# **Linear Regression model on Boston Housing Dataset**

#### Import the required Libraries

```
In [1]:
```

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

%matplotlib inline
```

#### Load the Boston Housing DataSet from scikit-learn

```
In [2]:
```

```
from sklearn.datasets import load_boston

boston_dataset = load_boston()
boston_dataset.keys()

C:\Users\gptkgf\anaconda3\lib\site-packages\sklearn\utils\deprecation.py:87: FutureWarning: Function load_boston is deprecated...\land \land \lan
```

ted; `load\_boston` is deprecated in 1.0 and will be removed in 1.2.

The Boston housing prices dataset has an ethical problem. You can refer to the documentation of this function for further details.

The scikit-learn maintainers therefore strongly discourage the use of this dataset unless the purpose of the code is to study and educate about ethical issues in data science and machine learning.

In this special case, you can fetch the dataset from the original source::

```
import pandas as pd
import numpy as np

data_url = "http://lib.stat.cmu.edu/datasets/boston"
raw_df = pd.read_csv(data_url, sep="\s+", skiprows=22, header=None)
data = np.hstack([raw_df.values[::2, :], raw_df.values[1::2, :2]])
target = raw_df.values[1::2, 2]
```

Alternative datasets include the California housing dataset (i.e. :func:`~sklearn.datasets.fetch\_california\_housing`) and the Ames housing dataset. You can load the datasets as follows::

from sklearn.datasets import fetch\_california\_housing housing = fetch\_california\_housing()

for the California housing dataset and::

from sklearn.datasets import fetch\_openml
housing = fetch\_openml(name="house\_prices", as\_frame=True)

for the Ames housing dataset.
warnings.warn(msg, category=FutureWarning)

### Out[2]:

dict\_keys(['data', 'target', 'feature\_names', 'DESCR', 'filename', 'data\_module'])

### Load the data into pandas dataframe

### In [3]:

boston = pd.DataFrame(boston\_dataset.data, columns=boston\_dataset.feature\_names)
boston.head()

### Out[3]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	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
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 [4]:

```
boston.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):
    Column
             Non-Null Count Dtype
0
    CRIM
              506 non-null
                              float64
              506 non-null
                              float64
1
     ΖN
2
     INDUS
              506 non-null
                              float64
              506 non-null
                              float64
3
     CHAS
              506 non-null
                              float64
     NOX
              506 non-null
                              float64
5
     RM
              506 non-null
                              float64
6
     AGE
     DIS
              506 non-null
                              float64
7
              506 non-null
                              float64
8
     RAD
                              float64
 9
     TAX
              506 non-null
10 PTRATIO 506 non-null
                              float64
11 B
              506 non-null
                              float64
12 LSTAT
              506 non-null
                              float64
dtypes: float64(13)
memory usage: 51.5 KB
```

The target values is missing from the data. Create a new column of target values and add it to dataframe

```
In [22]:
```

```
boston['TARGET'] = boston_dataset.target
```

### In [23]:

boston

### Out[23]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	LSTAT	Target	TARGET
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	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	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	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	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	36.2
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	9.67	22.4	22.4
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90	9.08	20.6	20.6
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	5.64	23.9	23.9
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	6.48	22.0	22.0
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90	7.88	11.9	11.9

506 rows × 15 columns

## Data preprocessing

### In [12]:

```
boston.isnull().sum()
```

### Out[12]:

CRIM ZN 0 INDUS 0 0 CHAS 0 NOX RM 0 AGE 0 DIS RAD TAX PTRATIO LSTAT Target 0 TARGET dtype: int64

### **Data Visualization**

```
In [17]:
cor_matrix = boston.corr()
In [18]:
sns.heatmap(data=cor_matrix, annot=True)
Out[18]:
<AxesSubplot:>
                                                                           - 1.0
    CRIM - 1 -0.20.4-D.056.420.220.350.38.630.580.290.390.460.390.39
       ZN -0.2 1 0.50.040.520.310.50.660.310.310.310.390.180.410.360.3
                                                                            0.8
   INDUS -
            CHAS -0.0506040306 1 0.090109010807.0990004036.10.0409.054.180.18
                                                                           - 0.6
     NOX -0.420.520.76.091 1 -0.30.730.770.610.670.190.380.590.430.43
                                                                           - 0.4
      RM -0.220.310.39.0910.3 1 0.240.210.210.290.360.130.610.7 0.7
             .3<mark>5</mark>0.57<mark>0.60</mark>.08<mark>0.73</mark>0.24<mark>1 0.75</mark>0.460.510.260.270.6-0.380.38
     AGE
                                                                           - 0.2
      DIS -0.3(0.660.7(0.09)0.770.210.75 1 0.490.530.230.29-0.50.250.2
     RAD -0.6=0.310.6.007046±0.210.460.49 1 0.910.460.440.490.380.38
                                                                            0.0
      TAX -0.580.30.720.030.670.290.510.50.91 1 0.460.440.540.470.4
                                                                            -0.2
 PTRATIO -0.290.390.380.120.190.360.260.230.460.46 1 0.180.370.530.5
```

LSTAT

#### Prepare the data for training

```
In [24]:
```

```
X = pd.DataFrame(np.c_[boston['LSTAT'], boston['RM']], columns = ['LSTAT','RM'])
Y = boston['TARGET']
```

-0.4

-0.6

### Split the data into training and testing sets

B-0.390.180.366.0490.380.130.270.290.440.440.18 1 0.370.330.3

LSTAT -0.460.410.60.054.590.610.6 -0.50.490.540.370.37 1 0.740.74 Target -0.39.360.480.180.430.7-0.380.250.380.470.510.330.74

TARGET -0.39.360.48.180.430.7-0.380.250.380.470.510.330.74

### In [25]:

```
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=5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
(404, 2)
(102, 2)
(404,)
(102,)
```

### Train the model using sklearn LinearRegression

### In [26]:

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
lin_model = LinearRegression()
lin_model.fit(X_train, Y_train)
```

```
Out[26]:
```

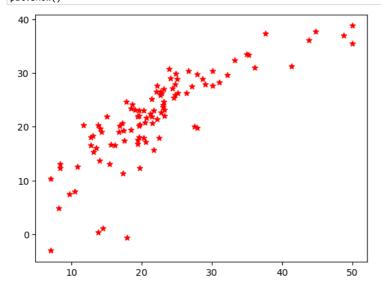
```
▼ LinearRegression
LinearRegression()
```

```
In [27]:
```

#### In [28]:

#### In [34]:

```
plt.scatter(Y_test, y_test_predict,color='red',marker='*')
plt.show()
```



### In [ ]: