IMPORTING ALL THE LIBRARY

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

In [2]:

```
#loading the dataset from sklearn
from sklearn.datasets import load_boston
```

In [4]:

```
boston=load_boston()
```

In [5]:

```
boston
```

Loading [MathJax]/extensions/Safe.js

Out[5]:


```
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         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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        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,
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D',
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--\n\n**Data Set Characteristics:**  \n\n    :Number of Instances: 506 \n\n    :Number o
```


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```
f Attributes: 13 numeric/categorical predictive. Median Value (attribute 14) is usually
the target.\n\n    :Attribute Information (in order):\n        - CRIM     per capita cri
me rate by town\n        - ZN       proportion of residential land zoned for lots over 2
5,000 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       averag
e number of rooms per dwelling\n        - AGE      proportion of owner-occupied units bu
ilt prior to 1940\n        - DIS      weighted distances to five Boston employment centr
es\n        - RAD      index of accessibility to radial highways\n        - TAX      ful
l-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-oc
cupied homes in $1000's\n\n    :Missing Attribute Values: None\n\n    :Creator: Harriso
n, 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-p
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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 u
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n used in many machine learning papers that address regression\nproblems.   \n     \n..
topic:: References\n\n   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying I
nfluential Data and Sources of Collinearity', Wiley, 1980. 244-261.\n   - Quinlan,R. (19
93). Combining Instance-Based and Model-Based Learning. In Proceedings on the Tenth Inte
rnational Conference of Machine Learning, 236-243, University of Massachusetts, Amherst.
Morgan Kaufmann.\n",
 'filename': 'boston_house_prices.csv',
 'data_module': 'sklearn.datasets.data'}
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In [7]:
```
print(boston)
```

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         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,
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        23.6, 28.7, 22.6, 22. , 22.9, 25. , 20.6, 28.4, 21.4, 38.7, 43.8,
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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,
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s': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'), 'DESCR': ".. _boston_dataset:\n\nB
oston 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 Informa
```

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```
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roportion of residential land zoned for lots over 25,000 sq.ft.\n        - INDUS    prop
ortion of non-retail business acres per town\n        - CHAS     Charles River dummy var
iable (= 1 if tract bounds river; 0 otherwise)\n        - NOX      nitric oxides concent
ration (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      we
ighted distances to five Boston employment centres\n        - RAD      index of accessib
ility 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 populat
ion\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 co
py of UCI ML housing dataset.\nhttps://archive.ics.uci.edu/ml/machine-learning-database
s/housing/\n\n\nThis dataset was taken from the StatLib library which is maintained at C
arnegie 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 & Managemen
t,\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 t
he 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 Collinear
ity', Wiley, 1980. 244-261.\n   - Quinlan,R. (1993). Combining Instance-Based and Model-
Based Learning. In Proceedings on the Tenth International Conference of Machine Learnin
g, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.\n", 'filename': 'bost
on_house_prices.csv', 'data_module': 'sklearn.datasets.data'}
```

In [6]:
```
boston.keys()
```

Out[6]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename', 'data_module'])
```

In [9]:
```
print(boston.DESCR)
```

Loading [MathJax]/extensions/Safe.js

```
.. _boston_dataset:

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

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value (attribute 1
4) is usually the target.

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over 25,000 sq.ft.
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        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)
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        - 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/


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

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 r
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problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and So
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   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceeding
s on the Tenth International Conference of Machine Learning, 236-243, University of Mass
achusetts, Amherst. Morgan Kaufmann.
```

In [10]:
```
print(boston.data)
```

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```
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 [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 [11]:

```
print(boston.target)
```

```
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 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 [12]:

```
print(boston.feature_names)
```

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

In [13]:

```
##let's Prepare the data frame
```

In [146…

```
#organsing the dataset
dataset=pd.DataFrame(boston.data,columns=boston.feature_names)
```

In [15]:

```
dataset.head()
```

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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 [147…

```
#adding the dependent or target feature
dataset["Price"]=boston.target
```

In [17]:

```
dataset.head()
```

Out[17]:

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

In [19]:

```
#basic eda
```

In [20]:

```
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 [21]:

```
dataset.describe().T
```

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Out[21]:

	count	mean	std	min	25%	50%	75%	max
CRIM	506.0	3.613524	8.601545	0.00632	0.082045	0.25651	3.677083	88.9762
ZN	506.0	11.363636	23.322453	0.00000	0.000000	0.00000	12.500000	100.0000
INDUS	506.0	11.136779	6.860353	0.46000	5.190000	9.69000	18.100000	27.7400
CHAS	506.0	0.069170	0.253994	0.00000	0.000000	0.00000	0.000000	1.0000
NOX	506.0	0.554695	0.115878	0.38500	0.449000	0.53800	0.624000	0.8710
RM	506.0	6.284634	0.702617	3.56100	5.885500	6.20850	6.623500	8.7800
AGE	506.0	68.574901	28.148861	2.90000	45.025000	77.50000	94.075000	100.0000
DIS	506.0	3.795043	2.105710	1.12960	2.100175	3.20745	5.188425	12.1265
RAD	506.0	9.549407	8.707259	1.00000	4.000000	5.00000	24.000000	24.0000
TAX	506.0	408.237154	168.537116	187.00000	279.000000	330.00000	666.000000	711.0000
PTRATIO	506.0	18.455534	2.164946	12.60000	17.400000	19.05000	20.200000	22.0000
B	506.0	356.674032	91.294864	0.32000	375.377500	391.44000	396.225000	396.9000
LSTAT	506.0	12.653063	7.141062	1.73000	6.950000	11.36000	16.955000	37.9700
Price	506.0	22.532806	9.197104	5.00000	17.025000	21.20000	25.000000	50.0000

In [22]:

```
#check the missing value
```

In [23]:

```
dataset.isnull().sum()
```

Out[23]:

```
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 [25]:

```
dataset.corr().T
```

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Out[25]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670	0.625505	0.5
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408	-0.311948	-0.3
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.595129	0.7
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.099176	-0.007368	-0.0
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.769230	0.611441	0.6
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.205246	-0.209847	-0.2
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.747881	0.456022	0.5
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.000000	-0.494588	-0.5
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.494588	1.000000	0.9
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.534432	0.910228	1.0
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	0.464741	0.4
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.291512	-0.444413	-0.4
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.496996	0.488676	0.5
Price	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.249929	-0.381626	-0.4

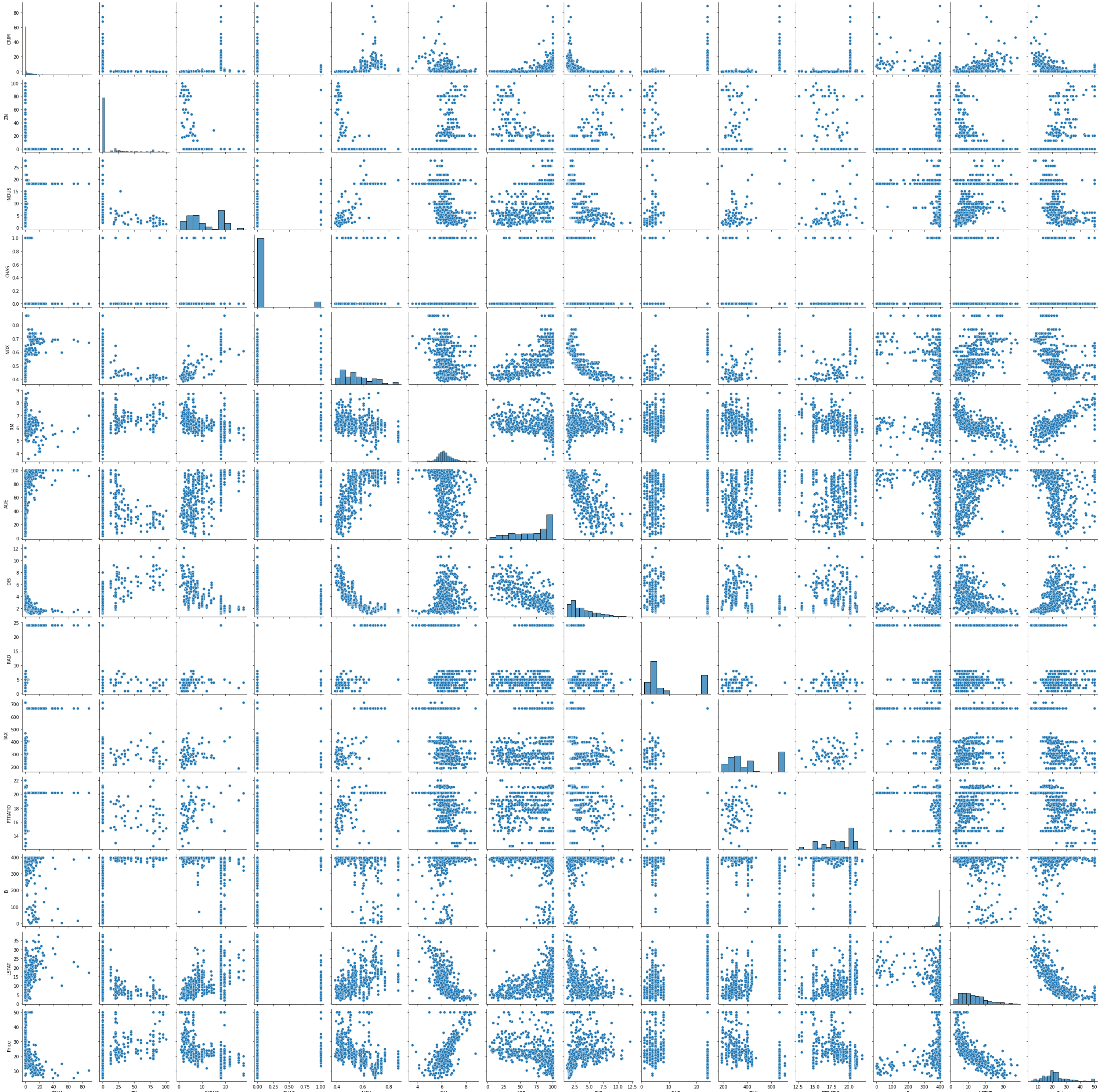
In [26]:

```
sns.pairplot(dataset)
```

Out[26]:

<seaborn.axisgrid.PairGrid at 0x22b791347c0>

Loading [MathJax]/extensions/Safe.js

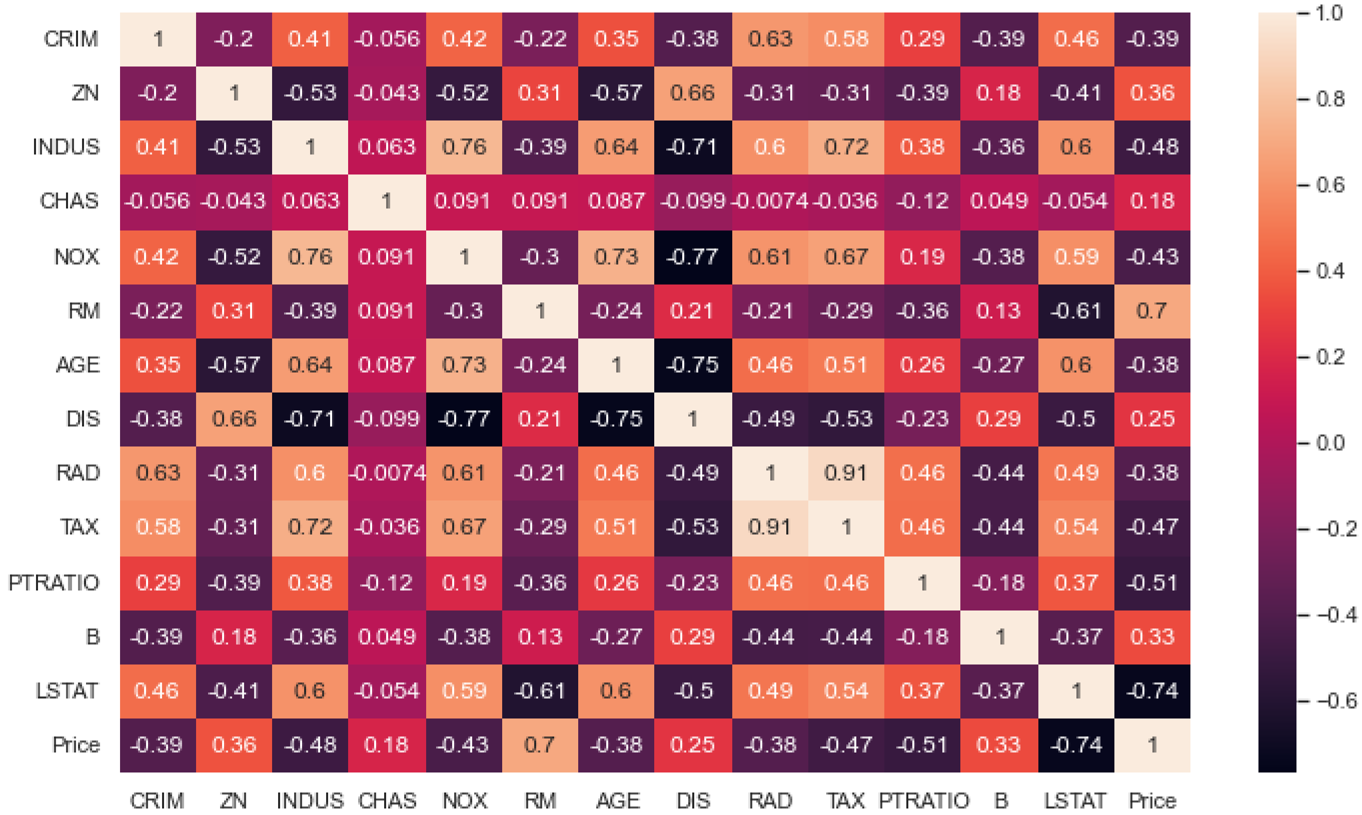


In [40]:

```python
sns.set(rc={"figure.figsize":(12,7)})
sns.heatmap(dataset.corr(),annot=True)
```

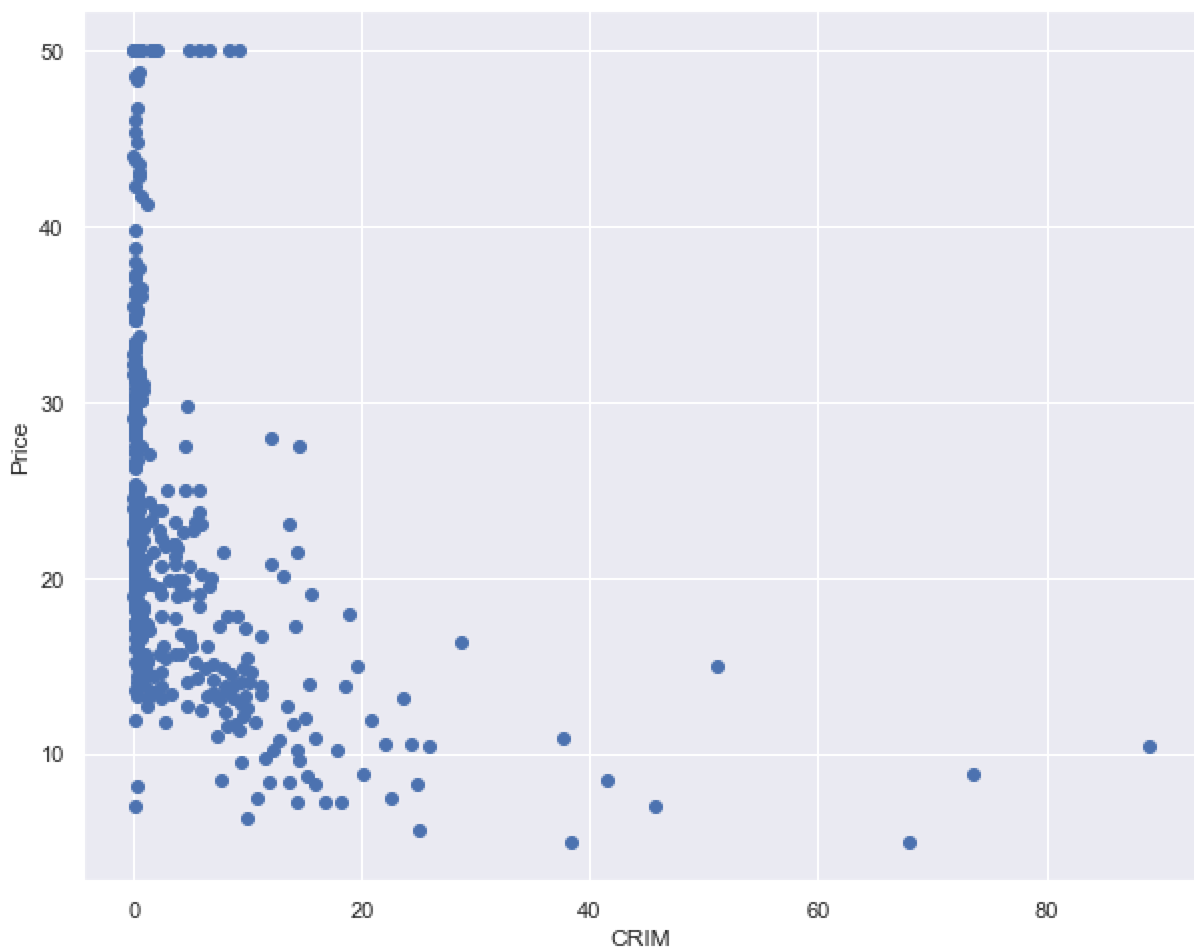
Out[40]: <AxesSubplot:>

Loading [MathJax]/extensions/Safe.js

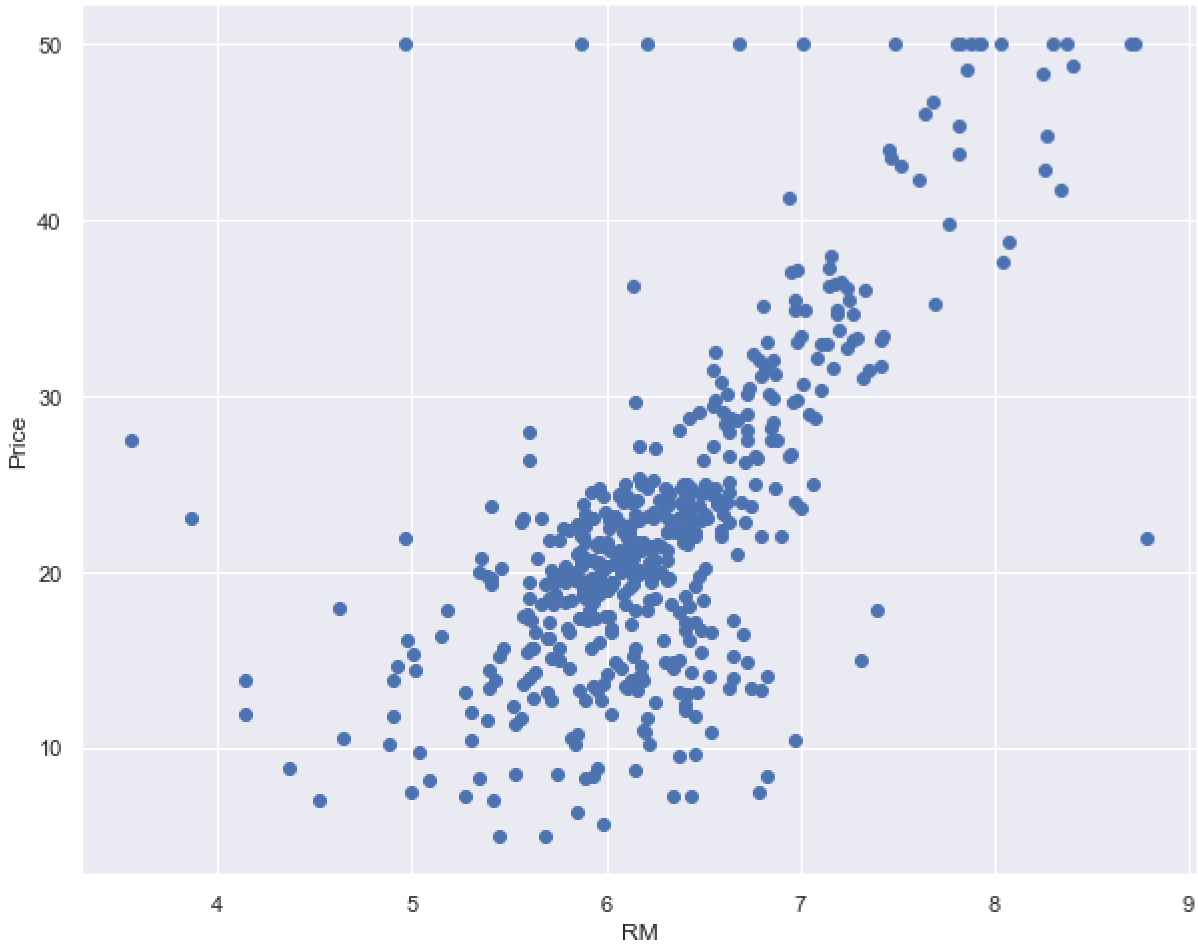


In [35]:
```python
sns.set(rc={"figure.figsize":(10,8)})
plt.scatter(dataset["CRIM"],dataset["Price"])
plt.xlabel("CRIM")
plt.ylabel("Price")
```

Out[35]:
```
Text(0, 0.5, 'Price')
```

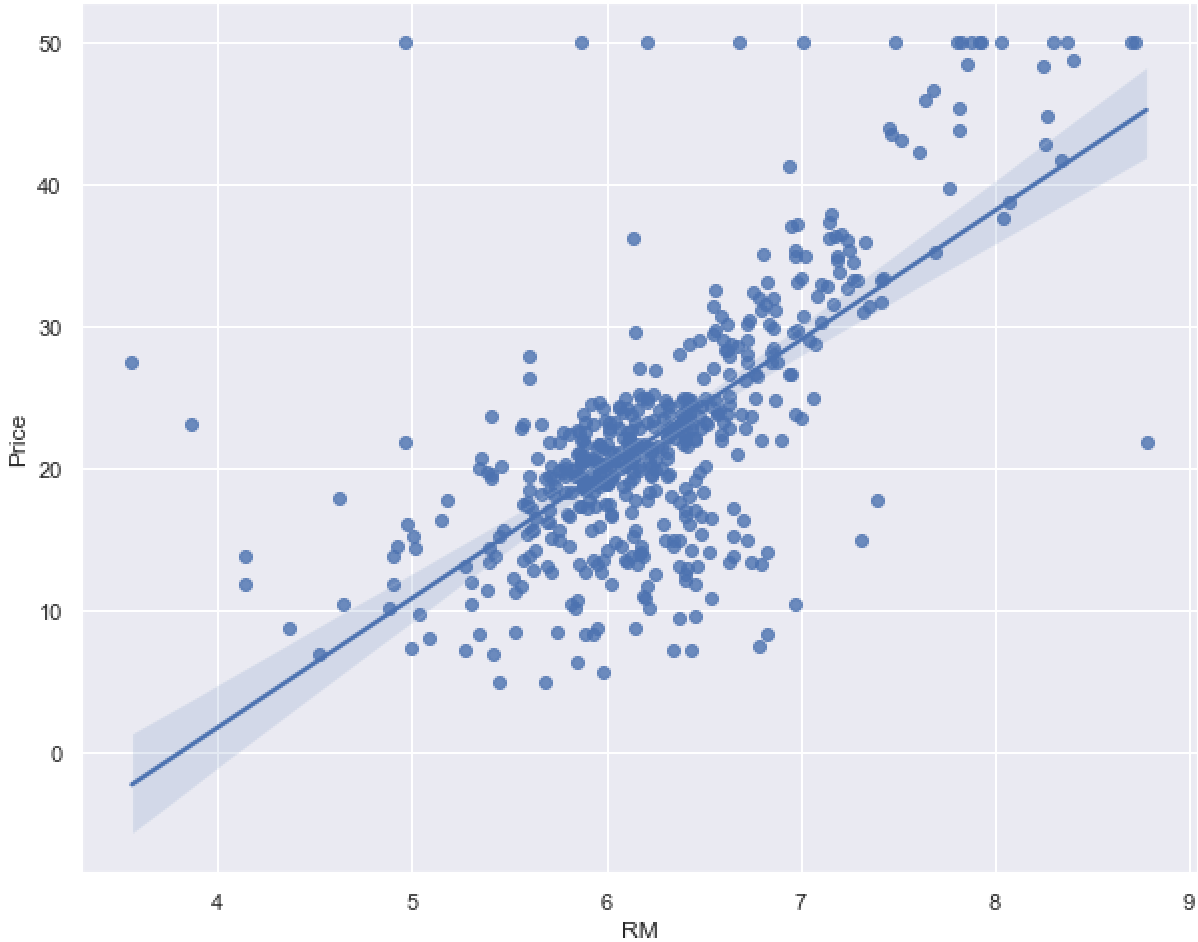


Loading [MathJax]/extensions/Safe.js

In [42]:
```
sns.set(rc={"figure.figsize":(10,8)})
plt.scatter(dataset["RM"],dataset["Price"])
plt.xlabel("RM")
plt.ylabel("Price")
```
Out[42]:
```
Text(0, 0.5, 'Price')
```


In [44]:
```
#for visulaization of best fit line
sns.regplot(x="RM",y="Price",data=dataset)
```
Out[44]:
```
<AxesSubplot:xlabel='RM', ylabel='Price'>
```

Loading [MathJax]/extensions/Safe.js

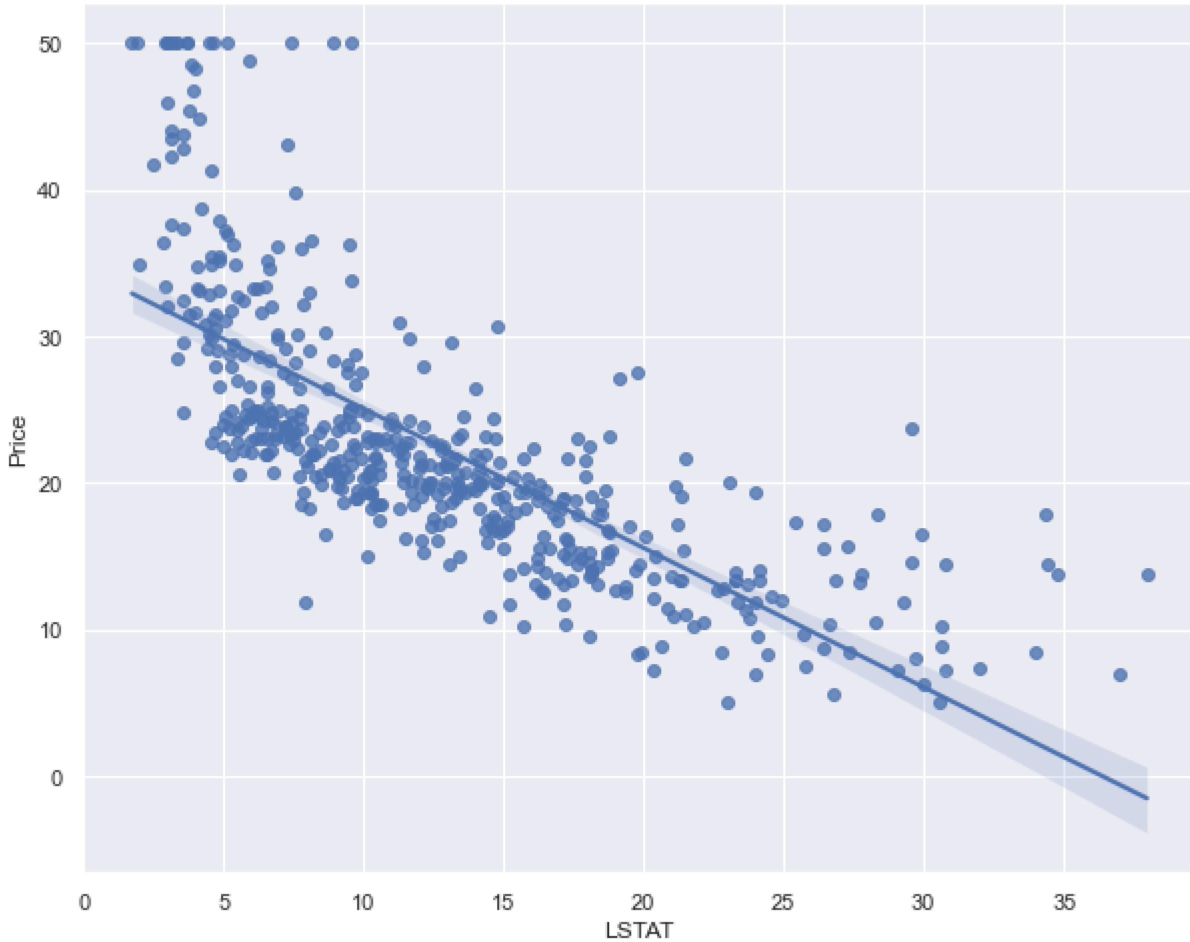


In [45]:
```
#the shades region are ridge and laso regression to reduce the over fitting
```

In [46]:
```
#for visulaization of best fit line
sns.regplot(x="LSTAT",y="Price",data=dataset)
```

Out[46]:
```
<AxesSubplot:xlabel='LSTAT', ylabel='Price'>
```

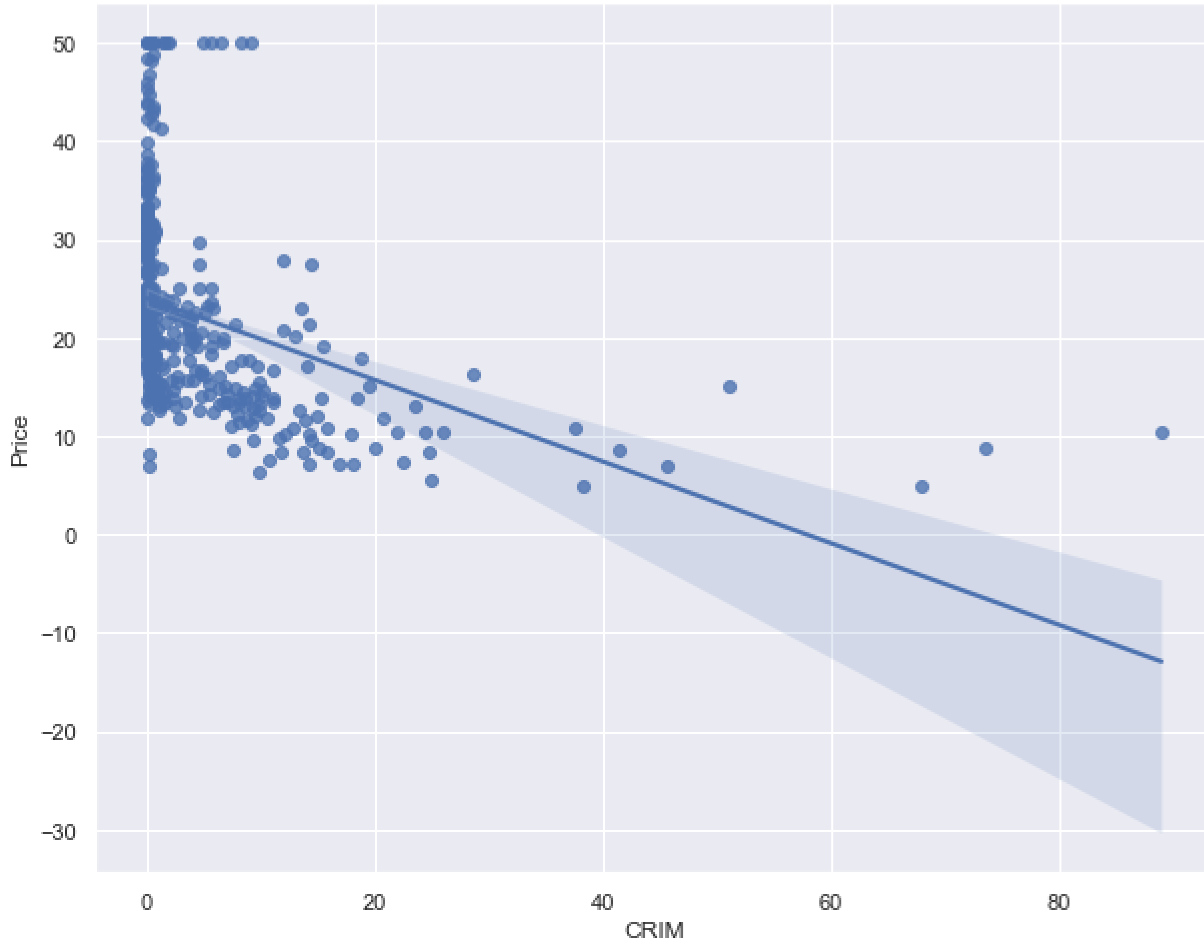
Loading [MathJax]/extensions/Safe.js



In [47]:
```
#for visulaization of best fit line
sns.regplot(x="CRIM",y="Price",data=dataset)
```

Out[47]:
```
<AxesSubplot:xlabel='CRIM', ylabel='Price'>
```

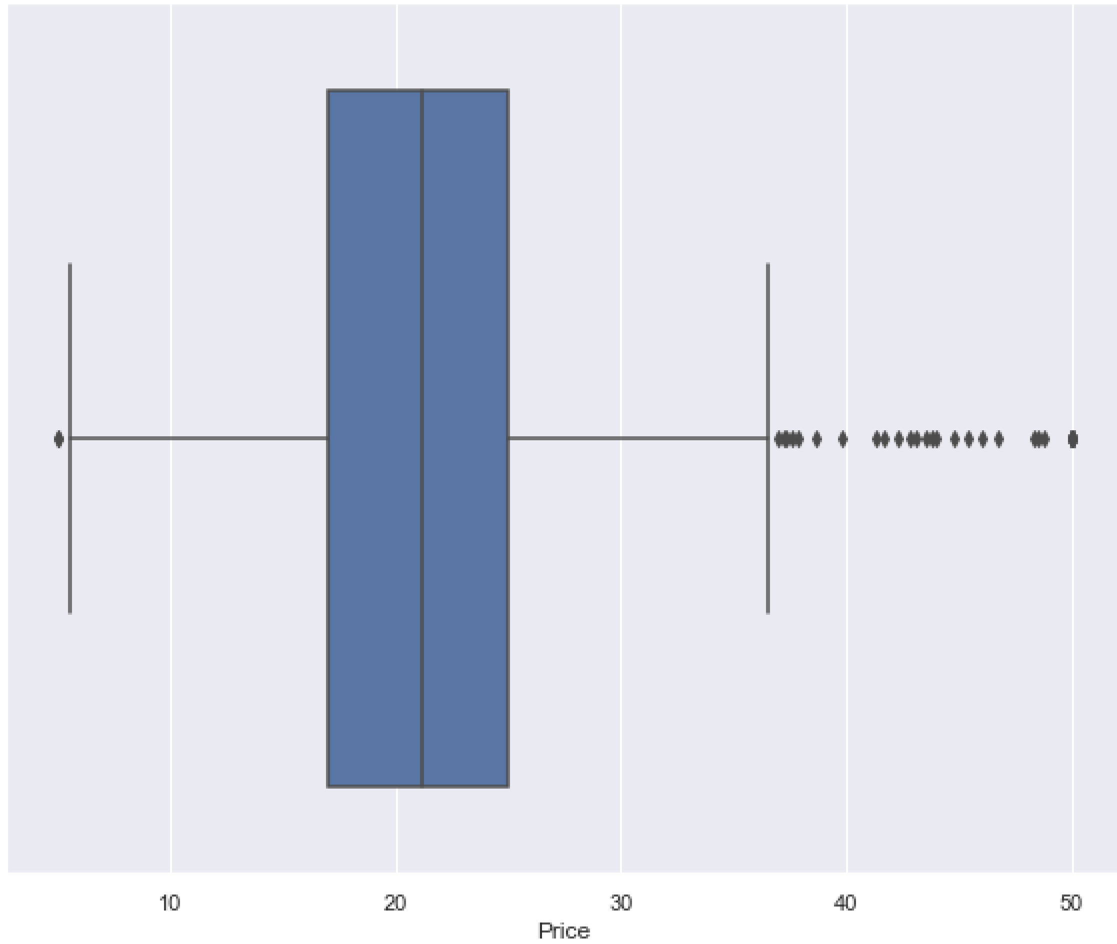
Loading [MathJax]/extensions/Safe.js



In [48]:
```
sns.boxplot(dataset["Price"])
#for dependent feature we dont do any things to outliers
```

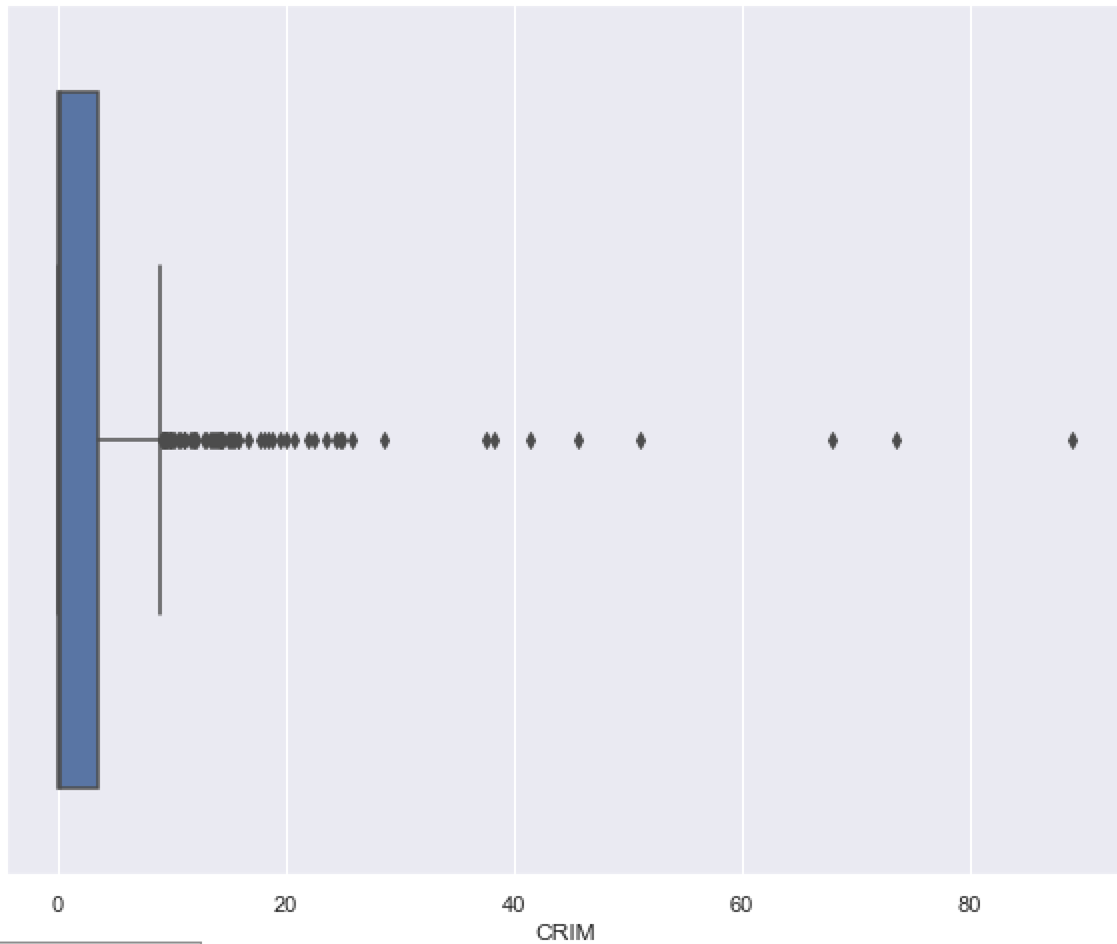
Out[48]: <AxesSubplot:xlabel='Price'>

Loading [MathJax]/extensions/Safe.js



In [49]:
```
sns.boxplot(dataset["CRIM"])
```

Out[49]: <AxesSubplot:xlabel='CRIM'>



Loading [MathJax]/extensions/Safe.js

In [50]:
```python
dataset.head()
```

Out[50]:

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

In [56]:
```python
##Independent and Dependent Features
x=dataset.iloc[:,:-1]
y=dataset.iloc[:,-1]
```

In [54]:
```python
y
```

Out[54]:
```
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
```

In [57]:
```python
x
```

Out[57]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...
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
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
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
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
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

506 rows × 13 columns

In [58]:
```python
#after Eda we have to do train test split
```

In [59]:
```python
from sklearn.model_selection import train_test_split
```

In [60]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1
```

Loading [MathJax]/extensions/Safe.js

In [62]:
```
X_train
```

Out[62]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
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	29.53
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	9.09
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	30.62
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	6.36
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	17.09
...	...	...	...	...	...	...	...	...	...	...	...	...	...
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	7.20
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	8.47
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	13.34
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	14.81
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	10.45

339 rows × 13 columns

In [64]:
```
y_train
```

Out[64]:
```
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 [67]:
```
X_train.shape
```

Out[67]:
```
(339, 13)
```

In [68]:
```
y_train.shape
```

Out[68]:
```
(339,)
```

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

Out[69]:
```
(167, 13)
```

In [70]:
```
y_test.shape
```

Out[70]:
```
(167,)
```

In [72]:
```
#standardize the datasets
#feature scaling
```

In [73]:
```
from sklearn.preprocessing import StandardScaler
```

```
rdScaler()
```

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In [76]:
```
X_train=scaler.fit_transform(X_train)
```

In [77]:
```
X_test=scaler.transform(X_test)
#to avoid data leakage we use only transform not fit_transform
```

In [83]:
```
X_train
```

Out[83]:
```
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 [78]:
```
##Model Training
```

In [79]:
```
from sklearn.linear_model import LinearRegression
```

In [80]:
```
regression=LinearRegression()
```

In [82]:
```
regression
```

Out[82]:
```
▼ LinearRegression
LinearRegression()
```

In [84]:
```
#training the data
regression.fit(X_train,y_train)
```

Out[84]:
```
▼ LinearRegression
LinearRegression()
```

In [85]:
```
#print the co-efficeints and the intercept
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 [86]:
```
print(regression.intercept_)
```

```
22.077286135693214
```

In [87]:
```
#prediction for test data
```

In [88]:
```
reg_pred=regression.predict(X_test)
```

In [89]:
```
reg_pred
```

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Out[89]:
```
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 Regresssion

In [93]:
```
plt.scatter(y_test,reg_pred)
plt.xlabel("Test truth Data")
plt.ylabel("Test pred Data")
```

Out[93]:
```
Text(0, 0.5, 'Test pred Data')
```

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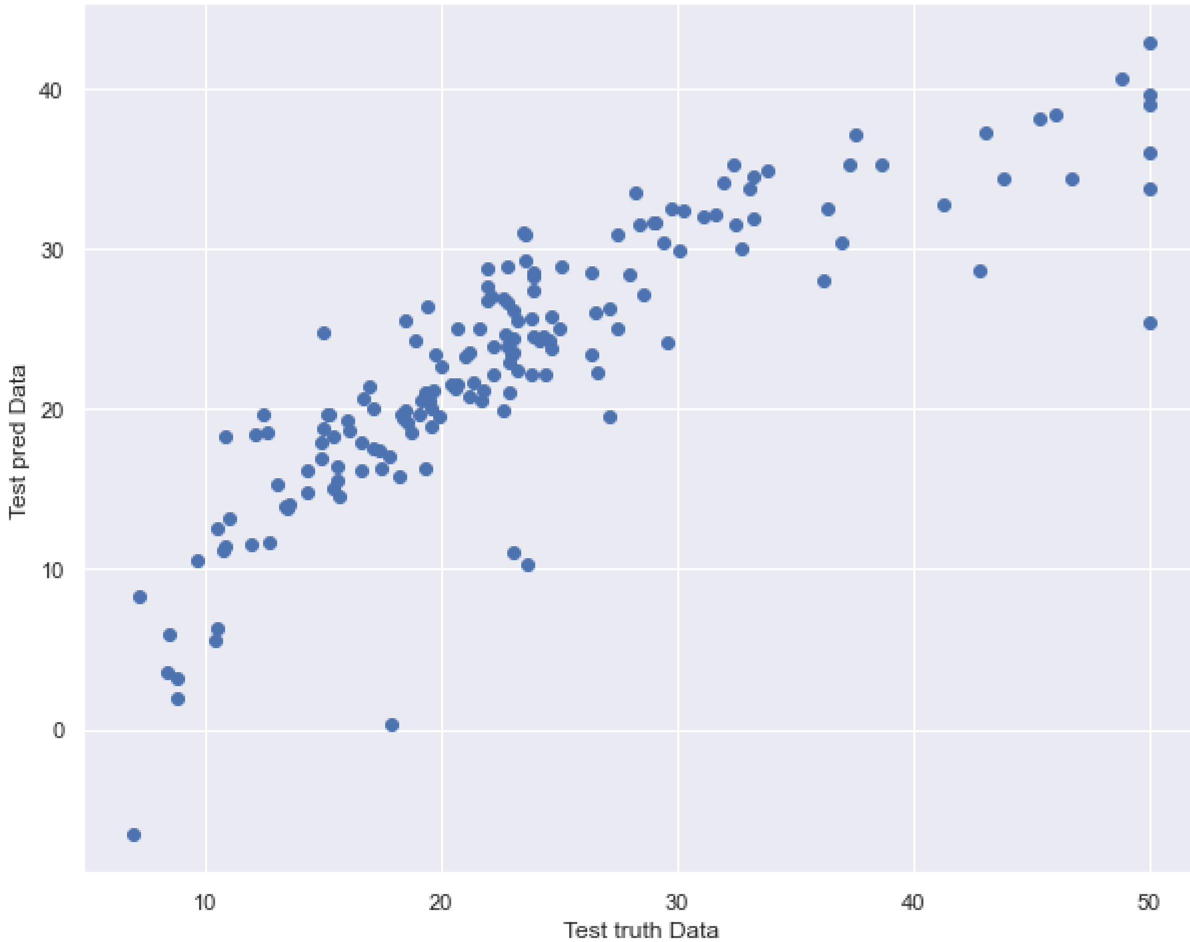


#1 truth point and your predicted point if you try to plot into scatter plot this should be in linear manner (X incearsing y is incresing)

In [95]:
```
#calculate the residuals
```

In [96]:
```
residuals=y_test-reg_pred
```

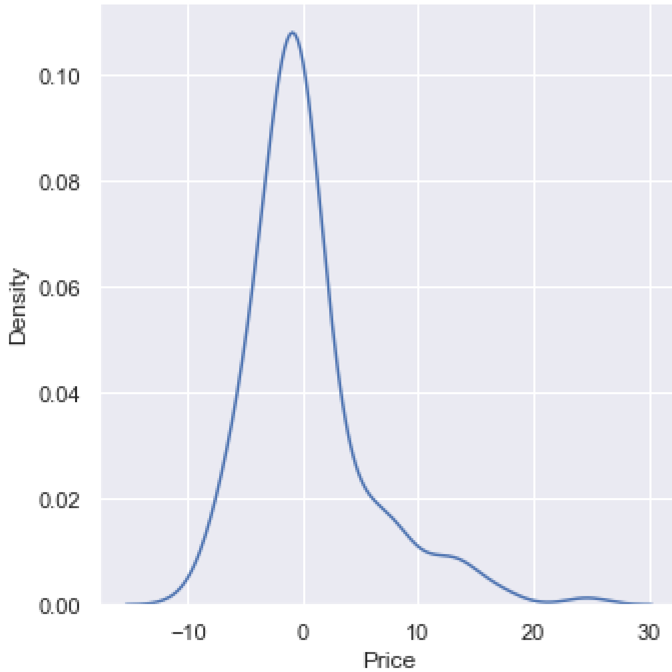
In [97]:
```
residuals
```

Out[97]:
```
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 [100…
```
sns.displot(residuals,kind="kde")
```

Out[100]:
```
<seaborn.axisgrid.FacetGrid at 0x22b0bc80e50>
```

Loading [MathJax]/extensions/Safe.js



#if we try to plot residuals in dis plot it should be coming into normal/guassian distribution

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In [101…

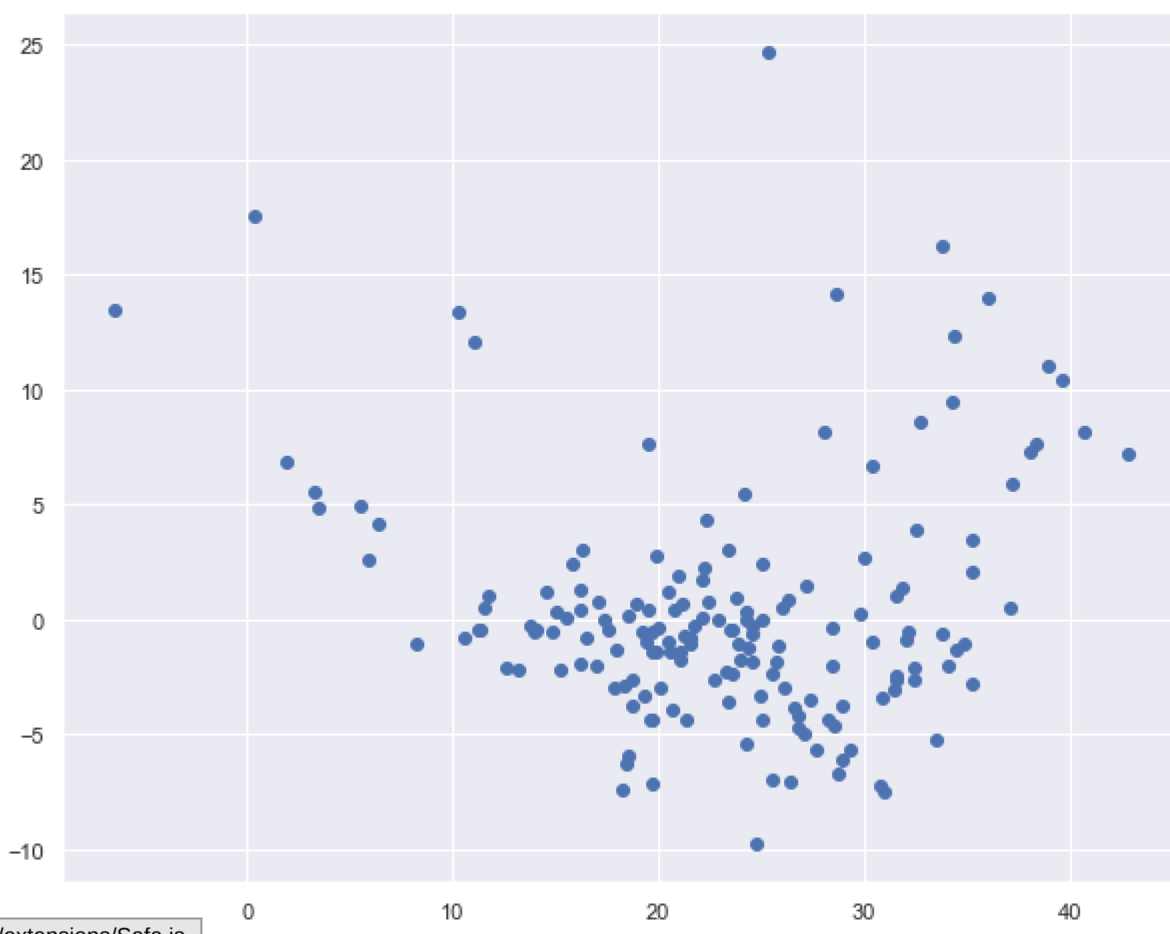
```
#scatter plot with predictions and residuals
```

In [106…

```
#uniform distribution
#Homoscedasticity
plt.scatter(reg_pred,residuals)
```

Out[106]:

```
<matplotlib.collections.PathCollection at 0x22b104f4b80>
```



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Performance Metrics

In [107…
```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,reg_pred))
print(mean_absolute_error(y_test,reg_pred))
print(np.sqrt(mean_squared_error(y_test,reg_pred)))
```

```
27.100991709962493
3.520658529879791
5.205861284164465
```

In [108…
```
#R^2 and Adusted R^2
```

In [111…
```
from sklearn.metrics import r2_score
score=r2_score(y_test,reg_pred)
print(score)
```

```
0.7165219393967555
```

In [114…
```
#adusted R^2
1- (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[114]:
```
0.6924355682343882
```

Ridge Regression

In [115…
```
from sklearn.linear_model import Ridge
ridge=Ridge()
```

In [116…
```
#model training
ridge.fit(X_train,y_train)
```

Out[116]:
```
▾ Ridge
Ridge()
```

In [119…
```
#model prection
ridge_pred=ridge.predict(X_test)
```

In [120…
```
ridge_pred
```

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Out[120]:
```
array([31.32951625, 31.98180665, 30.96523995, 22.45112285, 18.93171888,
       16.21770197, 35.96932532, 14.8453389 , 25.00644473, 37.08826243,
       21.49615236, 30.86395535, 27.9880323 , 33.98239498, 33.72731108,
       40.61743429, 24.27292247, 23.33888547, 25.52862017, 21.42716828,
       32.68689234, 17.88582539, 25.50293435, 25.01797349, 32.58757636,
       20.48521647, 19.51598666, 16.94098815, 38.35803356,  0.33567931,
       32.44411299, 32.10347472, 26.13567232, 23.81384315, 20.64388179,
       19.71829821,  3.56174179, 35.17319673, 27.02020897, 27.65038259,
       34.3408154 , 29.77237182, 18.39828682, 31.55283209, 17.92580288,
       28.51408759, 19.49631857, 21.65517408, 38.03589465, 16.47721333,
       24.56300743, 19.66060562, 24.490545  , 34.33513167, 26.7462751 ,
       34.83714079, 21.08524522, 19.88396747, 18.65820105, 24.71538111,
       20.00248822, 23.58585608, 39.60689645, 42.79543819, 30.3548884 ,
       17.07425788, 23.84421168,  3.23169724, 31.42539336, 28.75103892,
       18.49739555, 27.14667811, 19.64621723, 25.28950017, 25.07871104,
       10.32212282, 38.94009655,  8.26854141, 18.50624966, 30.39028455,
       22.88702308, 21.08817927, 20.09060901, 28.70289649, 30.81533585,
       28.22566424, 26.28189093, 31.61850553, 22.15784726, -6.42142112,
       21.55950809, 19.89786415, 24.96571959, 23.47361425, 19.25709566,
       18.80383821, 27.37954116, 22.19229114, 26.78224659, 23.40784376,
       23.92754566, 19.18858516, 21.09794643, 10.90877661, 13.8058827 ,
       20.78603584, 23.49652544, 14.19685075, 28.86443391, 15.85586096,
       15.26402087, 22.3935837 , 26.6360939 , 28.87654523, 24.25975975,
       18.26463183, 16.26557102, 17.44937859, 15.58602415, 21.2407358 ,
       33.72594686, 30.0710014 , 21.17366551, 14.04587364, 16.21847821,
       29.26644762, 13.18724919, 22.07232566, 24.34918815, 31.88230457,
       33.34230018,  5.95941842, 35.14730418, 24.25694454, 17.55532023,
       24.27022839, 28.4213874 , 34.47544702,  6.3238347 ,  2.03912756,
       28.40127604, 12.59079125, 18.32110122, 19.75915926,  5.51559383,
       14.42137586, 37.15183113, 25.8605775 , 23.29888263, 26.39528404,
       11.42000684, 20.48891462, 35.29528497, 20.61619917, 11.45777136,
       16.36445822, 24.57014519, 10.51041916, 15.13830095, 26.01152356,
       11.22987126, 11.70179781, 19.39451509, 19.59207236, 32.42949   ,
       22.67098418, 25.68376364])
```

Performance Matrix

In [121…
```
#cost function mse,mae,rmse
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)))
```

```
27.076490001440607
3.5161044263484236
5.203507471066089
```

In [122…
```
#R square Metrics
```

In [134…
```
from sklearn.metrics import r2_score
score=r2_score(y_test,ridge_pred)
print(score)
```

```
0.716778228793379
```

In [135…
```
#adusted R^2
1- (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[135]:
```
0.6927136338542543
```

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laso Regression

In [124…
```
from sklearn.linear_model import Lasso
lasso=Lasso()
```

In [126…
```
lasso
```

Out[126]:
```
▼ Lasso
Lasso()
```

In [127…
```
lasso.fit(X_train,y_train)
```

Out[127]:
```
▼ Lasso
Lasso()
```

In [129…
```
lasso_pred=lasso_pred=lasso.predict(X_test)
```

In [130…
```
lasso_pred
```

Out[130]:
```
array([25.64194382, 29.81425297, 27.94324255, 27.55256464, 20.99640298,
       18.74520609, 34.28217994, 15.93009427, 20.70883387, 34.07542731,
       19.90502439, 26.60490365, 24.07990755, 29.92866139, 29.22037693,
       36.40160499, 26.2514407 , 19.88117334, 23.967085  , 22.50869347,
       30.87428332, 18.78300957, 23.92041383, 25.68996484, 32.43275786,
       21.59346217, 20.77097939, 19.17145706, 34.09829244,  2.83421427,
       30.5699873 , 29.29565261, 26.85558827, 25.25346658, 19.26477827,
       19.73302762,  7.84289608, 29.77239449, 25.40207471, 25.60513357,
       32.3846261 , 26.89227407, 18.03007537, 29.36340326, 18.91119501,
       27.26813644, 20.46203931, 21.03622196, 34.39115891, 18.05973586,
       23.67935365, 18.6389767 , 22.52686697, 32.78082702, 26.03741902,
       30.39354515, 20.51475327, 20.94796259, 17.76992156, 24.71515119,
       21.39562999, 22.87363803, 36.66878913, 37.88636344, 28.19838095,
       17.67593653, 24.95639783,  5.16197744, 27.44103022, 33.73592095,
       19.49826488, 28.55803328, 19.79798303, 21.76346312, 24.39060267,
       10.72390653, 35.69760879,  8.87515321, 19.7342389 , 30.44923304,
       23.5731452 , 25.969039  , 21.53759864, 26.56759106, 29.08985079,
       27.11618087, 27.52241607, 31.13762774, 25.19009251,  1.294237  ,
       24.63082225, 20.35958514, 25.20780706, 25.3136586 , 19.78586427,
       20.81458041, 26.18578331, 20.65389528, 23.63766687, 22.07598695,
       24.48709112, 20.92346851, 21.99207783, 11.28215423, 15.85225507,
       22.37860011, 20.11691913, 17.8652717 , 27.92655648, 20.66334411,
       16.27505897, 21.25931319, 25.72062784, 25.92038934, 22.43890052,
       18.21105925, 13.73609426, 19.70671479, 19.16823222, 20.81634433,
       28.98351303, 31.19474714, 20.47647933, 14.48614909, 18.32476473,
       25.90552665, 15.20476004, 22.61771889, 24.11123534, 30.06699424,
       27.18076864, 10.97444888, 29.31613765, 29.11544566, 18.4851049 ,
       25.5516343 , 26.58527747, 29.79753531,  7.90378337, 13.9914479 ,
       27.53958439, 15.07581206, 19.1010104 , 20.2136539 ,  9.56591918,
       12.35215313, 32.65105454, 27.04505972, 22.60389757, 23.38431025,
       18.14439345, 21.46916879, 33.35149732, 21.68370567, 11.686795  ,
       22.46129098, 24.462044  , 10.63445232, 17.62333713, 25.46239518,
       13.61074004, 15.25814185, 19.3752538 , 20.11939071, 29.36108994,
       22.66082095, 25.30493792])
```

In [131…
```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,lasso_pred))
```

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```
print(mean_absolute_error(y_test,lasso_pred))
print(np.sqrt(mean_squared_error(y_test,lasso_pred)))
```

```
32.16822537607396
3.9064325476573205
5.67170392175702
```

In [132…
```
from sklearn.metrics import r2_score
score=r2_score(y_test,lasso_pred)
print(score)
```

```
0.6635183597615237
```

In [133…
```
#adusted R^2
1- (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[133]:
```
0.6349284164732871
```

ElasticNet Regression

In [136…
```
from sklearn.linear_model import ElasticNet
```

In [137…
```
elastic=ElasticNet()
```

In [138…
```
elastic
```

Out[138]:
```
▾ ElasticNet
ElasticNet()
```

In [139…
```
elastic.fit(X_train,y_train)
```

Out[139]:
```
▾ ElasticNet
ElasticNet()
```

In [140…
```
elastic_pred=elastic.predict(X_test)
```

In [141…
```
elastic_pred
```

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Out[141]:
```
array([26.0417533 , 29.72847396, 28.13249256, 27.33126697, 20.42880538,
       17.74088482, 31.34694254, 16.67485774, 22.66361605, 32.11606238,
       20.44062928, 27.05265082, 24.30388496, 29.10453835, 29.42032134,
       34.87404662, 25.31690008, 21.08018038, 24.04009667, 22.78241695,
       28.62957505, 18.35172223, 23.50225053, 24.94025282, 31.31440303,
       21.87551246, 22.30554751, 18.38033279, 33.5961939 ,  5.07350586,
       31.03524275, 28.19235387, 27.2862085 , 24.92462838, 19.28719449,
       20.2043877 ,  9.65913955, 29.64752478, 24.48773946, 25.34376165,
       30.68019641, 26.22751049, 18.01125345, 29.21052894, 20.61959202,
       27.27830384, 19.56149084, 19.72195809, 33.16071763, 19.16416141,
       23.05862027, 18.66118548, 22.77766754, 31.26962741, 25.0249516 ,
       29.94893114, 20.8407824 , 19.87498778, 18.27542547, 22.76517295,
       20.81723461, 22.76805785, 34.51940602, 36.11020157, 27.24493161,
       18.27047552, 24.17101249,  7.04406772, 26.85508847, 32.20329184,
       18.80351309, 27.46659498, 19.30788561, 20.8108208 , 23.90532445,
       14.22176442, 33.73545716, 10.78055539, 20.93445818, 29.78172162,
       23.99677889, 25.93581443, 22.61951728, 26.7428785 , 28.14408623,
       25.89892069, 26.67011775, 30.84900884, 24.58079972,  2.73998551,
       24.21010745, 20.83883219, 25.05619448, 24.60834531, 21.10174986,
       22.49049602, 26.06687733, 22.19194864, 23.68670917, 22.18041458,
       25.06905312, 20.26607354, 23.08760718, 10.49569995, 17.33370695,
       22.43253387, 21.15234101, 17.76115425, 26.58899485, 21.8834536 ,
       16.2603945 , 20.64765689, 25.09688902, 26.39218729, 22.53942481,
       18.04368235, 17.14638997, 20.67683019, 18.81134056, 19.82073711,
       26.78232308, 30.65570208, 20.62008364, 17.08768963, 19.18709774,
       25.65086934, 15.16746519, 21.83976175, 23.88029317, 29.16441724,
       27.25789963, 10.94687118, 29.43663882, 28.05096936, 18.27555631,
       24.83638128, 26.62936138, 30.15776119,  9.24328778, 10.68301626,
       27.04760052, 14.96584806, 18.73604079, 20.41851801,  9.92593546,
       14.91131492, 31.67918212, 27.61903571, 22.57544206, 24.72549427,
       15.35714158, 22.50035819, 31.86456612, 21.15334479, 12.67869784,
       22.65361671, 24.53650868, 11.9779066 , 18.36583206, 24.65573814,
       13.97917875, 14.8116782 , 18.92727223, 19.69541499, 28.7493839 ,
       22.61167089, 24.82104593])
```

In [142…
```python
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,elastic_pred))
print(mean_absolute_error(y_test,elastic_pred))
print(np.sqrt(mean_squared_error(y_test,elastic_pred)))
```

```
35.341543853934674
4.035696708769101
5.944875427957652
```

In [143…
```python
from sklearn.metrics import r2_score
score=r2_score(y_test,elastic_pred)
print(score)
```

```
0.6303252509112042
```

In [144…
```python
#adusted R^2
1- (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[144]:
```
0.5989149781128098
```

In [ ]:

Loading [MathJax]/extensions/Safe.js