://www.kaggle.com/c/boston-housing). The Boston Housing dataset contains information about various houses in Boston through different parameters. There are 506 samples and 14 feature variables in this dataset.

[4]:
```
# Importing Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# Importing Data
from sklearn.datasets import load_boston
boston = load_boston()
```

[5]:
```
boston.data.shape
```

[5]:
```
(506, 13)
```

[6]:
```
boston.feature_names
```

[6]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

[7]:
```
data = pd.DataFrame(boston.data)
data.columns = boston.feature_names

data.head(10)
```

[7]:

| | CRIM | ZN | INDUS | CHAS | NOX | RM | AGE | DIS | RAD | TAX |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.00632 | 18.0 | 2.31 | 0.0 | 0.538 | 6.575 | 65.2 | 4.0900 | 1.0 | 296.0 |
| 1 | 0.02731 | 0.0 | 7.07 | 0.0 | 0.469 | 6.421 | 78.9 | 4.9671 | 2.0 | 242.0 |
| 2 | 0.02729 | 0.0 | 7.07 | 0.0 | 0.469 | 7.185 | 61.1 | 4.9671 | 2.0 | 242.0 |
| 3 | 0.03237 | 0.0 | 2.18 | 0.0 | 0.458 | 6.998 | 45.8 | 6.0622 | 3.0 | 222.0 |
| 4 | 0.06905 | 0.0 | 2.18 | 0.0 | 0.458 | 7.147 | 54.2 | 6.0622 | 3.0 | 222.0 |
| 5 | 0.02985 | 0.0 | 2.18 | 0.0 | 0.458 | 6.430 | 58.7 | 6.0622 | 3.0 | 222.0 |
| 6 | 0.08829 | 12.5 | 7.87 | 0.0 | 0.524 | 6.012 | 66.6 | 5.5605 | 5.0 | 311.0 |
| 7 | 0.14455 | 12.5 | 7.87 | 0.0 | 0.524 | 6.172 | 96.1 | 5.9505 | 5.0 | 311.0 |
| 8 | 0.21124 | 12.5 | 7.87 | 0.0 | 0.524 | 5.631 | 100.0 | 6.0821 | 5.0 | 311.0 |

```
9  0.17004  12.5   7.87   0.0  0.524  6.004   85.9  6.5921  5.0  311.0

   PTRATIO       B  LSTAT
0     15.3  396.90   4.98
1     17.8  396.90   9.14
2     17.8  392.83   4.03
3     18.7  394.63   2.94
4     18.7  396.90   5.33
5     18.7  394.12   5.21
6     15.2  395.60  12.43
7     15.2  396.90  19.15
8     15.2  386.63  29.93
9     15.2  386.71  17.10
```

[8]:
```
data['Price'] = boston.target
data.head(10)
```

[8]:
```
      CRIM    ZN  INDUS  CHAS    NOX     RM    AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31   0.0  0.538  6.575   65.2  4.0900  1.0  296.0
1  0.02731   0.0   7.07   0.0  0.469  6.421   78.9  4.9671  2.0  242.0
2  0.02729   0.0   7.07   0.0  0.469  7.185   61.1  4.9671  2.0  242.0
3  0.03237   0.0   2.18   0.0  0.458  6.998   45.8  6.0622  3.0  222.0
4  0.06905   0.0   2.18   0.0  0.458  7.147   54.2  6.0622  3.0  222.0
5  0.02985   0.0   2.18   0.0  0.458  6.430   58.7  6.0622  3.0  222.0
6  0.08829  12.5   7.87   0.0  0.524  6.012   66.6  5.5605  5.0  311.0
7  0.14455  12.5   7.87   0.0  0.524  6.172   96.1  5.9505  5.0  311.0
8  0.21124  12.5   7.87   0.0  0.524  5.631  100.0  6.0821  5.0  311.0
9  0.17004  12.5   7.87   0.0  0.524  6.004   85.9  6.5921  5.0  311.0

   PTRATIO       B  LSTAT  Price
0     15.3  396.90   4.98   24.0
1     17.8  396.90   9.14   21.6
2     17.8  392.83   4.03   34.7
3     18.7  394.63   2.94   33.4
4     18.7  396.90   5.33   36.2
5     18.7  394.12   5.21   28.7
6     15.2  395.60  12.43   22.9
7     15.2  396.90  19.15   27.1
8     15.2  386.63  29.93   16.5
9     15.2  386.71  17.10   18.9
```

[9]:
```
data.describe()
```

[9]:
```
              CRIM          ZN       INDUS        CHAS         NOX          RM  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean     3.613524   11.363636   11.136779    0.069170    0.554695    6.284634
std      8.601545   23.322453    6.860353    0.253994    0.115878    0.702617
```

```
min      0.006320    0.000000    0.460000    0.000000    0.385000    3.561000
25%      0.082045    0.000000    5.190000    0.000000    0.449000    5.885500
50%      0.256510    0.000000    9.690000    0.000000    0.538000    6.208500
75%      3.677083   12.500000   18.100000    0.000000    0.624000    6.623500
max     88.976200  100.000000   27.740000    1.000000    0.871000    8.780000

              AGE         DIS         RAD         TAX     PTRATIO           B  \
count  506.000000  506.000000  506.000000  506.000000  506.000000  506.000000
mean    68.574901    3.795043    9.549407  408.237154   18.455534  356.674032
std     28.148861    2.105710    8.707259  168.537116    2.164946   91.294864
min      2.900000    1.129600    1.000000  187.000000   12.600000    0.320000
25%     45.025000    2.100175    4.000000  279.000000   17.400000  375.377500
50%     77.500000    3.207450    5.000000  330.000000   19.050000  391.440000
75%     94.075000    5.188425   24.000000  666.000000   20.200000  396.225000
max    100.000000   12.126500   24.000000  711.000000   22.000000  396.900000

            LSTAT       Price
count  506.000000  506.000000
mean    12.653063   22.532806
std      7.141062    9.197104
min      1.730000    5.000000
25%      6.950000   17.025000
50%     11.360000   21.200000
75%     16.955000   25.000000
max     37.970000   50.000000
```

[10]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    float64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  Price    506 non-null    float64
```

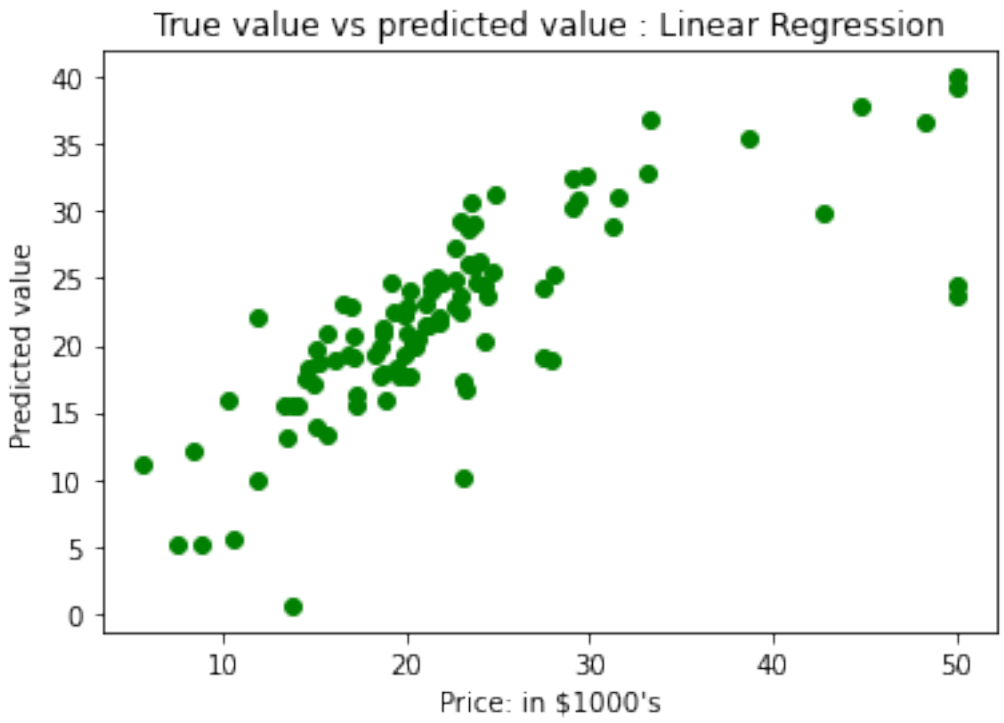
```
dtypes: float64(14)
memory usage: 55.5 KB
```

[11]:
```
# Input Data
x = boston.data
# Output Data
y = boston.target
# splitting data to training and testing dataset.

from sklearn.model_selection import train_test_split

xtrain, xtest, ytrain, ytest = train_test_split(x, y, test_size =0.
 ↪2,random_state = 0)

print("xtrain shape : ", xtrain.shape)
print("xtest shape : ", xtest.shape)
print("ytrain shape : ", ytrain.shape)
print("ytest shape : ", ytest.shape)
```

```
xtrain shape :  (404, 13)
xtest shape :  (102, 13)
ytrain shape :  (404,)
ytest shape :  (102,)
```

[12]:
```
# Fitting Multi Linear regression model to training model
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(xtrain, ytrain)

# predicting the test set results
y_pred = regressor.predict(xtest)
```

[13]:
```
# Plotting Scatter graph to show the prediction
# results - 'ytrue' value vs 'y_pred' value
plt.scatter(ytest, y_pred, c = 'green')
plt.xlabel("Price: in $1000's")
plt.ylabel("Predicted value")
plt.title("True value vs predicted value : Linear Regression")
plt.show()
```




[14]:
```
from sklearn.metrics import mean_squared_error

mse = mean_squared_error(ytest, y_pred)
print("Mean Square Error : ", mse)
```

```
Mean Square Error :  33.44897999767661
```