Machine Learning Pipeline Steps

- Step 1: Data Preprocessing. ...
- Step 2: Data Cleaning. ...
- Step 3: Feature Engineering. ...
- Step 4: Model Selection. ...
- Step 5: Prediction Generation.

Required Packages

In [324]:
```
1 import pandas as pd
2 import numpy as np
3 import seaborn as sns
4 import matplotlib.pyplot as plt
5 %matplotlib inline
6 import warnings
7 warnings.filterwarnings('ignore')
```

Data Importing

In [325]:
```
1 from sklearn.datasets import load_boston
```

In [326]:
```
boston=load_boston()
boston
```

Out[326]:
```
{'data': array([[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]]),
 'target': array([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,
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        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,
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         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,
```

```
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       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
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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': 'C:\\Users\\soume\\anaconda3\\lib\\site-packages\\sklearn\\dataset
s\\data\\boston_house_prices.csv'}
```

In [327]:
```
1 print(boston)
```

```
{'data': array([[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]]), 'target': array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9, 15. ,
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       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,
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       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,
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       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,
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       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,
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       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,
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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', 'DIS', '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 order):\n   - CRIM   per capita crime rate by town\n   - ZN   proportion of residential land zoned for lots over 25,000 sq.ft.\n   - INDUS   proportion of non-retail business acres per town\n   - CHAS   Charles River 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 units built prior to 1940\n   - DIS   weighted distances to five Boston employment centres\n   - RAD   index of accessibility to radial highways\n   - TAX   full-value property-tax rate per $10,000\n   - PTRATIO 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 $1000's\n\n   :Missing Attribute Values: None\n\n   :Creator: Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing dataset.\nhttps://archive.ics.uci.edu/ml/machine-learning-databases/housing/\n\n\nThis dataset was taken from the StatLib library which is maintained at Carnegie Mellon University.\n\nThe 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, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics\n...', Wiley, 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 learning papers that address regression\nproblems.   \n   \n.. topic:: References\n\n   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of Collinearity', Wiley, 1980. 244-261.\n   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the Tenth International Conference of Machine Learning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.\n", 'filename': 'C:\\Users\\soume\\anaconda3\\lib\\site-packages\\sklearn\\datasets\\data\\boston_house_prices.csv'}

In [328]:
```
1 boston.keys()
```

Out[328]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

In [329]:
```
1 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
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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 [330]:
```
1 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 [331]:
```
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]
```

Fetures Names

In [332]:
```
print(boston.feature_names)
```

```
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
```

In [333]:
```
dataset=pd.DataFrame(boston.data,columns=boston.feature_names)
```

In [334]:
```
1 dataset.head()
```

Out[334]:

	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 [335]:
```
1 dataset['Price']=boston.target
```

In [336]:
```
1 dataset.head()
```

Out[336]:

	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

Check types of dataset

In [337]:
```
1 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
```

Summary of dataset

In [338]:
```
1 dataset.describe()
```

Out[338]:

	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

Checking Null Value

In [339]:
```
1 dataset.isnull().sum()
```

Out[339]:
```
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
```

Exploratory Data Analysis

Summary Of Data

In [340]:
```
1 dataset.corr()
```

Out[340]:

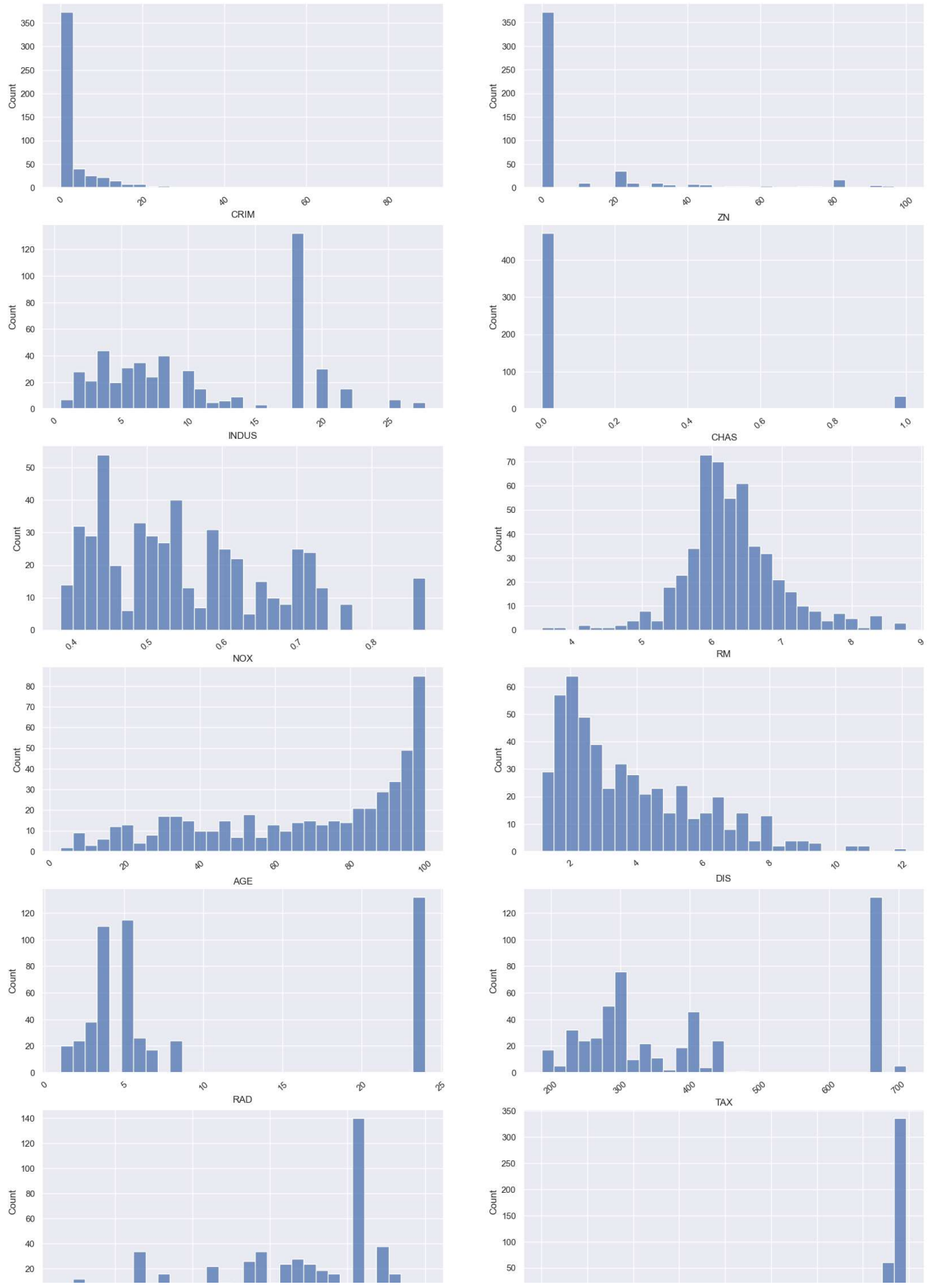
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670	0.
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408	-0
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.
CHAS	-0.055892	-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.

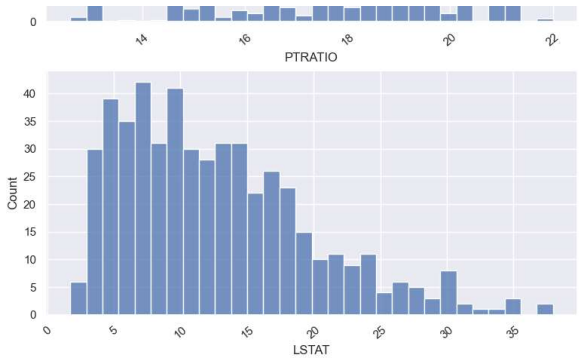
In [341]:
```
1 import seaborn as sns
```

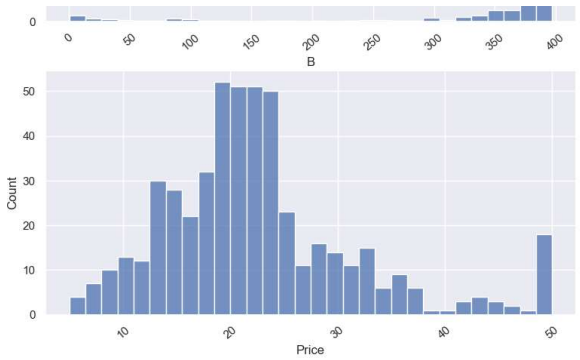
Visualize distribution off all independent features

In [397]:

```
plt.figure(figsize=(20,100))
for i in enumerate(dataset):
    plt.subplot(20, 2, i[0]+1)
    sns.set(rc={'figure.figsize':(5,5)})
    sns.histplot(data=dataset, x=i[1], bins=30)
    plt.xticks(rotation=40)
```





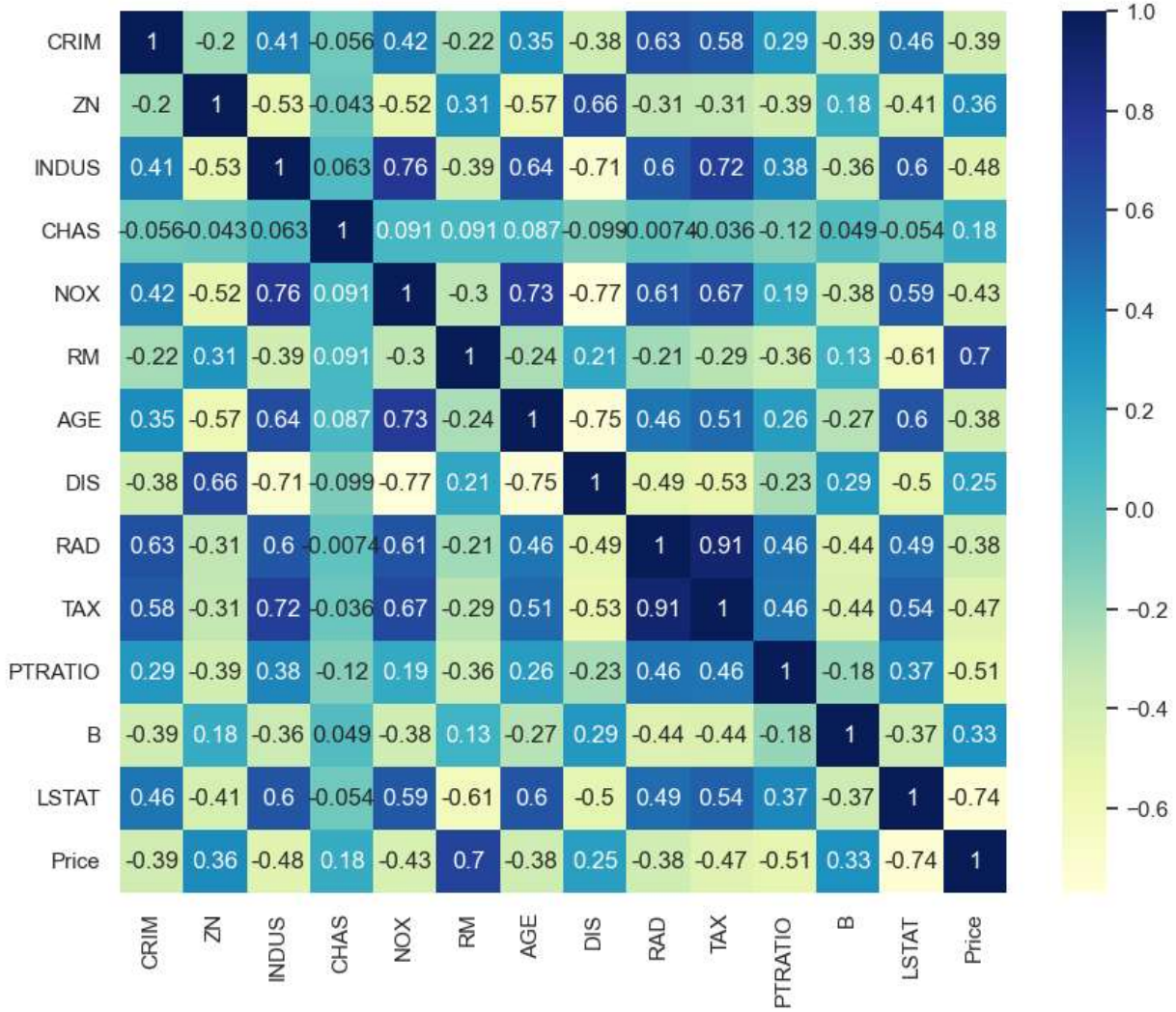


In [ ]:
```
1
```

Visualize correlation All Variables

In [343]:
```
1 sns.set(rc={'figure.figsize':(10,8)})
2 sns.heatmap(dataset.corr(),annot=True,cmap="YlGnBu")
```

Out[343]: <AxesSubplot:>

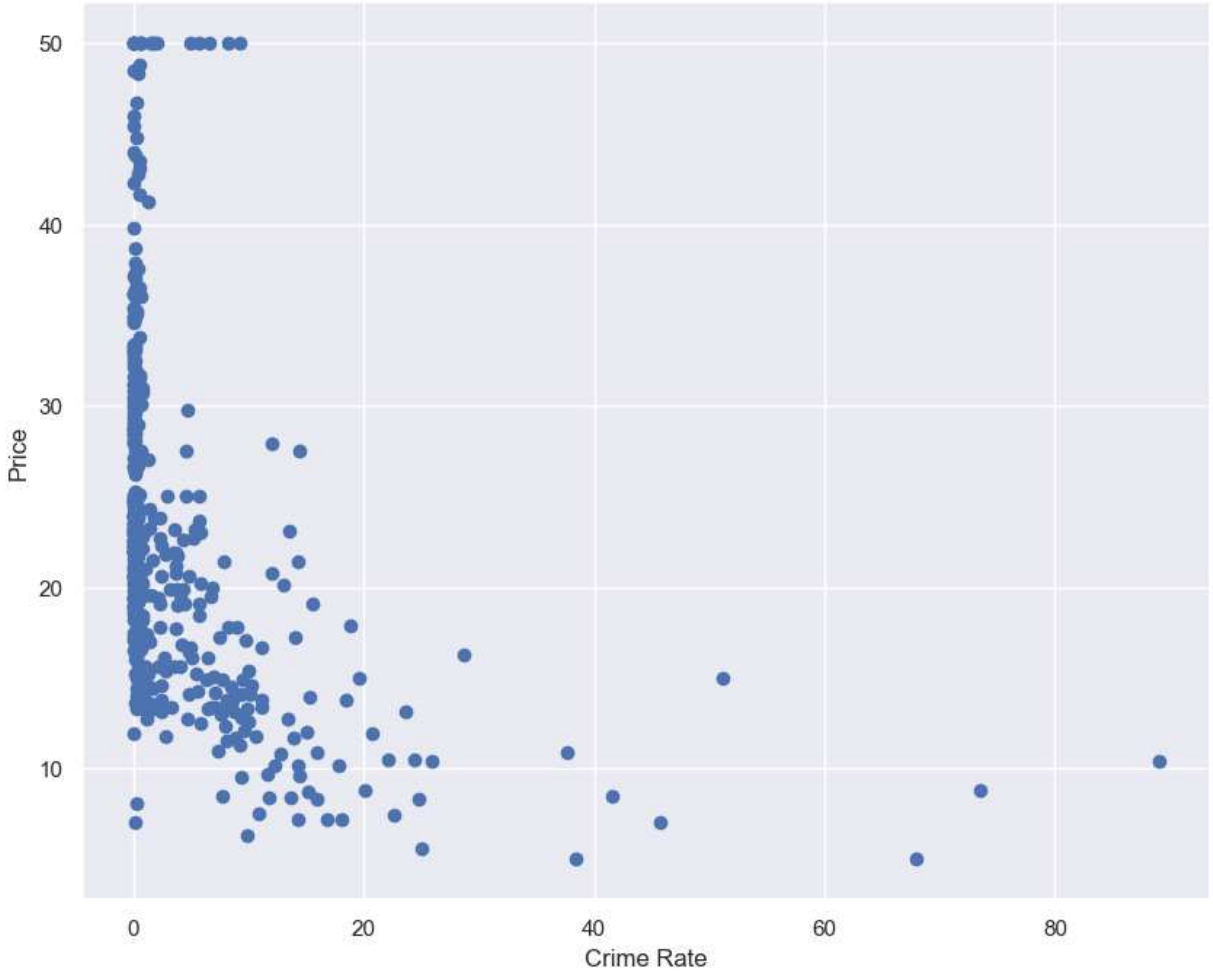


Scatter plot for visualize the relation of indepenedent variables with

dependent variables

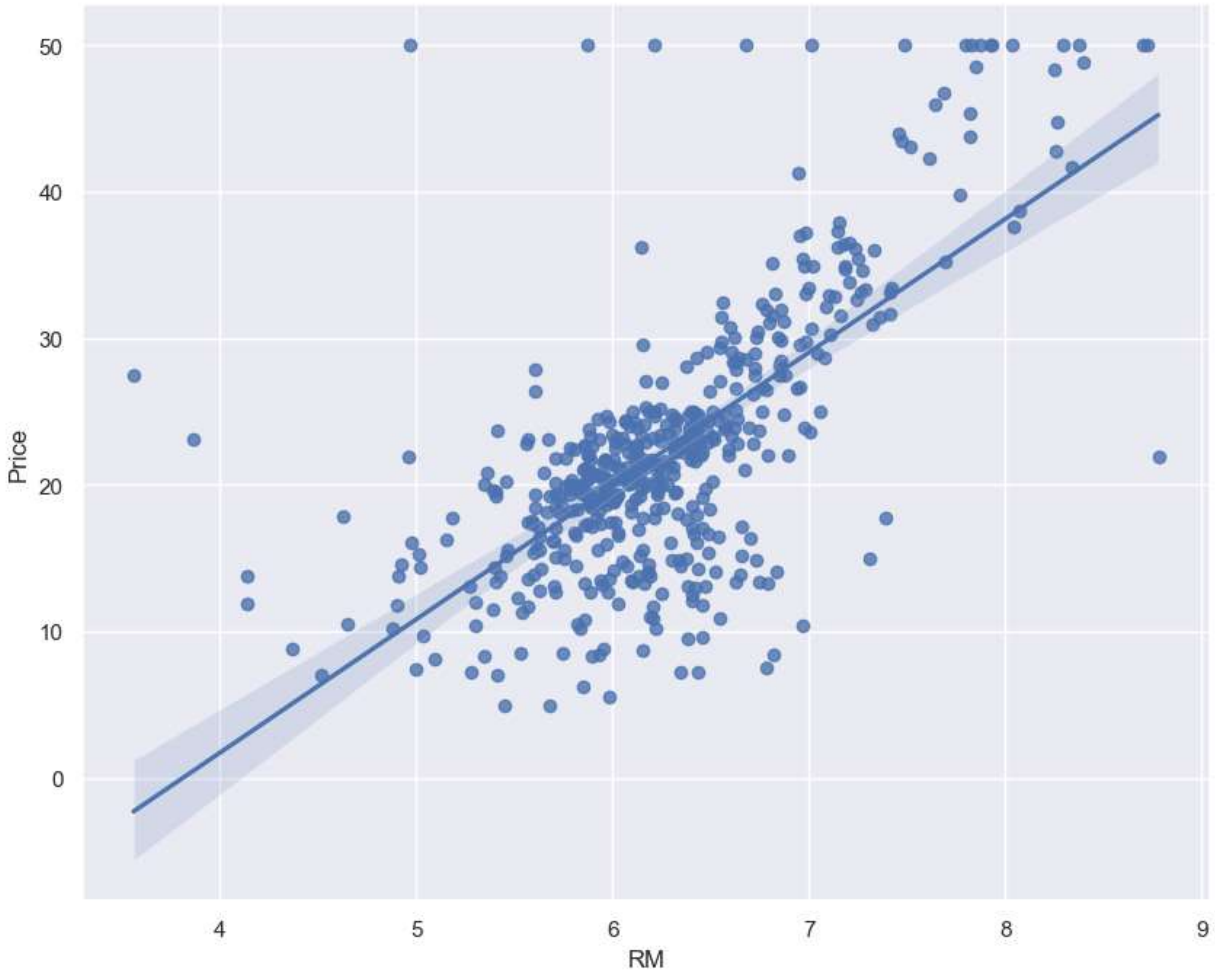
In [344]:
```
1 plt.scatter(dataset['CRIM'],dataset['Price'])
2 plt.xlabel("Crime Rate")
3 plt.ylabel("Price")
```

Out[344]: Text(0, 0.5, 'Price')



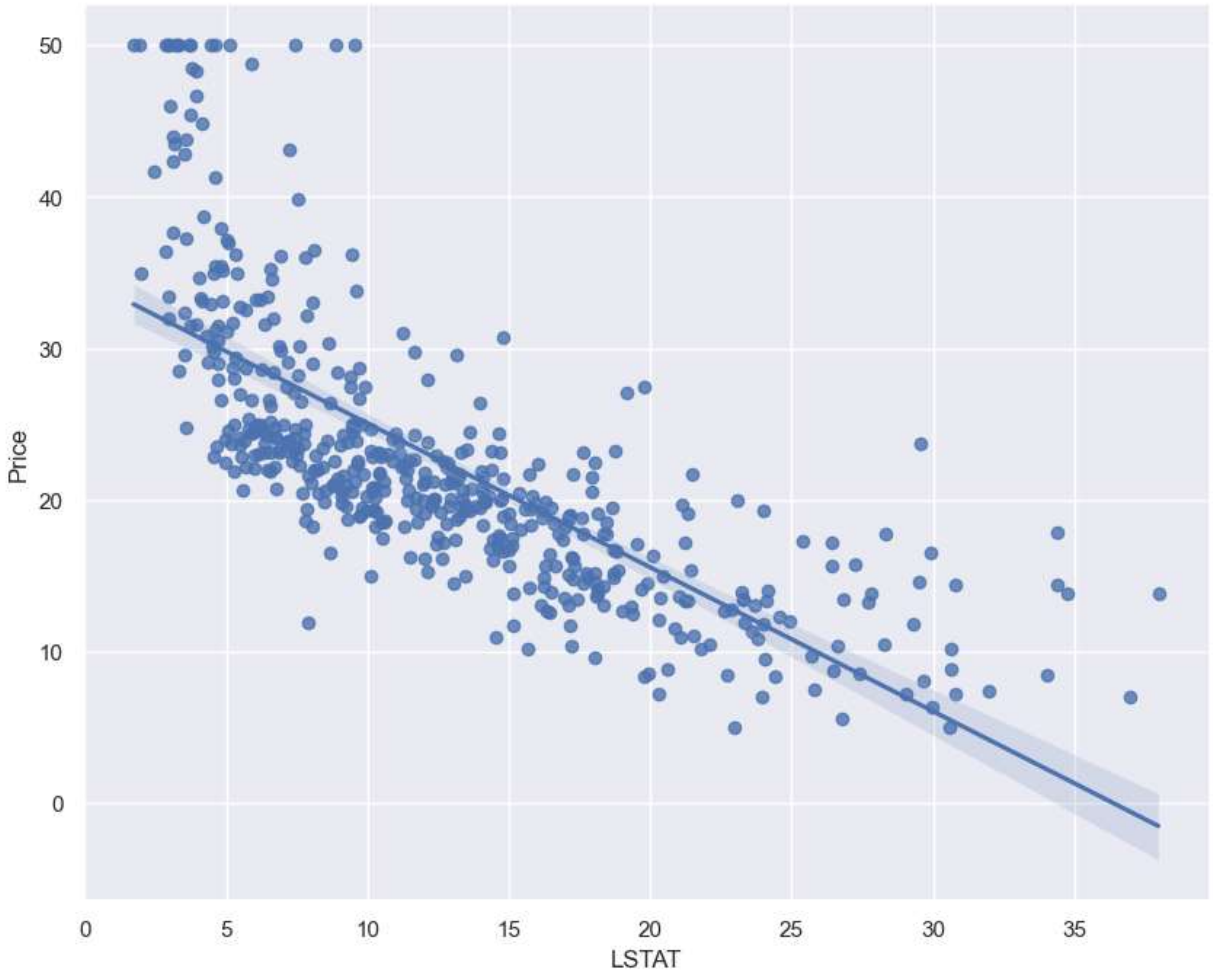
In [345]:
```
1 sns.regplot(x="RM",y="Price",data=dataset)
```

Out[345]: <AxesSubplot:xlabel='RM', ylabel='Price'>



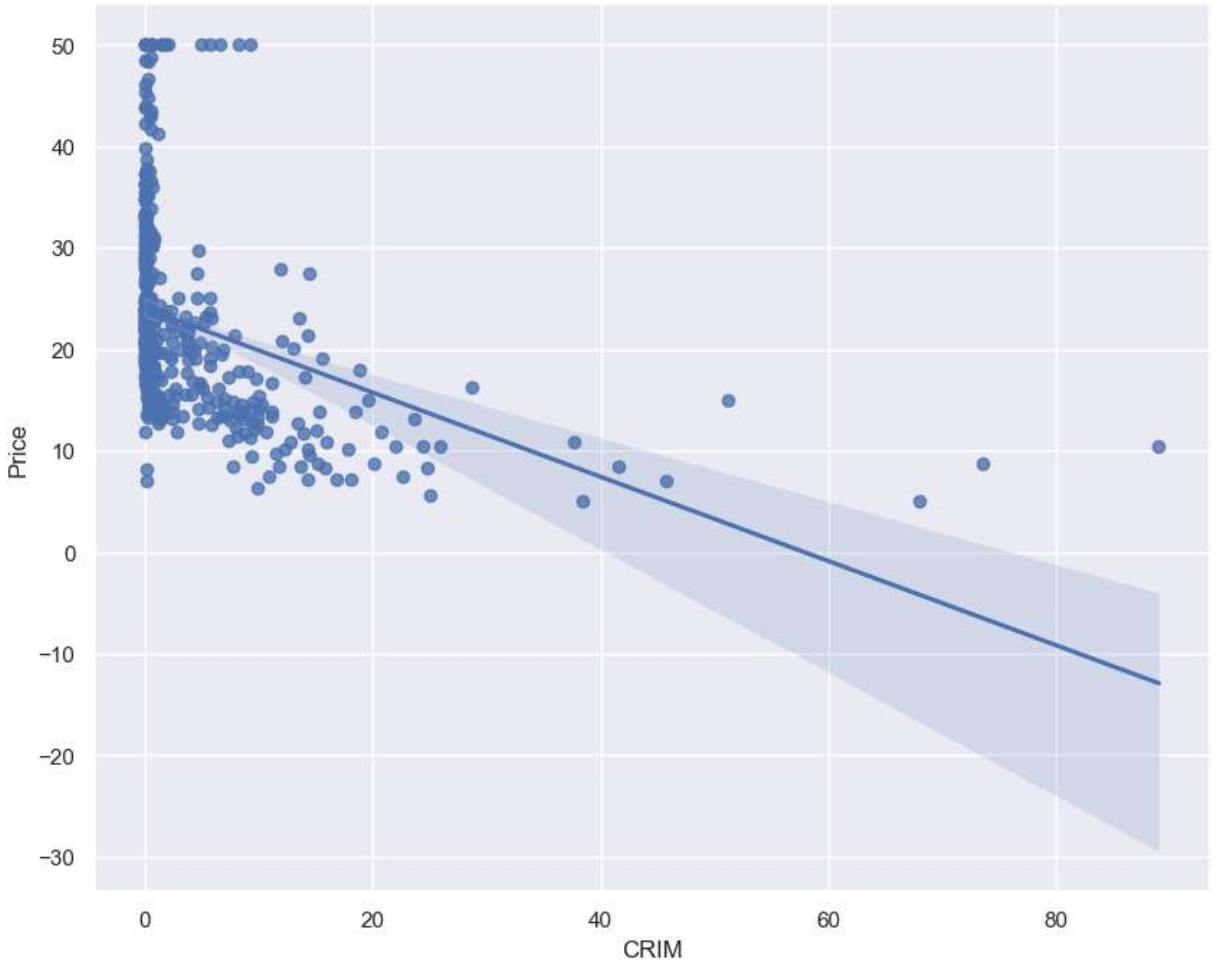
In [346]:
```
1 sns.regplot(x="LSTAT",y="Price",data=dataset)
```

Out[346]: <AxesSubplot:xlabel='LSTAT', ylabel='Price'>



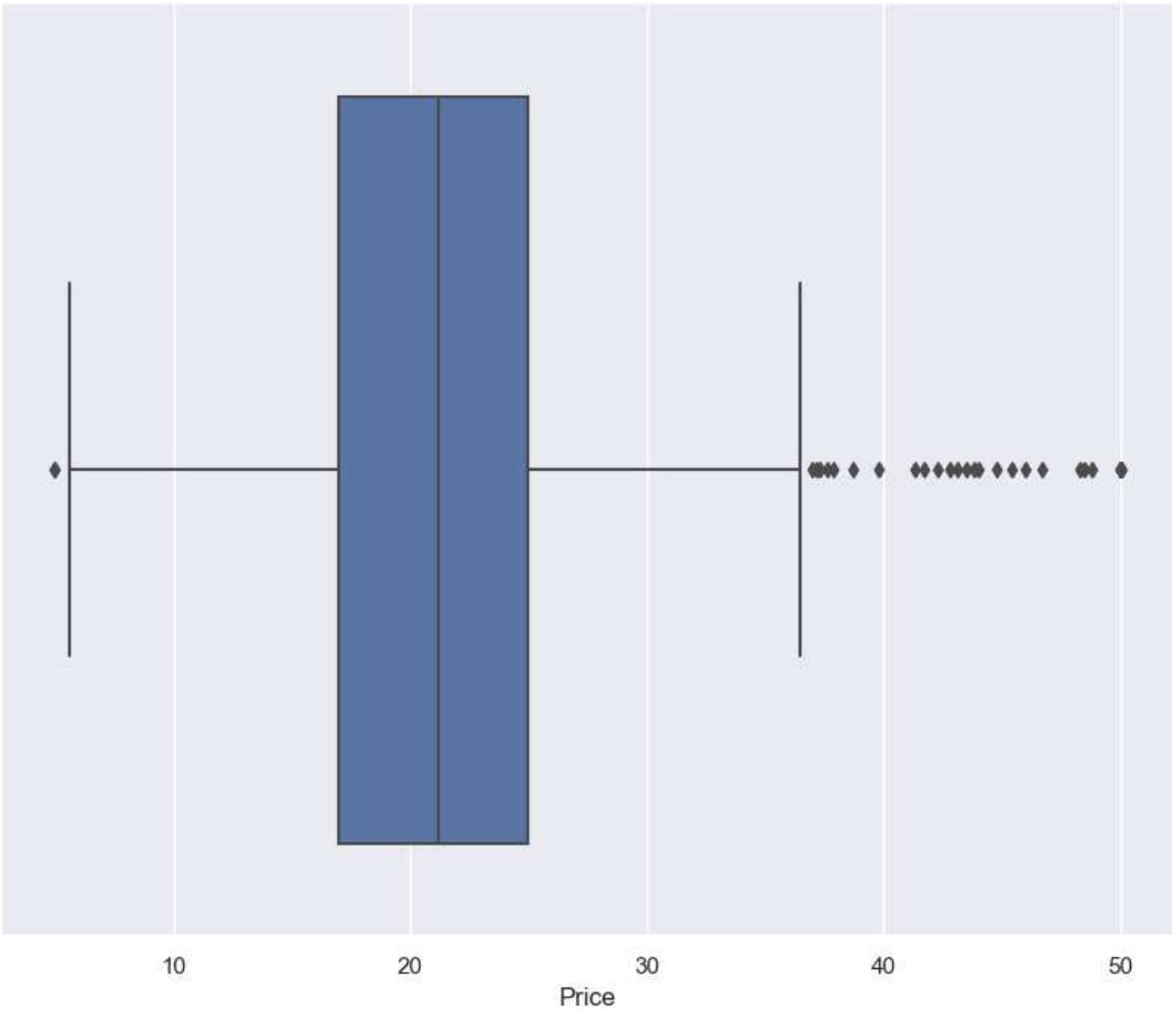
In [347]:
```
1 sns.regplot(x="CRIM",y="Price",data=dataset)
```

Out[347]: <AxesSubplot:xlabel='CRIM', ylabel='Price'>



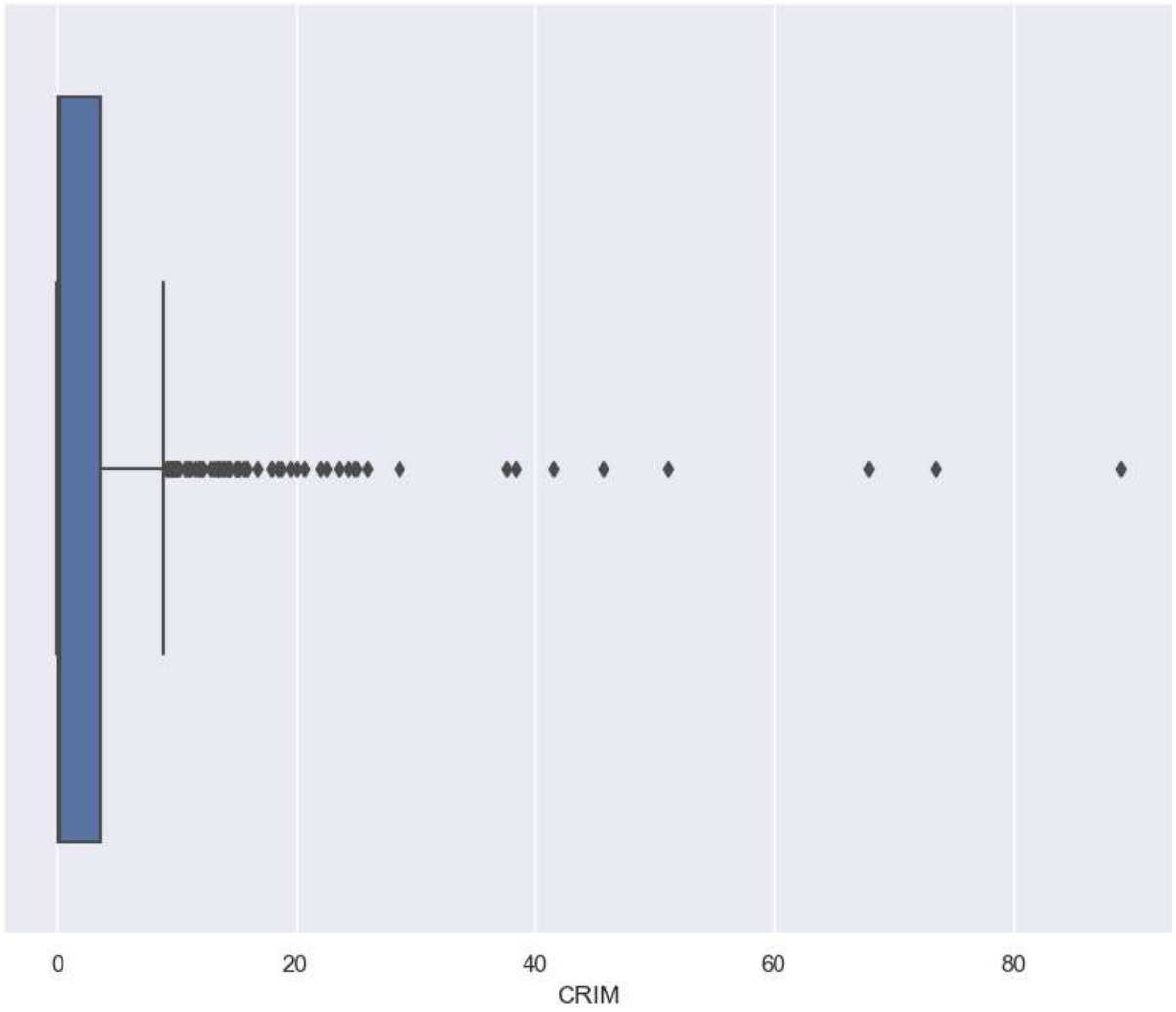
In [348]:
```
sns.boxplot(dataset['Price'])
# But it is outpput we can't do anything to ouput variable
```

Out[348]: <AxesSubplot:xlabel='Price'>



In [349]:
```
1 sns.boxplot(dataset['CRIM'])
```

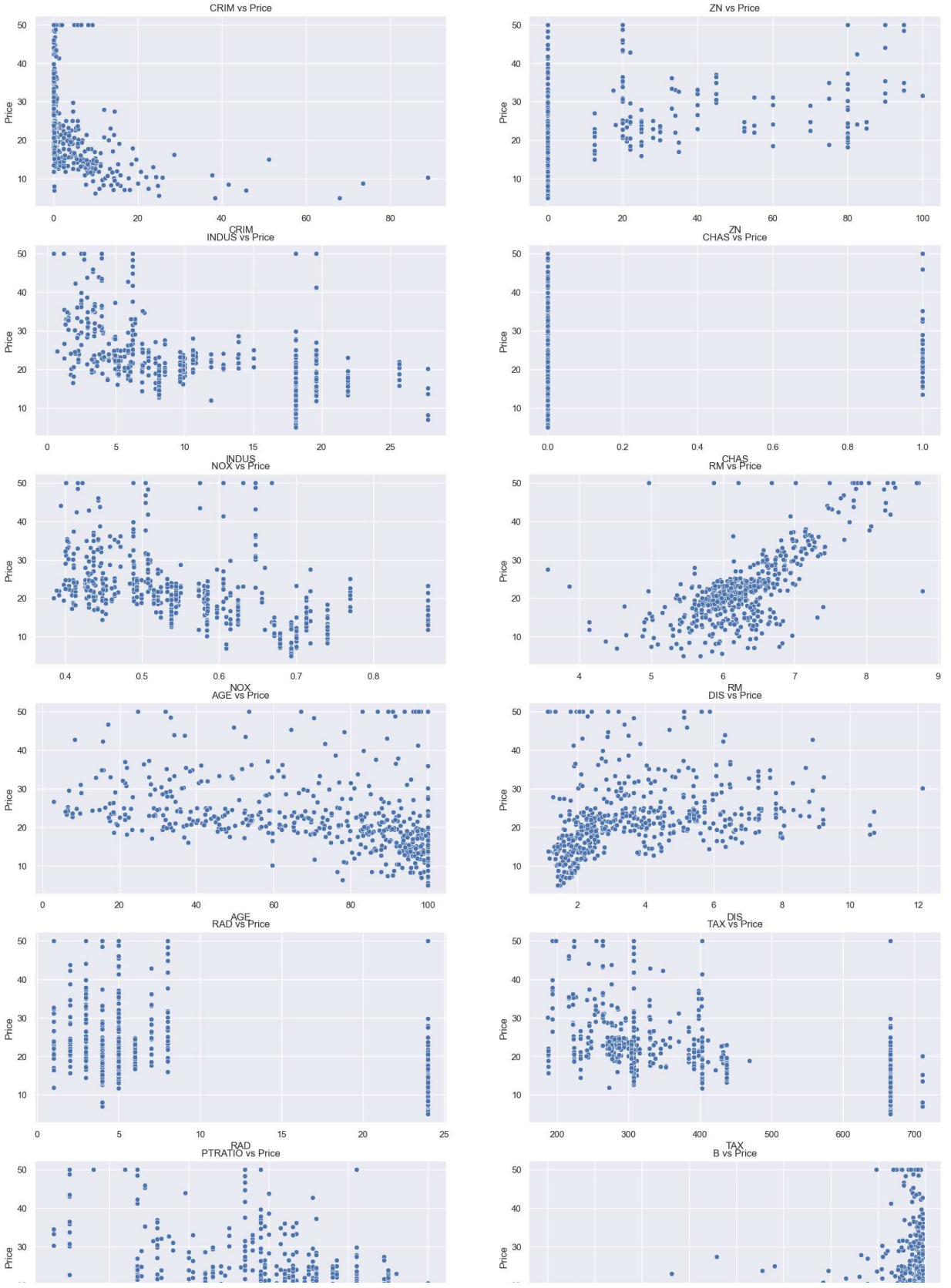
Out[349]: <AxesSubplot:xlabel='CRIM'>

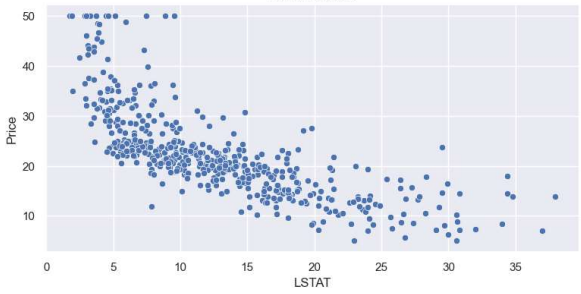


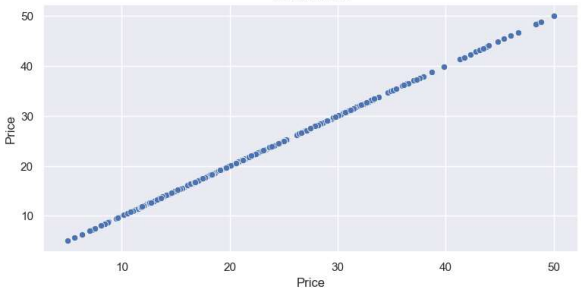
Visualize the relations between independent variables with Price

In [400]:

```
plt.figure(figsize=(20,50))
for feature in enumerate(dataset):
    plt.subplot(10,2,feature[0]+1)
    sns.scatterplot(data=dataset, x=dataset[feature[1]], y=dataset['Price'])
    plt.xlabel(feature[1])
    plt.ylabel('Price')
    plt.title("{} vs Price".format(feature[1]))
```

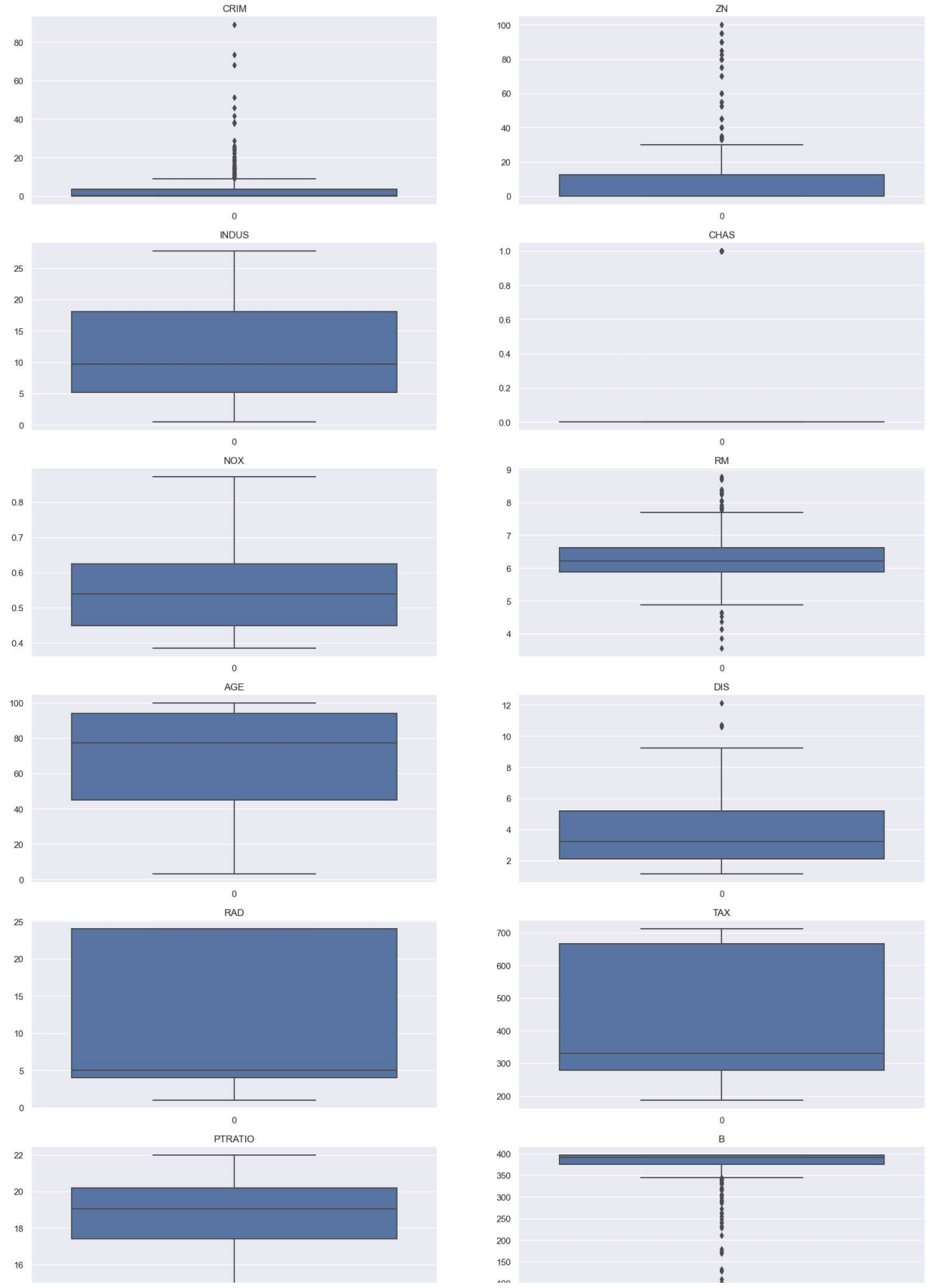


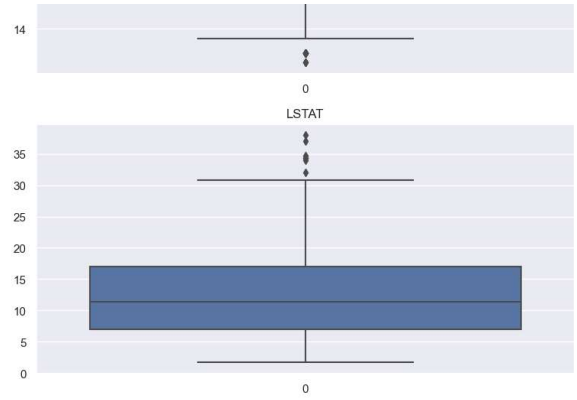




Boxplot of all variables

In [399]:
```
### getting outliers
plt.figure(figsize=(20,50))
for feature in enumerate(dataset):
    plt.subplot(10,2,feature[0]+1)
    sns.boxplot(data=dataset[feature[1]])
    plt.title(feature[1])
```





In [350]:
```
1 dataset.head()
```

Out[350]:

	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

Independent and Dependent features

In [351]:
```
1
2 X=dataset.iloc[:,:-1]
3 y=dataset.iloc[:,-1]
```

In [352]:
```
1 X.head()
```

Out[352]:

	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 [353]:
```
1 y
```

Out[353]:
```
0      24.0
1      21.6
2      34.7
3      33.4
4      36.2
       ...
501    22.4
502    20.6
503    23.9
504    22.0
505    11.9
Name: Price, Length: 506, dtype: float64
```

Splitting the data

In [354]:
```
1 from sklearn.model_selection import train_test_split
```

In [355]:
```
1 X_train, X_test, y_train, y_test = train_test_split(
2     X, y, test_size=0.33, random_state=10)
```

In [356]:
```
1 X_train
```

Out[356]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
147	2.36862	0.0	19.58	0.0	0.871	4.926	95.7	1.4608	5.0	403.0	14.7	391.71	2
330	0.04544	0.0	3.24	0.0	0.460	6.144	32.2	5.8736	4.0	430.0	16.9	368.57	
388	14.33370	0.0	18.10	0.0	0.700	4.880	100.0	1.5895	24.0	666.0	20.2	372.92	3
238	0.08244	30.0	4.93	0.0	0.428	6.481	18.5	6.1899	6.0	300.0	16.6	379.41	
113	0.22212	0.0	10.01	0.0	0.547	6.092	95.4	2.5480	6.0	432.0	17.8	396.90	1
...	...	...	...	...	...	...	...	...	...	...	...	...	
320	0.16760	0.0	7.38	0.0	0.493	6.426	52.3	4.5404	5.0	287.0	19.6	396.90	
15	0.62739	0.0	8.14	0.0	0.538	5.834	56.5	4.4986	4.0	307.0	21.0	395.62	
484	2.37857	0.0	18.10	0.0	0.583	5.871	41.9	3.7240	24.0	666.0	20.2	370.73	1
125	0.16902	0.0	25.65	0.0	0.581	5.986	88.4	1.9929	2.0	188.0	19.1	385.02	1
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	1

339 rows × 13 columns

In [357]:
```
1 y_train
```

Out[357]:
```
147    14.6
330    19.8
388    10.2
238    23.7
113    18.7
       ...
320    23.8
15     19.9
484    20.6
125    21.4
265    22.8
Name: Price, Length: 339, dtype: float64
```

In [358]:
```
1 X_test
2
```

Out[358]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
305	0.05479	33.0	2.18	0.0	0.472	6.616	58.1	3.3700	7.0	222.0	18.4	393.36	8
193	0.02187	60.0	2.93	0.0	0.401	6.800	9.9	6.2196	1.0	265.0	15.6	393.37	5
65	0.03584	80.0	3.37	0.0	0.398	6.290	17.8	6.6115	4.0	337.0	16.1	396.90	4
349	0.02899	40.0	1.25	0.0	0.429	6.939	34.5	8.7921	1.0	335.0	19.7	389.85	5
151	1.49632	0.0	19.58	0.0	0.871	5.404	100.0	1.5916	5.0	403.0	14.7	341.60	13
...	...	...	...	...	...	...	...	...	...	...	...	...	
442	5.66637	0.0	18.10	0.0	0.740	6.219	100.0	2.0048	24.0	666.0	20.2	395.69	16
451	5.44114	0.0	18.10	0.0	0.713	6.655	98.2	2.3552	24.0	666.0	20.2	355.29	17
188	0.12579	45.0	3.44	0.0	0.437	6.556	29.1	4.5667	5.0	398.0	15.2	382.84	4
76	0.10153	0.0	12.83	0.0	0.437	6.279	74.5	4.0522	5.0	398.0	18.7	373.66	11
314	0.36920	0.0	9.90	0.0	0.544	6.567	87.3	3.6023	4.0	304.0	18.4	395.69	9

167 rows × 13 columns

In [359]:
```
1 y_test
```

Out[359]:
```
305    28.4
193    31.1
65     23.5
349    26.6
151    19.6
       ...
442    18.4
451    15.2
188    29.8
76     20.0
314    23.8
Name: Price, Length: 167, dtype: float64
```

In [360]:
```
1 X_train.shape
```

Out[360]: (339, 13)

In [361]:
```
1 y_train.shape
```

Out[361]: (339,)

In [362]:
```
1 X_test.shape
```

Out[362]: (167, 13)

In [363]:
```
1 y_test.shape
```

Out[363]: (167,)

Why do we need to perform feature scaling?

Scaling the features makes the flow of gradient descent smooth and helps algorithms quickly reach the minima of the cost function. Without scaling features, the algorithm may be biased toward the feature which has values higher in magnitude.

Feature Scaling

In [370]:
```
1
2 from sklearn.preprocessing import StandardScaler
3 scaler=StandardScaler()
```

In [371]:
```
1 scaler
```

Out[371]: StandardScaler()

In [372]:
```
X_train_scaled=scaler.fit_transform(X_train)
X_train_scaled
```

Out[372]:
```
array([[-0.13641471, -0.47928013,  1.16787606, ..., -1.77731527,
         0.39261401,  2.36597873],
       [-0.41777807, -0.47928013, -1.18043314, ..., -0.75987458,
         0.14721899, -0.54115799],
       [ 1.31269177, -0.47928013,  0.95517731, ...,  0.76628645,
         0.19334986,  2.52100705],
       ...,
       [-0.13520965, -0.47928013,  0.95517731, ...,  0.76628645,
         0.17012536,  0.06331026],
       [-0.40281114, -0.47928013,  2.04022838, ...,  0.25756611,
         0.32166792,  0.27238516],
       [-0.33104058,  0.34161649, -1.07552092, ..., -2.56351944,
         0.39993132, -0.34772815]])
```

In [373]:
```
X_test_scaled=scaler.transform(X_test)
X_test_scaled
```

Out[373]:
```
array([[-0.41664568,  0.87519929, -1.33277144, ..., -0.06616502,
         0.41011193, -0.56391444],
       [-0.42063267,  1.98340973, -1.22498491, ..., -1.36108953,
         0.41021798, -1.11860295],
       [-0.41894074,  2.80430634, -1.16175014, ..., -1.12985301,
         0.44765291, -1.16980497],
       ...,
       [-0.40804678,  1.36773726, -1.15169007, ..., -1.54607875,
         0.29854946, -1.18545003],
       [-0.41098494, -0.47928013,  0.19779729, ...,  0.07257689,
         0.20119741, -0.13154186],
       [-0.37856708, -0.47928013, -0.22328875, ..., -0.06616502,
         0.43482111, -0.5141347 ]])
```

Model Training

In [374]:
```
from sklearn.linear_model import LinearRegression
```

In [375]:
```
regression=LinearRegression()
```

In [376]:
```
regression
```

Out[376]:
```
LinearRegression()
```

In [377]:
```
regression.fit(X_train_scaled,y_train)
```

Out[377]:
```
LinearRegression()
```

Print the coefficients and intercept

In [378]:
```
print(regression.coef_)
```

```
[-1.29099218  1.60949999 -0.14031574  0.37201867 -1.76205329  2.22752218
  0.32268871 -3.31184248  2.70288107 -2.09005699 -1.7609799   1.25191514
 -3.83392028]
```

In [379]:
```
print(regression.intercept_)
```

```
22.077286135693214
```

In [380]:
```
## Prediction for the test data
y_pred=regression.predict(X_test_scaled)
y_pred
```

Out[380]:
```
array([31.43849583, 31.98794389, 30.99895559, 22.31396689, 18.89492791,
       16.21371128, 35.9881236 , 14.81264582, 25.04500847, 37.12806894,
       21.49110158, 30.88757187, 28.05752881, 34.05600093, 33.75791114,
       40.63880011, 24.24023412, 23.41351375, 25.54158122, 21.34135664,
       32.71699711, 17.88341061, 25.49549436, 25.01006418, 32.54102925,
       20.48979076, 19.48816948, 16.92733183, 38.38530857,  0.36265208,
       32.42715816, 32.15306983, 26.10323665, 23.79611814, 20.67497128,
       19.69393973,  3.50784614, 35.26259797, 27.04725425, 27.66164435,
       34.35132103, 29.83057837, 18.40939436, 31.56953795, 17.91877807,
       28.50042742, 19.49382421, 21.69553078, 38.0954563 , 16.44490081,
       24.58507284, 19.67889486, 24.53954813, 34.30610423, 26.74699088,
       34.87803562, 21.06219662, 19.87980936, 18.68725139, 24.71786624,
       19.96344041, 23.56002479, 39.57630226, 42.81994338, 30.37060855,
       17.03737245, 23.83719412,  3.2425022 , 31.5046382 , 28.63779884,
       18.49288659, 27.14115768, 19.67125483, 25.34222917, 25.05430467,
       10.29463949, 38.96369453,  8.26774249, 18.52214761, 30.34082002,
       22.87681099, 20.96680268, 20.04604103, 28.73415756, 30.81726786,
       28.23002473, 26.28588806, 31.59181918, 22.13093608, -6.48201197,
       21.53000756, 19.90826887, 24.96686716, 23.44746617, 19.28521216,
       18.75729874, 27.40013804, 22.17867402, 26.82972   , 23.39779064,
       23.9260607 , 19.16632572, 21.09732823, 11.01452286, 13.7692535 ,
       20.74596484, 23.54892211, 14.04445469, 28.88171403, 15.77611741,
       15.25195598, 22.429474  , 26.60737213, 28.88742175, 24.29797261,
       18.26839956, 16.26943281, 17.40100292, 15.53131616, 21.27868825,
       33.78464602, 30.00899396, 21.16115702, 13.95560661, 16.18475215,
       29.30998858, 13.1866784 , 22.08393725, 24.34499386, 31.86829501,
       33.45923602,  5.90671516, 35.20153265, 24.17614831, 17.54200544,
       24.25032915, 28.44671354, 34.50123773,  6.33164665,  1.93565618,
       28.40727267, 12.56461105, 18.31045646, 19.71015745,  5.50105857,
       14.51366874, 37.193992  , 25.81821367, 23.31632083, 26.43254504,
       11.38255141, 20.46224115, 35.27645709, 20.57841598, 11.48799917,
       16.23913171, 24.56511742, 10.53131603, 15.07115005, 25.98488217,
       11.2136222 , 11.695686  , 19.40437966, 19.58768384, 32.43800883,
       22.66170871, 25.68576052])
```

Assumption of linear regression

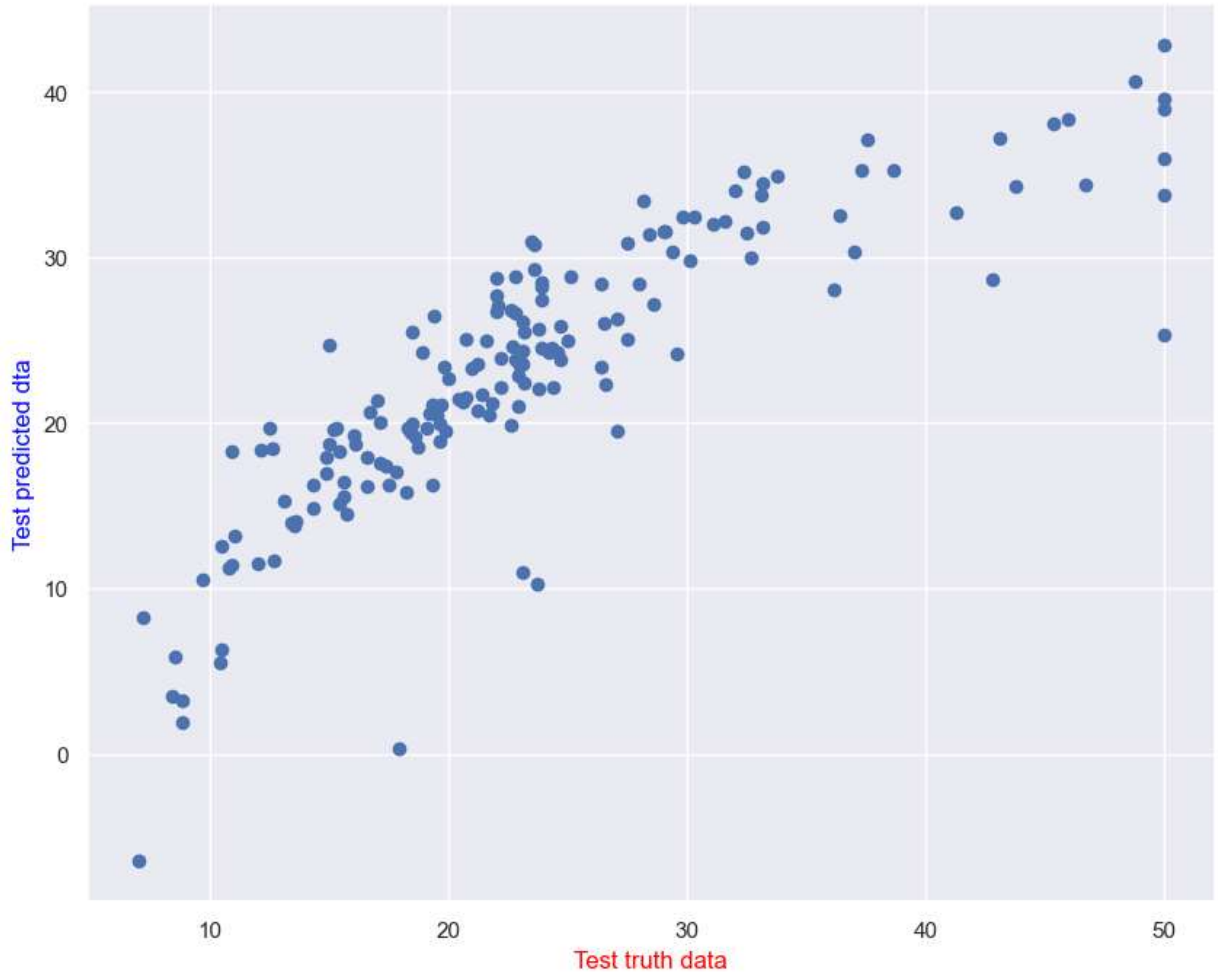
- Linearity: The relationship between X and the mean of Y is linear.
- Homoscedasticity: The variance of residual is the same for any value of X.

- Independence: Observations are independent of each other.
- Normality: For any fixed value of X, Y is normally distributed

Showing assumption of linear regression

In [382]:
```
1 plt.scatter(y_test,y_pred)
2 plt.xlabel("Test truth data",color='red')
3 plt.ylabel("Test predicted dta",color='blue')
```

Out[382]:
```
Text(0, 0.5, 'Test predicted dta')
```



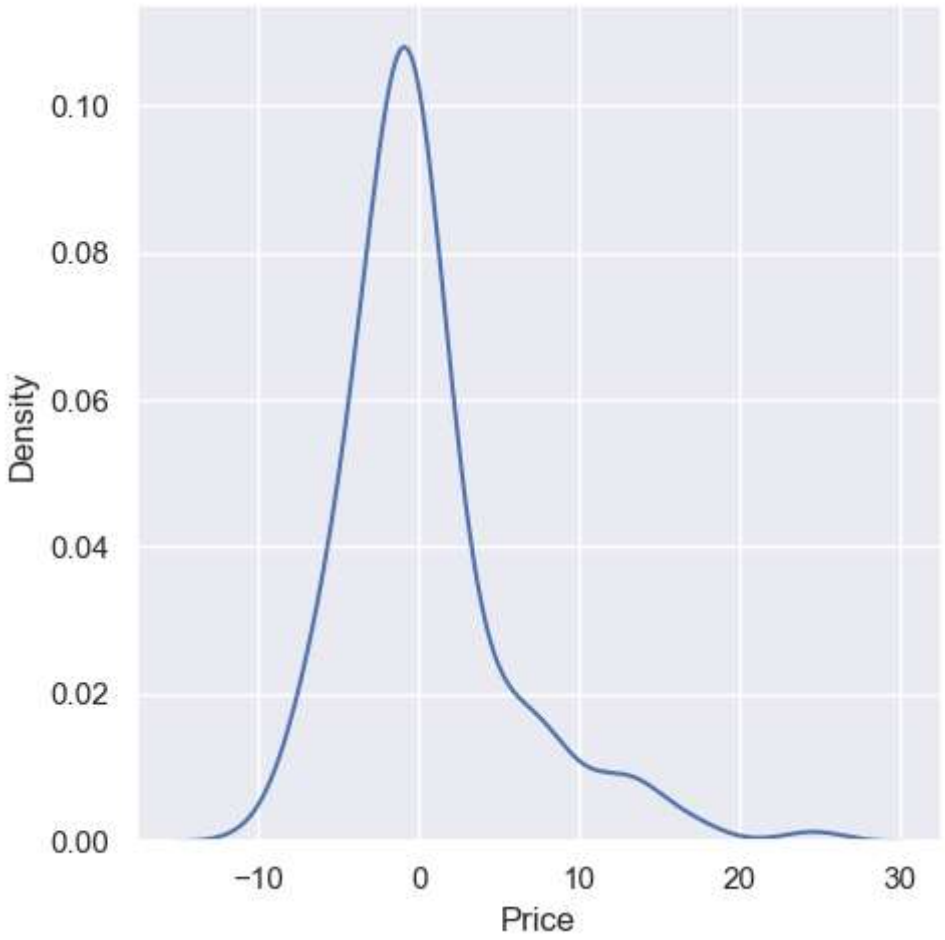
Residuals

In [384]:
```
1
2 residuals=y_test-y_pred
3 residuals
```

Out[384]:
```
305   -3.038496
193   -0.887944
65    -7.498956
349    4.286033
151    0.705072
         ...
442   -1.004380
451   -4.387684
188   -2.638009
76    -2.661709
314   -1.885761
Name: Price, Length: 167, dtype: float64
```

In [385]:
```
1 sns.displot(residuals,kind="kde")
```

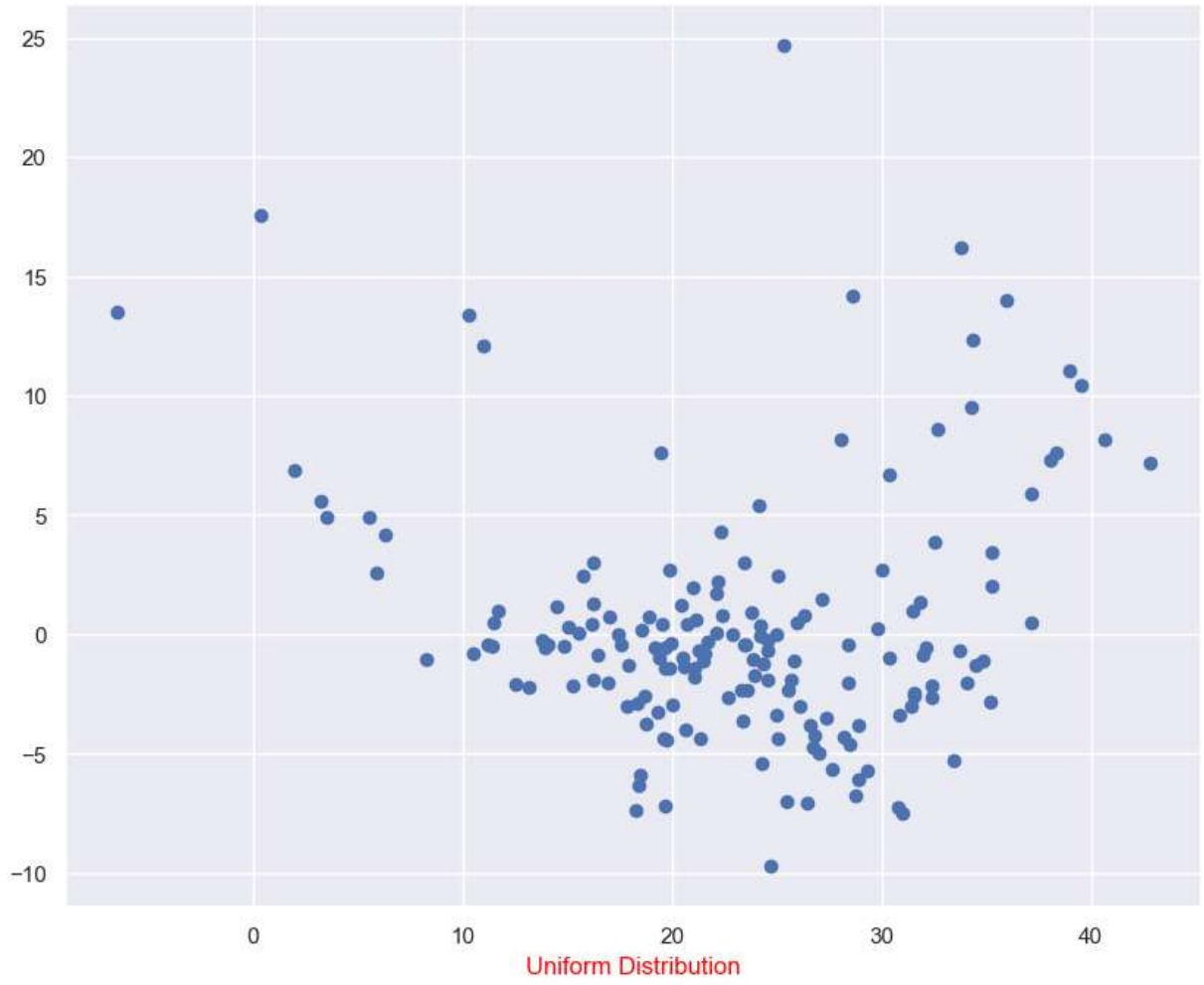
Out[385]:
```
<seaborn.axisgrid.FacetGrid at 0x24552c6ecd0>
```



Scatter plot with predictions and residual

In [386]:
```
##uniform distribution
plt.scatter(y_pred,residuals)
plt.xlabel("Uniform Distribution",color="red")
```

Out[386]: Text(0.5, 0, 'Uniform Distribution')



Performance Metrics for Linear Regression

In [387]:
```

from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,y_pred))
print(mean_absolute_error(y_test,y_pred))
print(np.sqrt(mean_squared_error(y_test,y_pred)))
```

```
27.100991709962464
3.5206585298797903
5.205861284164462
```

R2-score for Linear Regresssion

In [388]:
```
from sklearn.metrics import r2_score
score=r2_score(y_test,y_pred)
print(score)
```

```
0.7165219393967557
```

Adjusted R2-score for Linear Regresssion

In [389]:
```

1 - (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[389]:
```
0.6924355682343886
```

Ridge Regression Algorithm

In [282]:
```
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
ridge=Ridge()
```

In [283]:
```
parameters={'alpha':[1,2,5,10,20,30,40]}
ridge_cv=GridSearchCV(ridge,parameters,scoring='neg_mean_squared_error',cv=5
ridge_cv.fit(X_train,y_train)
```

Out[283]:
```
GridSearchCV(cv=5, estimator=Ridge(),
             param_grid={'alpha': [1, 2, 5, 10, 20, 30, 40]},
             scoring='neg_mean_squared_error')
```

In [284]:
```
print(ridge_cv.best_params_)
```

```
{'alpha': 20}
```

In [285]:
```
print(ridge_cv.best_score_)
```

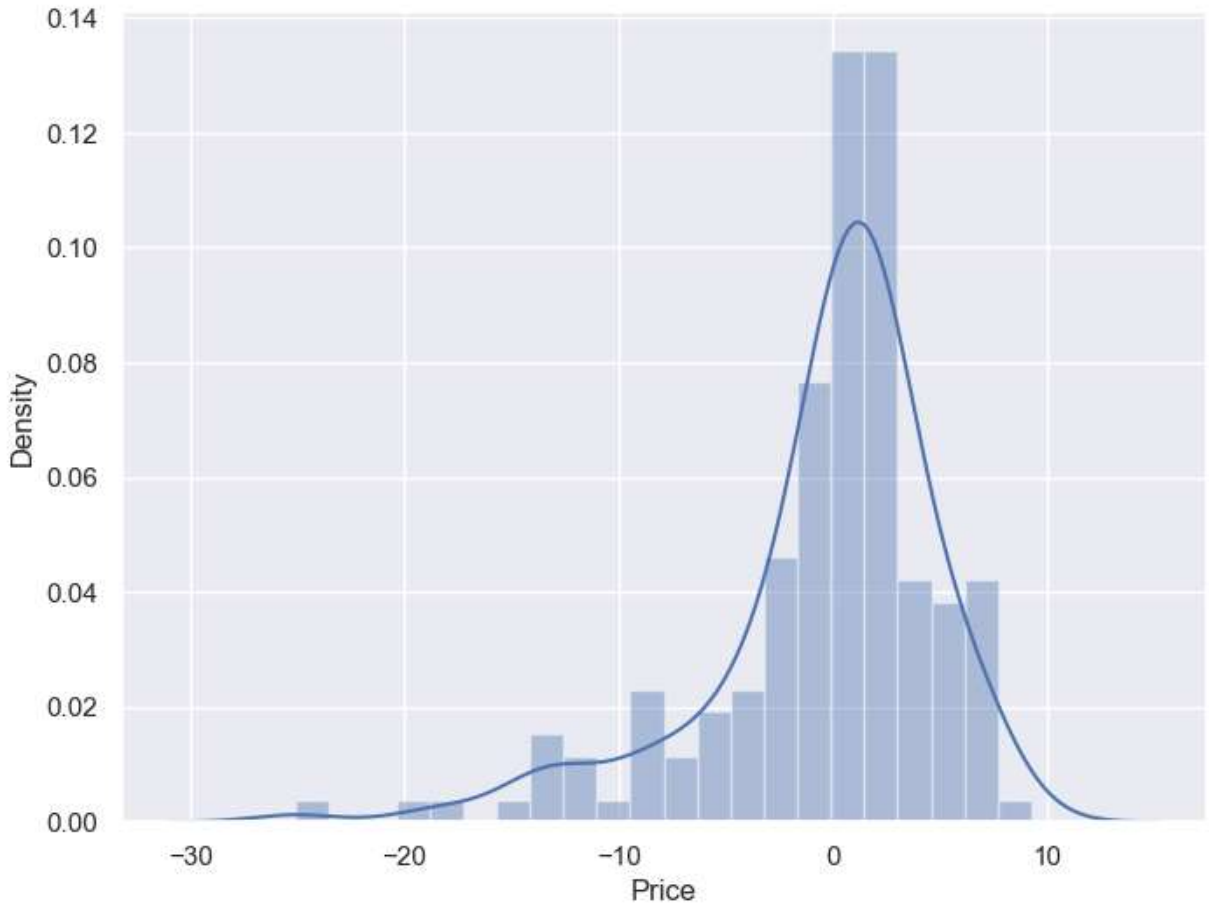
```
-23.021620343340334
```

In [286]:
```
ridge_pred=ridge_cv.predict(X_test)
ridge_pred
```

Out[286]:
```
array([31.26250761, 31.72290483, 30.9482677 , 23.15867751, 22.25207719,
       16.82744046, 35.26664846, 14.98348017, 23.87927736, 36.11118446,
       21.00392778, 29.36139443, 27.95902936, 33.76278925, 32.85296518,
       40.90685235, 25.12697028, 23.20141137, 25.67103585, 23.49079297,
       32.02212489, 18.78042937, 25.0004098 , 25.48350707, 32.20705998,
       21.72626817, 19.09311882, 17.80473397, 36.76605279, -1.05689757,
       31.56113713, 31.42806064, 26.87630221, 24.0774368 , 19.70088155,
       20.30755411,  3.69997843, 35.09603395, 27.51365246, 27.37312046,
       34.03932594, 29.35684059, 18.3537049 , 31.36143401, 17.03462275,
       28.82567767, 21.15770121, 21.17060424, 36.93350532, 16.87224671,
       24.21333027, 19.69519647, 24.2950541 , 33.37874195, 27.26857497,
       35.55289346, 20.91394843, 21.83460211, 19.42815235, 24.29315415,
       20.18730891, 23.22065682, 37.54489308, 42.90441818, 30.51917427,
       16.8520877 , 23.47720241,  3.76799959, 31.21212223, 28.73003775,
       19.57699737, 26.22502542, 19.03771218, 24.93132161, 24.73703876,
        9.58294029, 37.48384988,  8.29250257, 18.95827242, 30.02736951,
       23.06646751, 21.94730537, 20.19533964, 27.92047708, 30.37141261,
       28.64444688, 25.21311313, 31.33937825, 23.73728289, -6.37473794,
       23.07678073, 20.14259342, 24.59220624, 24.22293716, 19.22773183,
       18.30036538, 26.87402786, 20.93395572, 26.69003644, 22.82756535,
       23.50112988, 18.80464904, 20.98837545, 11.60180284, 13.68670403,
       19.49331889, 23.08934096, 12.82208464, 29.10950427, 17.82376362,
       14.76640174, 21.4984877 , 26.02906139, 27.72086331, 24.38576877,
       17.80562663, 14.46362868, 17.064275  , 18.54066971, 21.04748615,
       32.56607519, 29.89584462, 21.93850748, 15.70375227, 16.84090273,
       28.80223608, 13.1241004 , 21.73109155, 24.54284098, 30.79138065,
       33.10901161,  6.18732059, 34.1349616 , 24.90402178, 18.34260117,
       23.66214585, 27.89403419, 33.09345682,  6.84251541,  2.25281317,
       28.22428819, 13.57766042, 19.06915977, 22.59569727,  5.55831457,
       13.51697127, 37.79130918, 26.71604798, 23.84084432, 26.21222254,
       11.86307697, 20.71775583, 33.88953051, 20.66784136, 10.71590985,
       16.61177676, 24.28684107, 11.01241617, 17.91805152, 25.8243196 ,
       11.99455383, 12.4134269 , 20.39613222, 19.99959372, 31.8272145 ,
       21.01079405, 25.71396763])
```

In [287]:
```
1 import seaborn as sns
2 sns.distplot(ridge_pred-y_test)
```

Out[287]: <AxesSubplot:xlabel='Price', ylabel='Density'>



Performance Metrics for Ridge Rgression

In [288]:
```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,ridge_pred))
print(mean_absolute_error(y_test,ridge_pred))
print(np.sqrt(mean_squared_error(y_test,ridge_pred)))
```

```
29.28721653718942
3.6971299961099455
5.411766489529035
```

R2 Score of Ridge Rgression

In [289]:
```
from sklearn.metrics import r2_score
ridge_score=r2_score(y_test,ridge_pred)
print(score)
```

```
0.7165219393967557
```

Adjusted R2-Score of Ridge Rgression

In [290]:
```
1-(1-ridge_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[290]:
```
0.6676244836846394
```

Lasso Rgression

In [291]:
```
from sklearn.linear_model import Lasso
```

In [292]:
```
lasso=Lasso()
```

In [293]:
```
parameters={'alpha':[1,2,5,10,20,30,40]}
lasso_cv=GridSearchCV(lasso,parameters,scoring='neg_mean_squared_error',cv=5
lasso_cv.fit(X_train,y_train)
```

Out[293]:
```
GridSearchCV(cv=5, estimator=Lasso(),
             param_grid={'alpha': [1, 2, 5, 10, 20, 30, 40]},
             scoring='neg_mean_squared_error')
```

In [294]:
```
print(lasso_cv.best_params_)
```

```
{'alpha': 1}
```

In [295]:
```
lasso_pred=lasso_cv.predict(X_test)
lasso_pred
```

Out[295]:
```
array([30.05062227, 30.75863386, 31.79136406, 23.81132585, 24.46450905,
       16.51502359, 33.55687901, 16.18590265, 23.63422119, 32.67378583,
       20.62340113, 26.88616937, 27.50950406, 33.13800373, 31.26216912,
       35.51177715, 25.1322652 , 24.37702007, 25.3426104 , 22.79399868,
       31.42535013, 17.87518719, 24.62140298, 25.67592917, 30.8570178 ,
       23.19651817, 19.54532952, 17.48554848, 33.51934661,  1.0746952 ,
       30.2290915 , 29.6311516 , 28.3746209 , 24.09051453, 17.8996287 ,
       20.68626471,  2.03311885, 33.92194066, 27.84246939, 26.98859872,
       29.66201241, 28.76027267, 16.66430744, 31.3070688 , 17.76180501,
       28.8142132 , 20.84880796, 21.08094697, 33.95869027, 18.19713582,
       25.3790762 , 17.83141295, 24.62557761, 29.23048683, 27.09040407,
       32.30973738, 21.12865331, 21.8682558 , 21.45083035, 21.4927721 ,
       20.82460129, 22.70209723, 32.64112207, 36.46204926, 29.01296777,
       16.60412861, 24.21223336,  6.15819233, 31.29938975, 25.66665157,
       19.12096902, 26.07635104, 19.09894122, 25.20532246, 23.72293349,
        7.46519487, 31.78184104,  7.93417039, 21.66650902, 28.82264119,
       24.04887629, 23.99760225, 21.73647125, 27.1081459 , 29.34325776,
       28.04599659, 25.75769079, 30.4155572 , 25.14780952, -3.2483763 ,
       24.33980236, 22.19039081, 25.32648911, 24.73588935, 21.71166789,
       18.17949212, 27.40772395, 20.30800437, 26.99320873, 22.2873327 ,
       24.23833743, 19.64886888, 22.15222613, 18.57341744, 14.18514138,
       19.70755856, 23.78098739, 13.03503894, 29.45659639, 22.47550945,
       12.90394483, 20.25757185, 24.61575068, 26.37500077, 25.18758983,
       15.73313472, 14.49559824, 18.87614435, 20.19492705, 21.29726476,
       30.81860198, 28.94638256, 22.17757046, 14.71215667, 18.79736922,
       28.12286666, 12.19429838, 22.97031693, 24.30773588, 27.93884477,
       31.73300601,  6.81523194, 32.55092938, 25.22113859, 16.92807435,
       23.27550401, 26.92401426, 30.59006878,  8.93970768,  5.84737618,
       27.80566228, 13.58229434, 17.59584967, 24.93011863,  6.99103487,
       13.70103998, 34.3311626 , 29.01410928, 24.59277709, 27.81462485,
       13.65501713, 20.71519689, 30.01636162, 20.82701755, 11.58795903,
       18.72787631, 23.99187497, 12.02982796, 18.1481676 , 24.76157021,
       11.85369437, 13.24565577, 19.77471126, 18.29296243, 30.94733281,
       21.26773868, 25.73858979])
```

Performance Metrics for Lasso Rgression

In [296]:
```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,ridge_pred))
print(mean_absolute_error(y_test,ridge_pred))
print(np.sqrt(mean_squared_error(y_test,ridge_pred)))
```

```
29.28721653718942
3.6971299961099455
5.411766489529035
```

R2-Score of Lasso Rgression

In [297]:
```
from sklearn.metrics import r2_score
lasso_score=r2_score(y_test,lasso_pred)
print(score)
```

```
0.7165219393967557
```

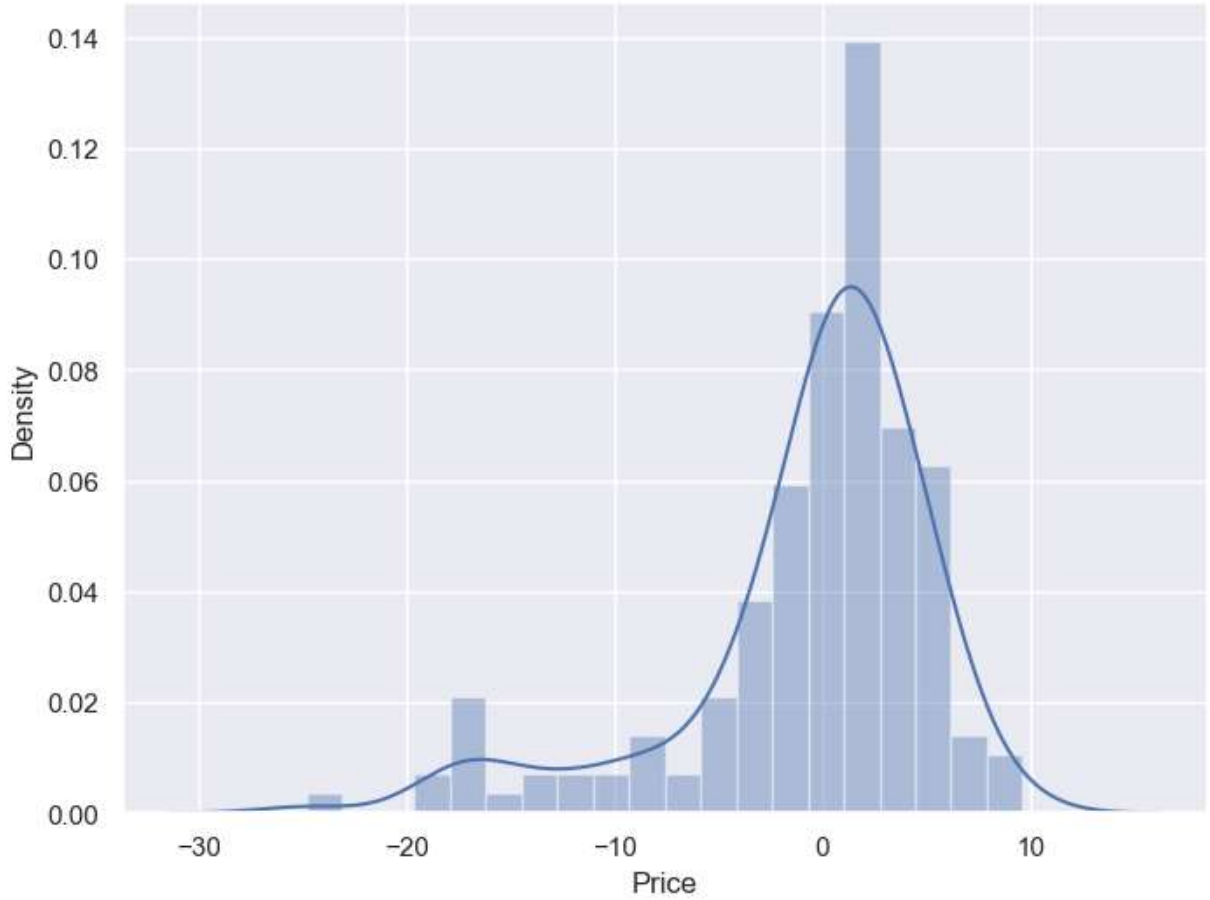
Adjusted R2-Score Lasso Rgression

In [298]:
```
1-(1-lasso_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[298]:
```
0.5901561369378114
```

In [299]:
```
import seaborn as sns
sns.distplot(lasso_pred-y_test)
```

Out[299]:
```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```



ElasticNet Regression

In [300]:
```
from sklearn.linear_model import ElasticNet
```

In [301]:
```
elastic_net_reg=ElasticNet(l1_ratio=0.5)
```

In [302]:
```
elastic_net_reg.fit(X_train,y_train)
```

Out[302]:
```
ElasticNet()
```

In [303]:
```
parameters={'alpha':[1,2,5,10,20,30]}
elastic_net_cv=GridSearchCV(lasso,parameters,scoring='neg_mean_squared_error
elastic_net_cv.fit(X_train,y_train)
```

Out[303]:
```
GridSearchCV(cv=5, estimator=Lasso(),
             param_grid={'alpha': [1, 2, 5, 10, 20, 30]},
             scoring='neg_mean_squared_error')
```

In [304]:
```
print(elastic_net_cv.best_params_)
```

```
{'alpha': 1}
```

In [305]:
```
print(elastic_net_cv.best_score_)
```

```
-26.640086954213285
```

In [306]:
```
elastic_net_pred=elastic_net_cv.predict(X_test)
```

Performance metrics of ElasticNet Regression

In [307]:
```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,elastic_net_pred))
print(mean_absolute_error(y_test,elastic_net_pred))
print(np.sqrt(mean_squared_error(y_test,elastic_net_pred)))
```

```
36.11332777156727
4.067062767559683
6.0094365602415065
```

R2-Score of ElasticNet Regression

In [308]:
```
from sklearn.metrics import r2_score
elastic_net_score=r2_score(y_test,elastic_net_pred)
print(score)
```

```
0.7165219393967557
```

Adjusted R2-score of ElasticNet Regression

In [309]:
```
1-(1-elastic_net_score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[309]:
```
0.5901561369378114
```

In [ ]:
```

```