In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

In [2]:
```
from sklearn.datasets import load_boston
```

In [3]:
```
boston = load_boston()
```

In [4]:
```
boston
```

Out[4]:
```
{'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690e+0
2,
         4.9800e+00],
        [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
         9.1400e+00],
        [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
         4.0300e+00],
        ...,
        [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         5.6400e+00],
        [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
         6.4800e+00],
        [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         7.8800e+00]]),
 'target': array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9, 1
5. ,
        18.9, 21.7, 20.4, 18.2, 19.9, 23.1, 17.5, 20.2, 18.2, 13.6, 19.6,
        15.2, 14.5, 15.6, 13.9, 16.6, 14.8, 18.4, 21. , 12.7, 14.5, 13.2,
        13.1, 13.5, 18.9, 20. , 21. , 24.7, 30.8, 34.9, 26.6, 25.3, 24.7,
        21.2, 19.3, 20. , 16.6, 14.4, 19.4, 19.7, 20.5, 25. , 23.4, 18.9,
        35.4, 24.7, 31.6, 23.3, 19.6, 18.7, 16. , 22.2, 25. , 33. , 23.5,
        19.4, 22. , 17.4, 20.9, 24.2, 21.7, 22.8, 23.4, 24.1, 21.4, 20. ,
        20.8, 21.2, 20.3, 28. , 23.9, 24.8, 22.9, 23.9, 26.6, 22.5, 22.2,
        23.6, 28.7, 22.6, 22. , 22.9, 25. , 20.6, 28.4, 21.4, 38.7, 43.8,
        33.2, 27.5, 26.5, 18.6, 19.3, 20.1, 19.5, 19.5, 20.4, 19.8, 19.4,
        21.7, 22.8, 18.8, 18.7, 18.5, 18.3, 21.2, 19.2, 20.4, 19.3, 22. ,
        20.3, 20.5, 17.3, 18.8, 21.4, 15.7, 16.2, 18. , 14.3, 19.2, 19.6,
        23. , 18.4, 15.6, 18.1, 17.4, 17.1, 13.3, 17.8, 14. , 14.4, 13.4,
        15.6, 11.8, 13.8, 15.6, 14.6, 17.8, 15.4, 21.5, 19.6, 15.3, 19.4,
        17. , 15.6, 13.1, 41.3, 24.3, 23.3, 27. , 50. , 50. , 50. , 22.7,
        25. , 50. , 23.8, 23.8, 22.3, 17.4, 19.1, 23.1, 23.6, 22.6, 29.4,
        23.2, 24.6, 29.9, 37.2, 39.8, 36.2, 37.9, 32.5, 26.4, 29.6, 50. ,
        32. , 29.8, 34.9, 37. , 30.5, 36.4, 31.1, 29.1, 50. , 33.3, 30.3,
        34.6, 34.9, 32.9, 24.1, 42.3, 48.5, 50. , 22.6, 24.4, 22.5, 24.4,
        20. , 21.7, 19.3, 22.4, 28.1, 23.7, 25. , 23.3, 28.7, 21.5, 23. ,
        26.7, 21.7, 27.5, 30.1, 44.8, 50. , 37.6, 31.6, 46.7, 31.5, 24.3,
        31.7, 41.7, 48.3, 29. , 24. , 25.1, 31.5, 23.7, 23.3, 22. , 20.1,
        22.2, 23.7, 17.6, 18.5, 24.3, 20.5, 24.5, 26.2, 24.4, 24.8, 29.6,
        42.8, 21.9, 20.9, 44. , 50. , 36. , 30.1, 33.8, 43.1, 48.8, 31. ,
        36.5, 22.8, 30.7, 50. , 43.5, 20.7, 21.1, 25.2, 24.4, 35.2, 32.4,
        32. , 33.2, 33.1, 29.1, 35.1, 45.4, 35.4, 46. , 50. , 32.2, 22. ,
        20.1, 23.2, 22.3, 24.8, 28.5, 37.3, 27.9, 23.9, 21.7, 28.6, 27.1,
        20.3, 22.5, 29. , 24.8, 22. , 26.4, 33.1, 36.1, 28.4, 33.4, 28.2,
        22.8, 20.3, 16.1, 22.1, 19.4, 21.6, 23.8, 16.2, 17.8, 19.8, 23.1,
        21. , 23.8, 23.1, 20.4, 18.5, 25. , 24.6, 23. , 22.2, 19.3, 22.6,
        19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
        32.7, 16.5, 23.9, 31.2, 17.5, 17.2, 23.1, 24.5, 26.6, 22.9, 24.1,
        18.6, 30.1, 18.2, 20.6, 17.8, 21.7, 22.7, 22.6, 25. , 19.9, 20.8,
        16.8, 21.9, 27.5, 21.9, 23.1, 50. , 50. , 50. , 50. , 50. , 13.8,
        13.8, 15. , 13.9, 13.3, 13.1, 10.2, 10.4, 10.9, 11.3, 12.3,  8.8,
         7.2, 10.5,  7.4, 10.2, 11.5, 15.1, 23.2,  9.7, 13.8, 12.7, 13.1,
        12.5,  8.5,  5. ,  6.3,  5.6,  7.2, 12.1,  8.3,  8.5,  5. , 11.9,
        27.9, 17.2, 27.5, 15. , 17.2, 17.9, 16.3,  7. ,  7.2,  7.5, 10.4,
         8.8,  8.4, 16.7, 14.2, 20.8, 13.4, 11.7,  8.3, 10.2, 10.9, 11. ,
         9.5, 14.5, 14.1, 16.1, 14.3, 11.7, 13.4,  9.6,  8.7,  8.4, 12.8,
```

```
        10.5, 17.1, 18.4, 15.4, 10.8, 11.8, 14.9, 12.6, 14.1, 13. , 13.4,
        15.2, 16.1, 17.8, 14.9, 14.1, 12.7, 13.5, 14.9, 20. , 16.4, 17.7,
        19.5, 20.2, 21.4, 19.9, 19. , 19.1, 19.1, 20.1, 19.9, 19.6, 23.2,
        29.8, 13.8, 13.3, 16.7, 12. , 14.6, 21.4, 23. , 23.7, 25. , 21.8,
        20.6, 21.2, 19.1, 20.6, 15.2,  7. ,  8.1, 13.6, 20.1, 21.8, 24.5,
        23.1, 19.7, 18.3, 21.2, 17.5, 16.8, 22.4, 20.6, 23.9, 22. , 11.9]),
 'feature_names': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DI
S', 'RAD',
        'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'),
 'DESCR': ".. _boston_dataset:\n\nBoston house prices dataset\n----------------
-----------\n\n**Data Set Characteristics:**  \n\n    :Number of Instances: 506
\n\n    :Number of Attributes: 13 numeric/categorical predictive. Median Value
(attribute 14) is usually the target.\n\n    :Attribute Information (in orde
r):\n        - CRIM     per capita crime rate by town\n        - ZN       propo
rtion of residential land zoned for lots over 25,000 sq.ft.\n        - INDUS
proportion of non-retail business acres per town\n        - CHAS     Charles Ri
ver dummy variable (= 1 if tract bounds river; 0 otherwise)\n        - NOX
nitric oxides concentration (parts per 10 million)\n        - RM       average
number of rooms per dwelling\n        - AGE      proportion of owner-occupied u
nits built prior to 1940\n        - DIS      weighted distances to five Boston
employment centres\n        - RAD      index of accessibility to radial highway
s\n        - TAX      full-value property-tax rate per $10,000\n        - PTRAT
IO  pupil-teacher ratio by town\n        - B        1000(Bk - 0.63)^2 where Bk
is the proportion of black people by town\n        - LSTAT    % lower status of
the population\n        - MEDV     Median value of owner-occupied homes in $100
0's\n\n    :Missing Attribute Values: None\n\n    :Creator: Harrison, D. and Ru
binfeld, D.L.\n\nThis is a copy of UCI ML housing dataset.\nhttps://archive.ic
s.uci.edu/ml/machine-learning-databases/housing/\n\n\nThis dataset was taken fr
om the StatLib library which is maintained at Carnegie Mellon University.\n\nTh
e Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic\nprices
and the demand for clean air', J. Environ. Economics & Management,\nvol.5, 81-1
02, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics\n...', Wile
y, 1980.   N.B. Various transformations are used in the table on\npages 244-261
of the latter.\n\nThe Boston house-price data has been used in many machine lea
rning papers that address regression\nproblems.   \n     \n.. topic:: Reference
s\n\n   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influenti
al Data and Sources of Collinearity', Wiley, 1980. 244-261.\n   - Quinlan,R. (1
993). Combining Instance-Based and Model-Based Learning. In Proceedings on the
Tenth International Conference of Machine Learning, 236-243, University of Mass
achusetts, Amherst. Morgan Kaufmann.\n",
 'filename': 'boston_house_prices.csv',
 'data_module': 'sklearn.datasets.data'}
```

In [5]:
```
boston.keys()
```

Out[5]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename', 'data_modul
e'])
```

In [6]:
```
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 (att
ribute 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 s
q.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 o
therwise)
        - 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 black people
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.

This is a copy of UCI ML housing dataset.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/ (https://arc
hive.ics.uci.edu/ml/machine-learning-databases/housing/)


This dataset was taken from the StatLib library which is maintained at Carnegie
Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers that
 address regression
problems.

.. topic:: References
```

```
   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Da
ta and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In P
roceedings on the Tenth International Conference of Machine Learning, 236-243,
 University of Massachusetts, Amherst. Morgan Kaufmann.
```

In [7]:
```
print(boston.data)
```

```
[[6.3200e-03 1.8000e+01 2.3100e+00 ... 1.5300e+01 3.9690e+02 4.9800e+00]
 [2.7310e-02 0.0000e+00 7.0700e+00 ... 1.7800e+01 3.9690e+02 9.1400e+00]
 [2.7290e-02 0.0000e+00 7.0700e+00 ... 1.7800e+01 3.9283e+02 4.0300e+00]
 ...
 [6.0760e-02 0.0000e+00 1.1930e+01 ... 2.1000e+01 3.9690e+02 5.6400e+00]
 [1.0959e-01 0.0000e+00 1.1930e+01 ... 2.1000e+01 3.9345e+02 6.4800e+00]
 [4.7410e-02 0.0000e+00 1.1930e+01 ... 2.1000e+01 3.9690e+02 7.8800e+00]]
```

In [8]:
```python
print(boston.target)
```

```
[24.  21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9 15.  18.9 21.7 20.4
 18.2 19.9 23.1 17.5 20.2 18.2 13.6 19.6 15.2 14.5 15.6 13.9 16.6 14.8
 18.4 21.  12.7 14.5 13.2 13.1 13.5 18.9 20.  21.  24.7 30.8 34.9 26.6
 25.3 24.7 21.2 19.3 20.  16.6 14.4 19.4 19.7 20.5 25.  23.4 18.9 35.4
 24.7 31.6 23.3 19.6 18.7 16.  22.2 25.  33.  23.5 19.4 22.  17.4 20.9
 24.2 21.7 22.8 23.4 24.1 21.4 20.  20.8 21.2 20.3 28.  23.9 24.8 22.9
 23.9 26.6 22.5 22.2 23.6 28.7 22.6 22.  22.9 25.  20.6 28.4 21.4 38.7
 43.8 33.2 27.5 26.5 18.6 19.3 20.1 19.5 19.5 20.4 19.8 19.4 21.7 22.8
 18.8 18.7 18.5 18.3 21.2 19.2 20.4 19.3 22.  20.3 20.5 17.3 18.8 21.4
 15.7 16.2 18.  14.3 19.2 19.6 23.  18.4 15.6 18.1 17.4 17.1 13.3 17.8
 14.  14.4 13.4 15.6 11.8 13.8 15.6 14.6 17.8 15.4 21.5 19.6 15.3 19.4
 17.  15.6 13.1 41.3 24.3 23.3 27.  50.  50.  50.  22.7 25.  50.  23.8
 23.8 22.3 17.4 19.1 23.1 23.6 22.6 29.4 23.2 24.6 29.9 37.2 39.8 36.2
 37.9 32.5 26.4 29.6 50.  32.  29.8 34.9 37.  30.5 36.4 31.1 29.1 50.
 33.3 30.3 34.6 34.9 32.9 24.1 42.3 48.5 50.  22.6 24.4 22.5 24.4 20.
 21.7 19.3 22.4 28.1 23.7 25.  23.3 28.7 21.5 23.  26.7 21.7 27.5 30.1
 44.8 50.  37.6 31.6 46.7 31.5 24.3 31.7 41.7 48.3 29.  24.  25.1 31.5
 23.7 23.3 22.  20.1 22.2 23.7 17.6 18.5 24.3 20.5 24.5 26.2 24.4 24.8
 29.6 42.8 21.9 20.9 44.  50.  36.  30.1 33.8 43.1 48.8 31.  36.5 22.8
 30.7 50.  43.5 20.7 21.1 25.2 24.4 35.2 32.4 32.  33.2 33.1 29.1 35.1
 45.4 35.4 46.  50.  32.2 22.  20.1 23.2 22.3 24.8 28.5 37.3 27.9 23.9
 21.7 28.6 27.1 20.3 22.5 29.  24.8 22.  26.4 33.1 36.1 28.4 33.4 28.2
 22.8 20.3 16.1 22.1 19.4 21.6 23.8 16.2 17.8 19.8 23.1 21.  23.8 23.1
 20.4 18.5 25.  24.6 23.  22.2 19.3 22.6 19.8 17.1 19.4 22.2 20.7 21.1
 19.5 18.5 20.6 19.  18.7 32.7 16.5 23.9 31.2 17.5 17.2 23.1 24.5 26.6
 22.9 24.1 18.6 30.1 18.2 20.6 17.8 21.7 22.7 22.6 25.  19.9 20.8 16.8
 21.9 27.5 21.9 23.1 50.  50.  50.  50.  50.  13.8 13.8 15.  13.9 13.3
 13.1 10.2 10.4 10.9 11.3 12.3  8.8  7.2 10.5  7.4 10.2 11.5 15.1 23.2
  9.7 13.8 12.7 13.1 12.5  8.5  5.   6.3  5.6  7.2 12.1  8.3  8.5  5.
 11.9 27.9 17.2 27.5 15.  17.2 17.9 16.3  7.   7.2  7.5 10.4  8.8  8.4
 16.7 14.2 20.8 13.4 11.7  8.3 10.2 10.9 11.   9.5 14.5 14.1 16.1 14.3
 11.7 13.4  9.6  8.7  8.4 12.8 10.5 17.1 18.4 15.4 10.8 11.8 14.9 12.6
 14.1 13.  13.4 15.2 16.1 17.8 14.9 14.1 12.7 13.5 14.9 20.  16.4 17.7
 19.5 20.2 21.4 19.9 19.  19.1 19.1 20.1 19.9 19.6 23.2 29.8 13.8 13.3
 16.7 12.  14.6 21.4 23.  23.7 25.  21.8 20.6 21.2 19.1 20.6 15.2  7.
  8.1 13.6 20.1 21.8 24.5 23.1 19.7 18.3 21.2 17.5 16.8 22.4 20.6 23.9
 22.  11.9]
```

In [9]:
```python
boston.feature_names
```

Out[9]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [10]:
```python
# lets prepare the dataframe
dataset = pd.DataFrame(boston.data, columns=boston.feature_names)
```

In [11]:
```
dataset.head()
```

Out[11]:

	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
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 [12]:
```
pd.read_csv(r'C:\Users\lenovo\Desktop\Boston Housing Data.csv')
```

Out[12]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTA
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.9
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.1
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.0
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.9
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	NaI
...	...	...	...	...	...	...	...	...	...	...	...	...	.
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	NaI
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.0
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.6
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.4
505	0.04741	0.0	11.93	0.0	0.573	6.030	NaN	2.5050	1	273	21.0	396.90	7.8

506 rows × 14 columns

In [13]:
```
dataset.shape
```

Out[13]: (506, 13)

In [14]:
```
dataset['Price']=boston.target
```

In [15]:
```
dataset.head()
```

Out[15]:

	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
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 [16]:
```
dataset.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
```

In [17]:
```
dataset.describe()
```

Out[17]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.00
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.79
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.10
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.12
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.10
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.20
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.18
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.12

In [18]:
```
#check the missing values
dataset.isnull().sum()
```

Out[18]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
Price      0
dtype: int64
```

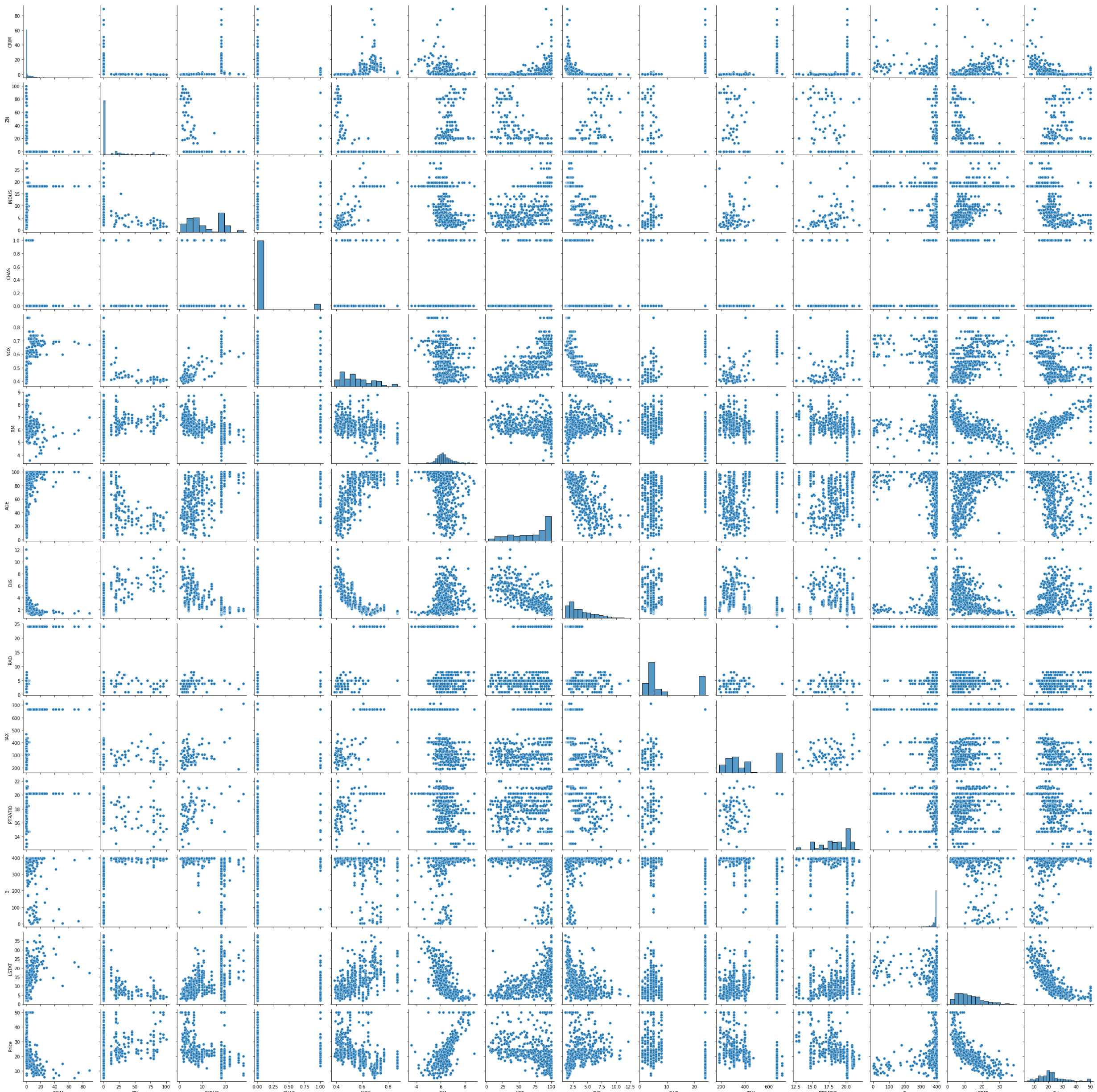
In [19]:
```
#EDA
dataset.corr()
```

Out[19]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670	0.
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408	-0
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.099176	-0.
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.769230	0
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.205246	-0.
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.747881	0.
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.000000	-0.
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.494588	1.
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.534432	0.
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	0.
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.291512	-0.
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.496996	0.
Price	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.249929	-0.

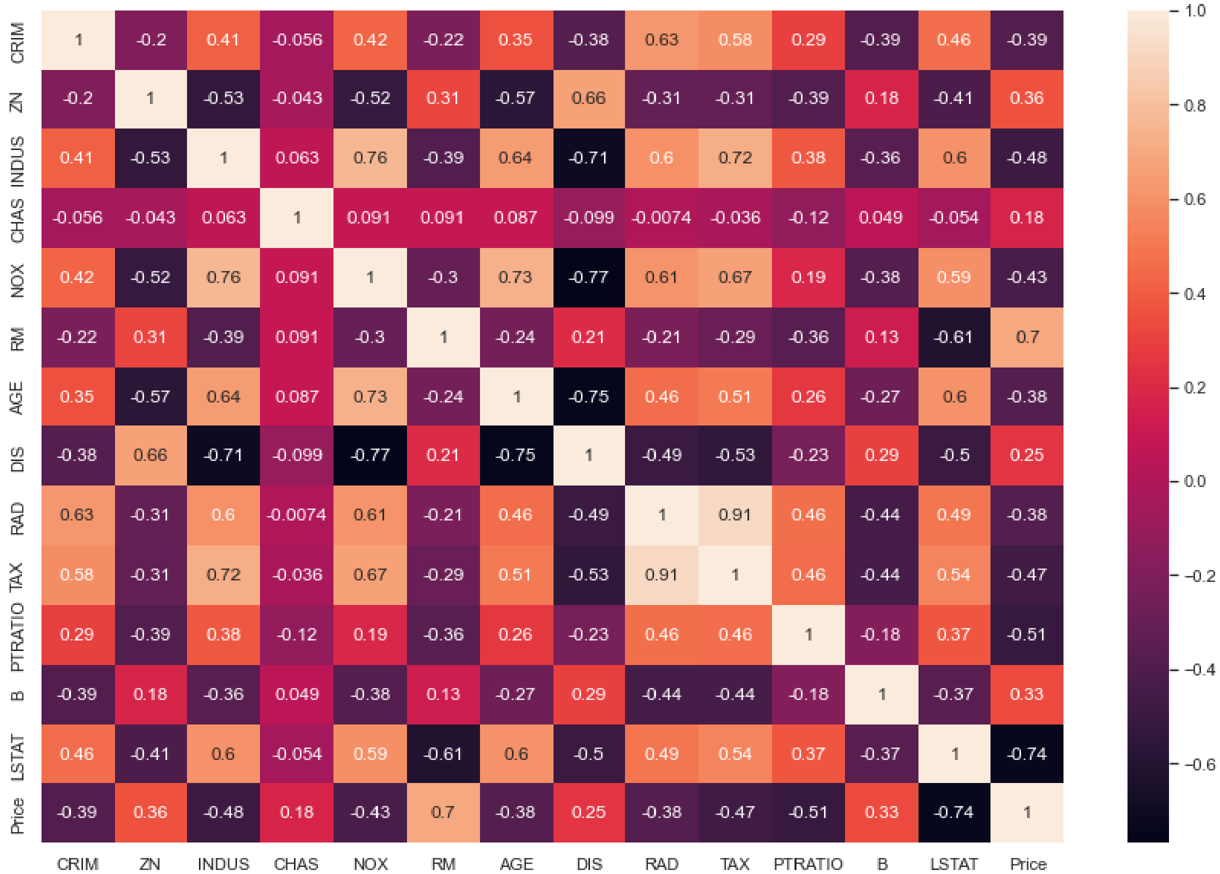
In [20]:
```
sns.pairplot(dataset)
```

Out[20]: <seaborn.axisgrid.PairGrid at 0x2739e060940>



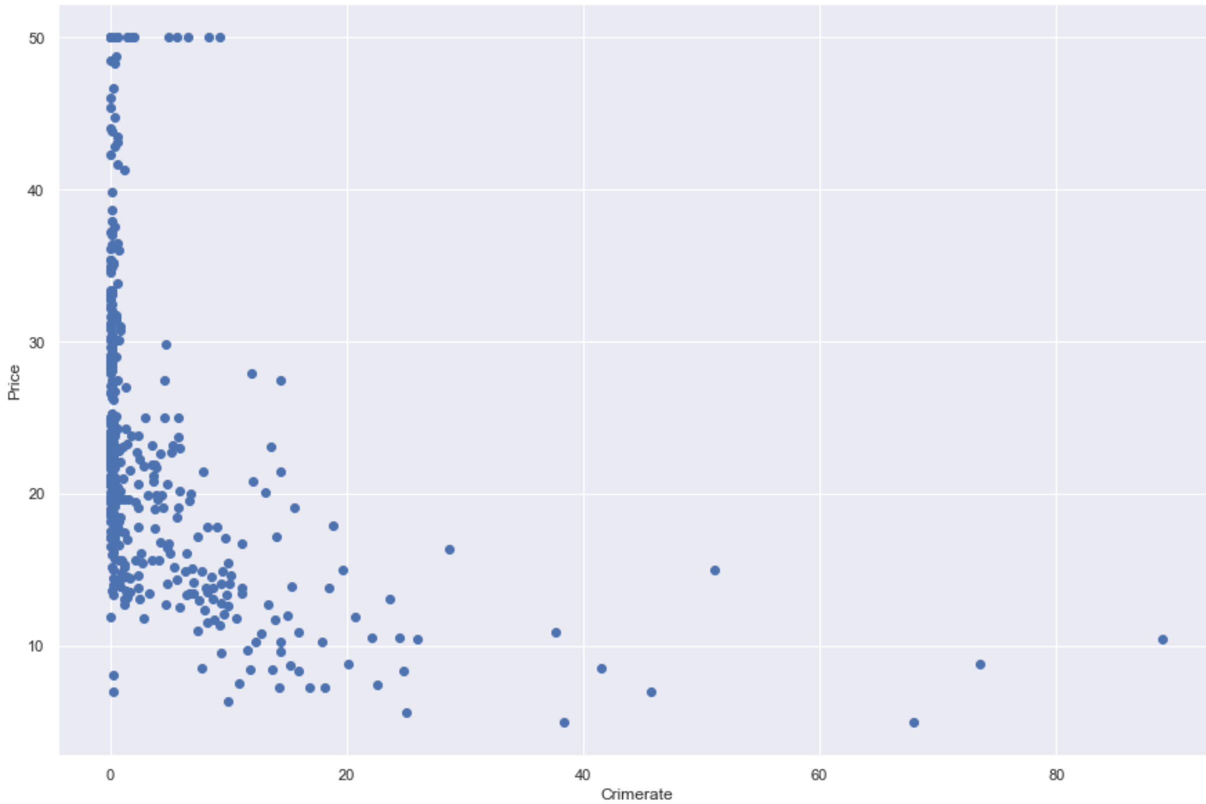
In [21]:
```python
sns.set(rc={'figure.figsize':(15,10)})
sns.heatmap(dataset.corr(), annot=True)
```

Out[21]: <AxesSubplot:>



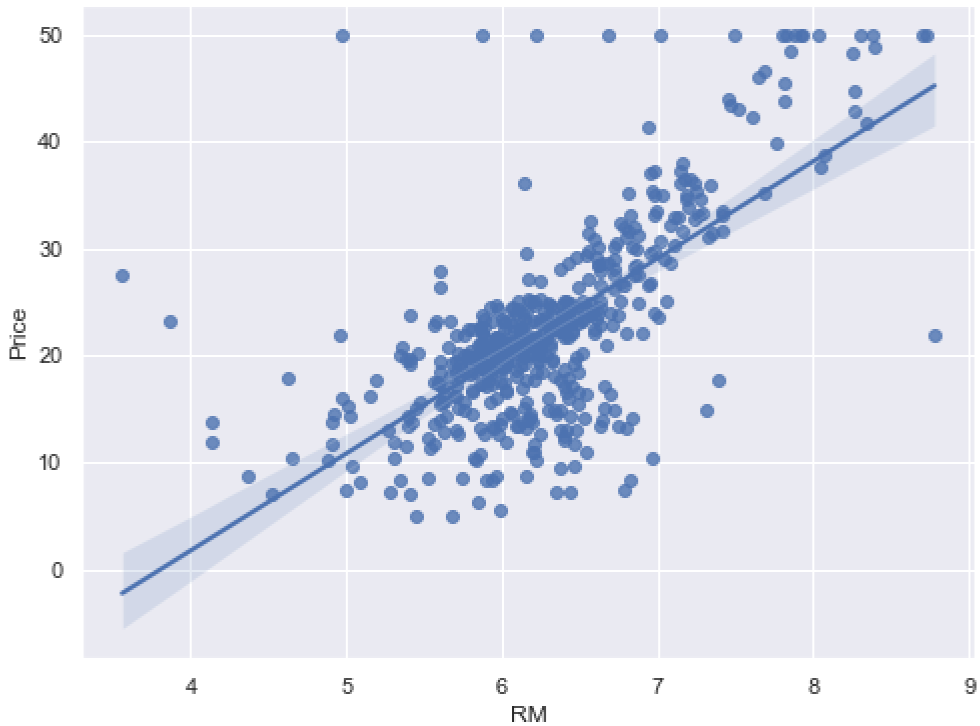
In [22]:
```
plt.scatter(dataset['CRIM'], dataset['Price'])
plt.xlabel('Crimerate')
plt.ylabel('Price')
```

Out[22]: Text(0, 0.5, 'Price')



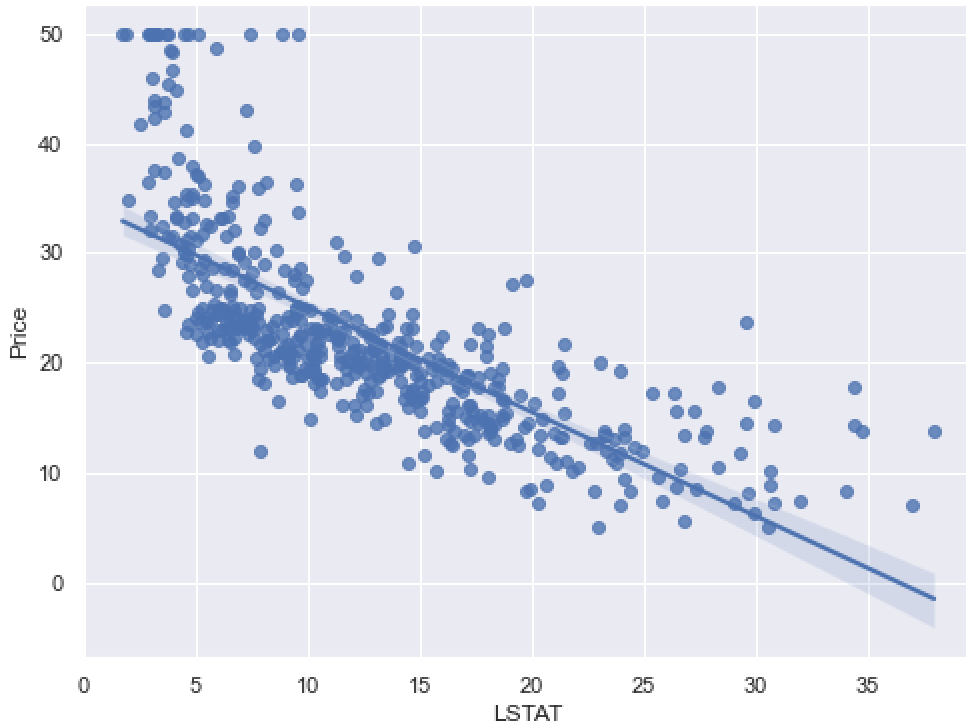
In [23]:
```
sns.set(rc={'figure.figsize':(8,6)})
sns.regplot(x='RM', y='Price', data=dataset)
```

Out[23]:
```
<AxesSubplot:xlabel='RM', ylabel='Price'>
```



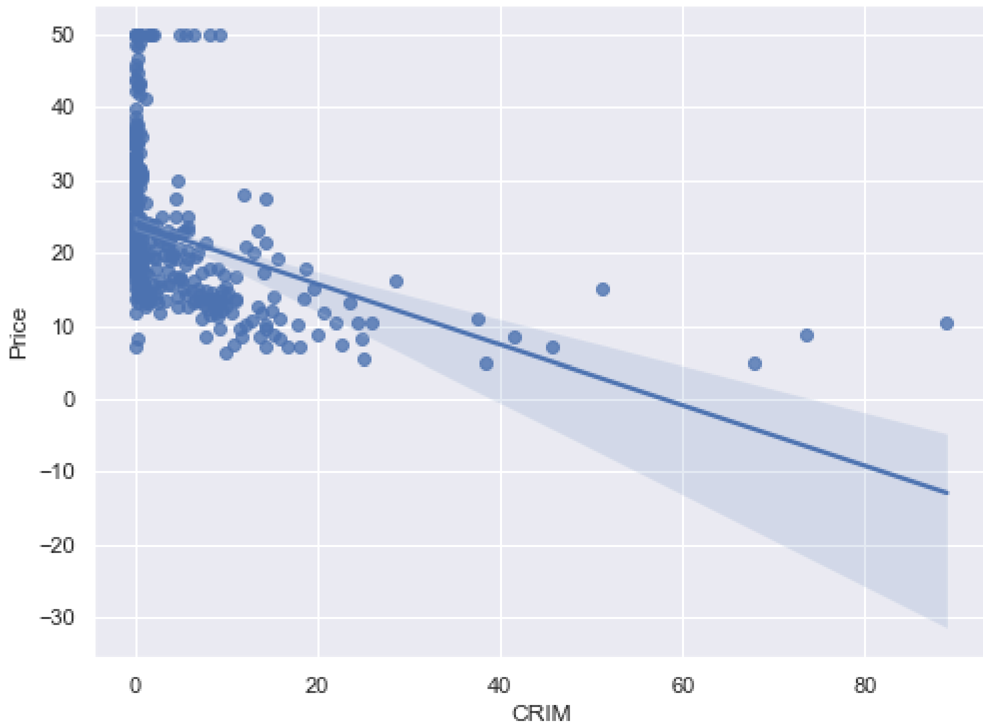
In [24]:
```
sns.regplot(x='LSTAT', y='Price', data=dataset)
```

Out[24]: <AxesSubplot:xlabel='LSTAT', ylabel='Price'>



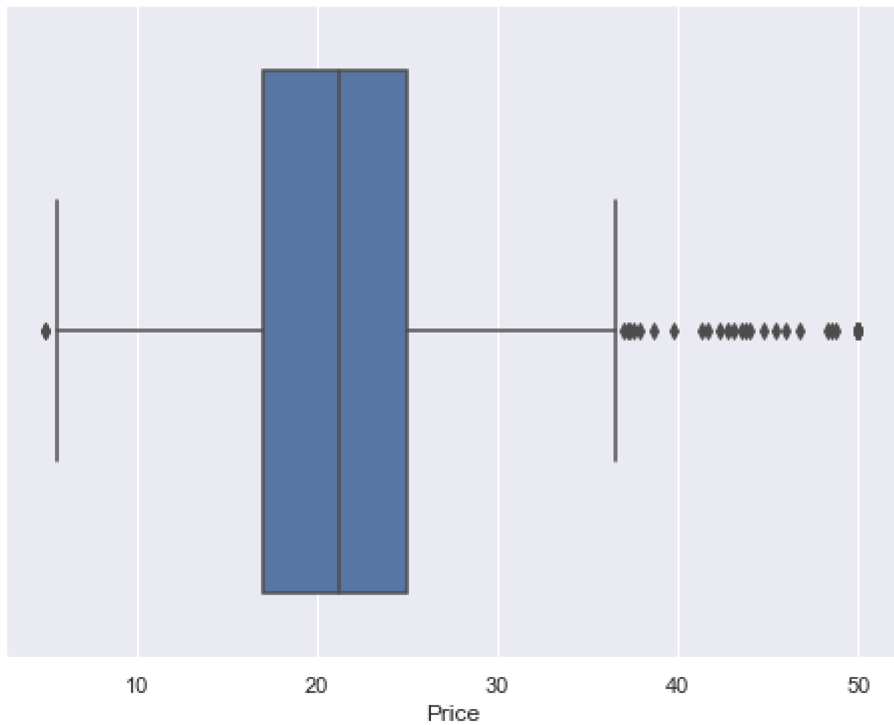
In [25]:
```
sns.regplot(x='CRIM', y='Price', data=dataset)
```

Out[25]: <AxesSubplot:xlabel='CRIM', ylabel='Price'>



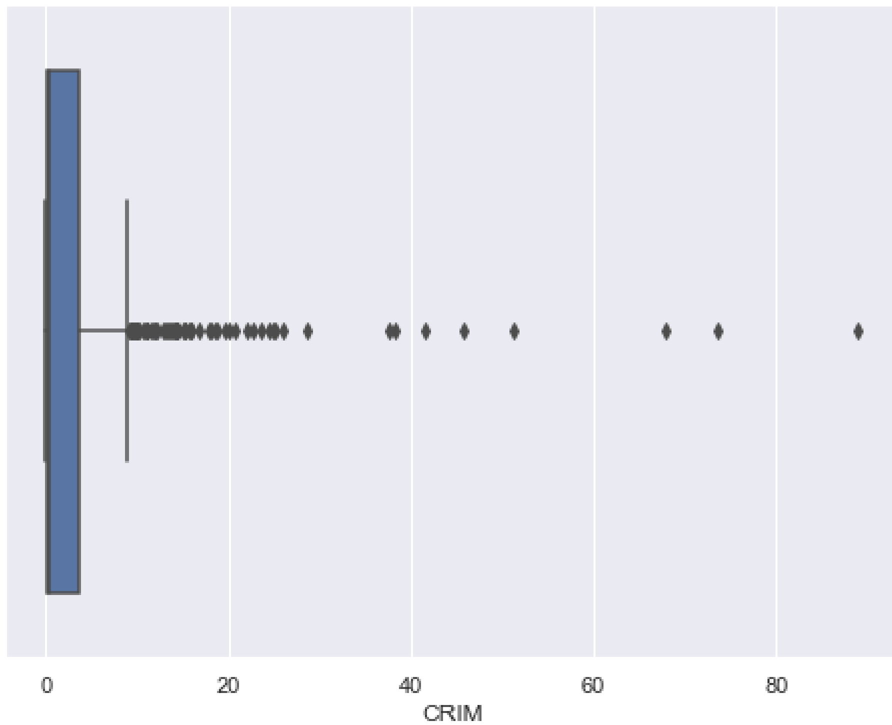
In [26]:
```
sns.boxplot(dataset['Price'])
```

Out[26]: <AxesSubplot:xlabel='Price'>



In [27]:
```
sns.boxplot(dataset['CRIM'])
```

Out[27]: <AxesSubplot:xlabel='CRIM'>



In [28]:
```
#Independent and Dependent features
X = dataset.iloc[:,:-1]
Y = dataset.iloc[:,-1]
```

In [29]:
```
X.head()
```

Out[29]:

	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
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 [30]:
```
Y.head()
```

Out[30]:
```
0    24.0
1    21.6
2    34.7
3    33.4
4    36.2
Name: Price, dtype: float64
```

In [31]:
```
#in Dependent feature we get series dataset
#in independent feature we get in array or in dataframe
```

In [32]:
```
from sklearn.model_selection import train_test_split
```

In [33]:
```
#X_train output is Y_train, X_test output is Y_test
```

In [34]:
```
X_train, X_test, Y_train, Y_test = train_test_split(
X, Y, test_size=0.33, random_state=42)
```

In [35]:
```
X_train
```

Out[35]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
478	10.23300	0.0	18.10	0.0	0.614	6.185	96.7	2.1705	24.0	666.0	20.2	379.70	18
26	0.67191	0.0	8.14	0.0	0.538	5.813	90.3	4.6820	4.0	307.0	21.0	376.88	14
7	0.14455	12.5	7.87	0.0	0.524	6.172	96.1	5.9505	5.0	311.0	15.2	396.90	19
492	0.11132	0.0	27.74	0.0	0.609	5.983	83.5	2.1099	4.0	711.0	20.1	396.90	13
108	0.12802	0.0	8.56	0.0	0.520	6.474	97.1	2.4329	5.0	384.0	20.9	395.24	12
...	...	...	...	...	...	...	...	...	...	...	...	...	
106	0.17120	0.0	8.56	0.0	0.520	5.836	91.9	2.2110	5.0	384.0	20.9	395.67	18
270	0.29916	20.0	6.96	0.0	0.464	5.856	42.1	4.4290	3.0	223.0	18.6	388.65	13
348	0.01501	80.0	2.01	0.0	0.435	6.635	29.7	8.3440	4.0	280.0	17.0	390.94	5
435	11.16040	0.0	18.10	0.0	0.740	6.629	94.6	2.1247	24.0	666.0	20.2	109.85	23
102	0.22876	0.0	8.56	0.0	0.520	6.405	85.4	2.7147	5.0	384.0	20.9	70.80	10

339 rows × 13 columns

In [36]:
```
Y_train
```

Out[36]:
```
478    14.6
26     16.6
7      27.1
492    20.1
108    19.8
       ...
106    19.5
270    21.1
348    24.5
435    13.4
102    18.6
Name: Price, Length: 339, dtype: float64
```

In [37]:
```
Y_train.shape
```

Out[37]:
```
(339,)
```

In [38]:
```
X_train.shape
```

Out[38]:
```
(339, 13)
```

In [39]:
```
X_test
```

Out[39]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST/
173	0.09178	0.0	4.05	0.0	0.510	6.416	84.1	2.6463	5.0	296.0	16.6	395.50	9.
274	0.05644	40.0	6.41	1.0	0.447	6.758	32.9	4.0776	4.0	254.0	17.6	396.90	3.
491	0.10574	0.0	27.74	0.0	0.609	5.983	98.8	1.8681	4.0	711.0	20.1	390.11	18.
72	0.09164	0.0	10.81	0.0	0.413	6.065	7.8	5.2873	4.0	305.0	19.2	390.91	5.
452	5.09017	0.0	18.10	0.0	0.713	6.297	91.8	2.3682	24.0	666.0	20.2	385.09	17.
...	...	...	...	...	...	...	...	...	...	...	...	...	
110	0.10793	0.0	8.56	0.0	0.520	6.195	54.4	2.7778	5.0	384.0	20.9	393.49	13.
321	0.18159	0.0	7.38	0.0	0.493	6.376	54.3	4.5404	5.0	287.0	19.6	396.90	6.
265	0.76162	20.0	3.97	0.0	0.647	5.560	62.8	1.9865	5.0	264.0	13.0	392.40	10.
29	1.00245	0.0	8.14	0.0	0.538	6.674	87.3	4.2390	4.0	307.0	21.0	380.23	11.
262	0.52014	20.0	3.97	0.0	0.647	8.398	91.5	2.2885	5.0	264.0	13.0	386.86	5.

167 rows × 13 columns

In [40]:
```
Y_test
```

Out[40]:
```
173    23.6
274    32.4
491    13.6
72     22.8
452    16.1
       ...
110    21.7
321    23.1
265    22.8
29     21.0
262    48.8
Name: Price, Length: 167, dtype: float64
```

In [41]:
```
#standardize or Feature scaling datasets
from sklearn.preprocessing import StandardScaler
```

In [42]:
```
scaler = StandardScaler()
```

In [43]:
```
scaler
```

Out[43]:
```
StandardScaler()
```

In [44]:
```
X_train = scaler.fit_transform(X_train)
```

In [45]:
```
X_test =scaler.transform(X_test)
```

In [46]:
```
X_train
```

Out[46]:
```
array([[ 0.89624872, -0.51060139,  0.98278223, ...,  0.86442095,
         0.24040357,  0.77155612],
       [-0.34895881, -0.51060139, -0.44867555, ...,  1.22118698,
         0.20852839,  0.32248963],
       [-0.41764058,  0.03413008, -0.48748013, ..., -1.36536677,
         0.43481957,  0.92775316],
       ...,
       [-0.43451148,  2.97567999, -1.32968321, ..., -0.56264319,
         0.36745216, -0.90756208],
       [ 1.01703049, -0.51060139,  0.98278223, ...,  0.86442095,
        -2.80977992,  1.50233514],
       [-0.40667333, -0.51060139, -0.38831288, ...,  1.17659123,
        -3.25117205, -0.26046005]])
```

In [47]:
```
X_test
```

Out[47]:
```
array([[-0.42451319, -0.51060139, -1.03649306, ..., -0.74102621,
         0.41899501, -0.48220406],
       [-0.42911576,  1.2325393 , -0.6973123 , ..., -0.29506866,
         0.43481957, -1.25063772],
       [-0.42269508, -0.51060139,  2.36824941, ...,  0.8198252 ,
         0.35807046,  0.77713459],
       ...,
       [-0.33727525,  0.36096896, -1.04799071, ..., -2.34647337,
         0.38395492, -0.28556314],
       [-0.30591027, -0.51060139, -0.44867555, ...,  1.22118698,
         0.2463943 , -0.07218683],
       [-0.36872487,  0.36096896, -1.04799071, ..., -2.34647337,
         0.32133488, -0.91871901]])
```

#Model Training

In [48]:
```
from sklearn.linear_model import LinearRegression
```

In [49]:
```
regression = LinearRegression()
```

In [50]:
```
regression
```

Out[50]:
```
LinearRegression()
```

In [51]:
```
regression.fit(X_train, Y_train)
```

Out[51]:
```
LinearRegression()
```

In [52]:
```
#print the coefficients and intercepts
print(regression.coef_)
```

```
[-0.98858032  0.86793276  0.40502822  0.86183791 -1.90009974  2.80813518
 -0.35866856 -3.04553498  2.03276074 -1.36400909 -2.0825356   1.04125684
 -3.92628626]
```

In [53]:
```
print(regression.intercept_)
```

```
22.970796460176988
```

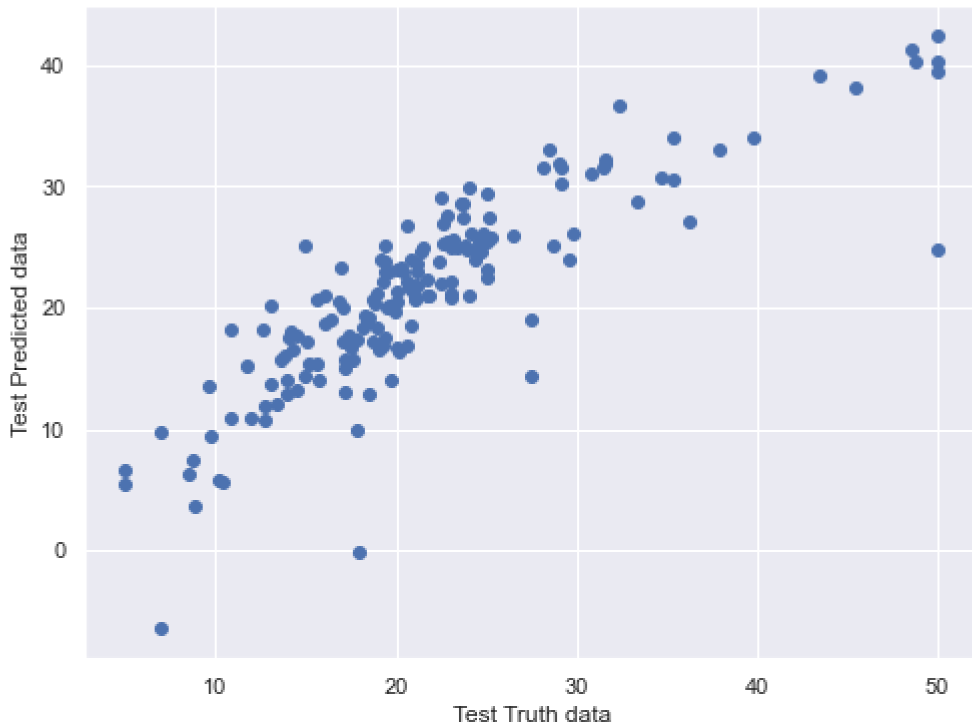
In [54]:
```
#prediction for the test data
reg_pre = regression.predict(X_test)
```

In [55]:
```
reg_pre
```

Out[55]:
```
array([28.53469469, 36.6187006 , 15.63751079, 25.5014496 , 18.7096734 ,
       23.16471591, 17.31011035, 14.07736367, 23.01064388, 20.54223482,
       24.91632351, 18.41098052, -6.52079687, 21.83372604, 19.14903064,
       26.0587322 , 20.30232625,  5.74943567, 40.33137811, 17.45791446,
       27.47486665, 30.2170757 , 10.80555625, 23.87721728, 17.99492211,
       16.02608791, 23.268288  , 14.36825207, 22.38116971, 19.3092068 ,
       22.17284576, 25.05925441, 25.13780726, 18.46730198, 16.60405712,
       17.46564046, 30.71367733, 20.05106788, 23.9897768 , 24.94322408,
       13.97945355, 31.64706967, 42.48057206, 17.70042814, 26.92507869,
       17.15897719, 13.68918087, 26.14924245, 20.2782306 , 29.99003492,
       21.21260347, 34.03649185, 15.41837553, 25.95781061, 39.13897274,
       22.96118424, 18.80310558, 33.07865362, 24.74384155, 12.83640958,
       22.41963398, 30.64804979, 31.59567111, 16.34088197, 20.9504304 ,
       16.70145875, 20.23215646, 26.1437865 , 31.12160889, 11.89762768,
       20.45432404, 27.48356359, 10.89034224, 16.77707214, 24.02593714,
        5.44691807, 21.35152331, 41.27267175, 18.13447647,  9.8012101 ,
       21.24024342, 13.02644969, 21.80198374,  9.48201752, 22.99183857,
       31.90465631, 18.95594718, 25.48515032, 29.49687019, 20.07282539,
       25.5616062 ,  5.59584382, 20.18410904, 15.08773299, 14.34562117,
       20.85155407, 24.80149389, -0.19785401, 13.57649004, 15.64401679,
       22.03765773, 24.70314482, 10.86409112, 19.60231067, 23.73429161,
       12.08082177, 18.40997903, 25.4366158 , 20.76506636, 24.68588237,
        7.4995836 , 18.93015665, 21.70801764, 27.14350579, 31.93765208,
       15.19483586, 34.01357428, 12.85763091, 21.06646184, 28.58470042,
       15.77437534, 24.77512495,  3.64655689, 23.91169589, 25.82292925,
       23.03339677, 25.35158335, 33.05655447, 20.65930467, 38.18917361,
       14.04714297, 25.26034469, 17.6138723 , 20.60883766,  9.8525544 ,
       21.06756951, 22.20145587, 32.2920276 , 31.57638342, 15.29265938,
       16.7100235 , 29.10550932, 25.17762329, 16.88159225,  6.32621877,
       26.70210263, 23.3525851 , 17.24168182, 13.22815696, 39.49907507,
       16.53528575, 18.14635902, 25.06620426, 23.70640231, 22.20167772,
       21.22272327, 16.89825921, 23.15518273, 28.69699805,  6.65526482,
       23.98399958, 17.21004545, 21.0574427 , 25.01734597, 27.65461859,
       20.70205823, 40.38214871])
```

In [57]:
```
#Assumptions of Linear Regression
plt.scatter(Y_test, reg_pre)
plt.xlabel("Test Truth data")
plt.ylabel("Test Predicted data")
```

Out[57]: Text(0, 0.5, 'Test Predicted data')



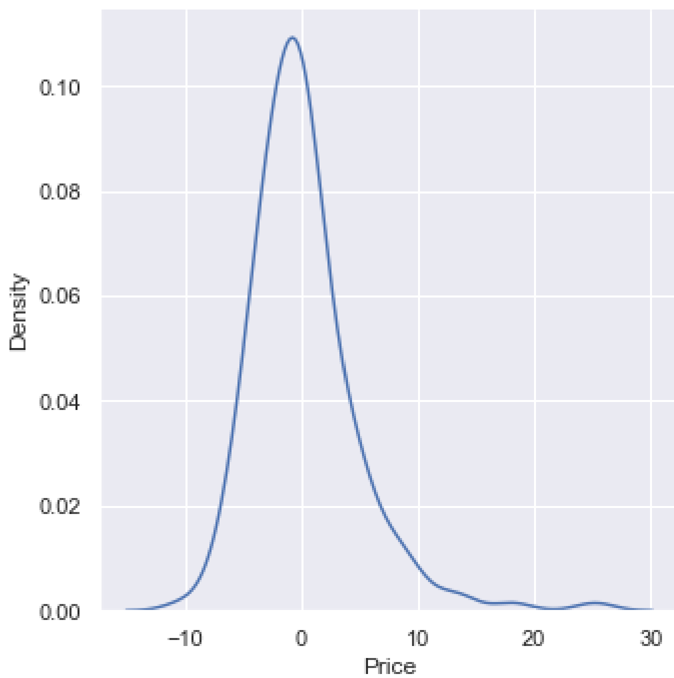
In [58]:
```
#residuals = errors
residuals = Y_test-reg_pre
```

In [59]:
```
residuals
```

Out[59]:
```
173   -4.934695
274   -4.218701
491   -2.037511
72    -2.701450
452   -2.609673
         ...
110    0.642557
321   -1.917346
265   -4.854619
29     0.297942
262    8.417851
Name: Price, Length: 167, dtype: float64
```

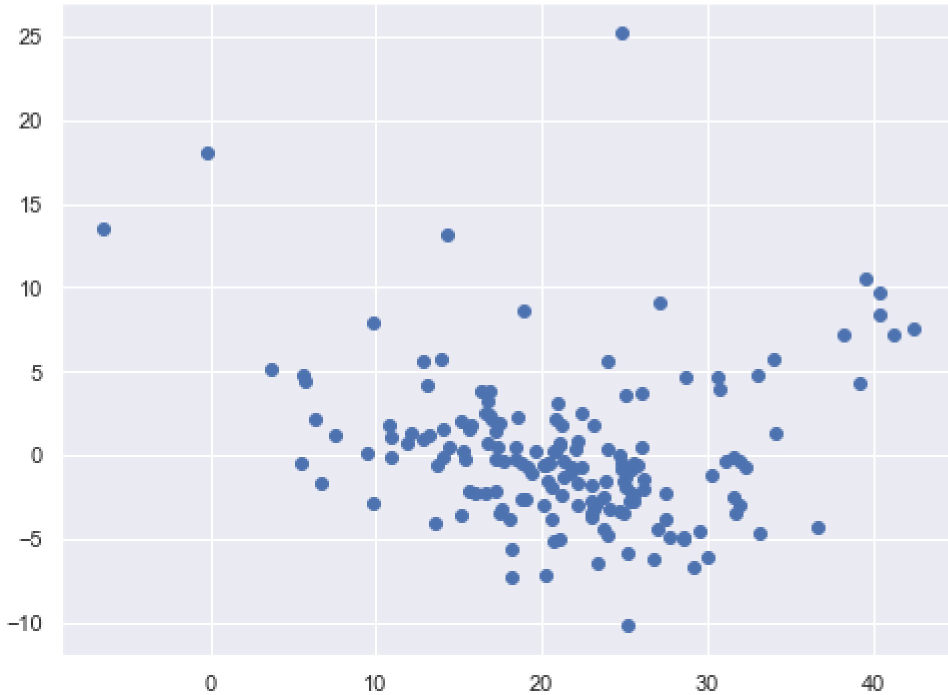
In [60]:
```
sns.displot(residuals, kind='kde')
```

Out[60]:
```
<seaborn.axisgrid.FacetGrid at 0x273a93b8520>
```



In [62]:
```
#scatter plot of predictions n residuals
#uniform distribution, Homoscedacity
plt.scatter(reg_pre, residuals)
```

Out[62]: <matplotlib.collections.PathCollection at 0x273ac64e0d0>



In [63]:
```
#Performance metrics

from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(Y_test, reg_pre))
```

```
20.724023437339753
```

In [64]:
```
print(mean_absolute_error(Y_test,reg_pre))
```

```
3.148255754816832
```

In [66]:
```
print(np.sqrt(mean_squared_error(Y_test, reg_pre)))
```

```
4.552364598463062
```

#adjusted R sqared is always less than R squared error

In [67]:
```
#R squared and adjusted squared
from sklearn.metrics import r2_score
score = r2_score(Y_test, reg_pre)
```

In [68]:
```
score
```

Out[68]:
```
0.7261570836552476
```

In [70]:
```
#adjusted R Square
1-(1-score)*(len(Y_test)-1)/(len(Y_test)-X_test.shape[1]-1)
```

Out[70]:
```
0.7028893848808568
```

In [ ]: