In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

Lets load the Boston House Pricing Dataset

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

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

In [4]:
```
boston.keys()
```

Out[4]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

In [5]:
```
## Lets check the description of the dataset
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 blacks by to
wn
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

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


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

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

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

.. topic:: References
```

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

In [6]:
```
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 [7]:
```
1 print(boston.target)
```

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

In [8]:
```
1 print(boston.feature_names)
```

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

Preparing The Dataset

In [9]:
```
1 dataset=pd.DataFrame(boston.data,columns=boston.feature_names)
```

In [10]:
```
1 dataset.head()
```

Out[10]:

	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 [11]:
```
1 dataset['Price']=boston.target
```

In [12]:
```
1 dataset.head()
```

Out[12]:

	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 [13]:
```
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
```

In [14]:
```
## Summarizing The Stats of the data
dataset.describe()
```

Out[14]:

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

In [15]:
```
## Check the missing Values
dataset.isnull().sum()
```

Out[15]:
```
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
```

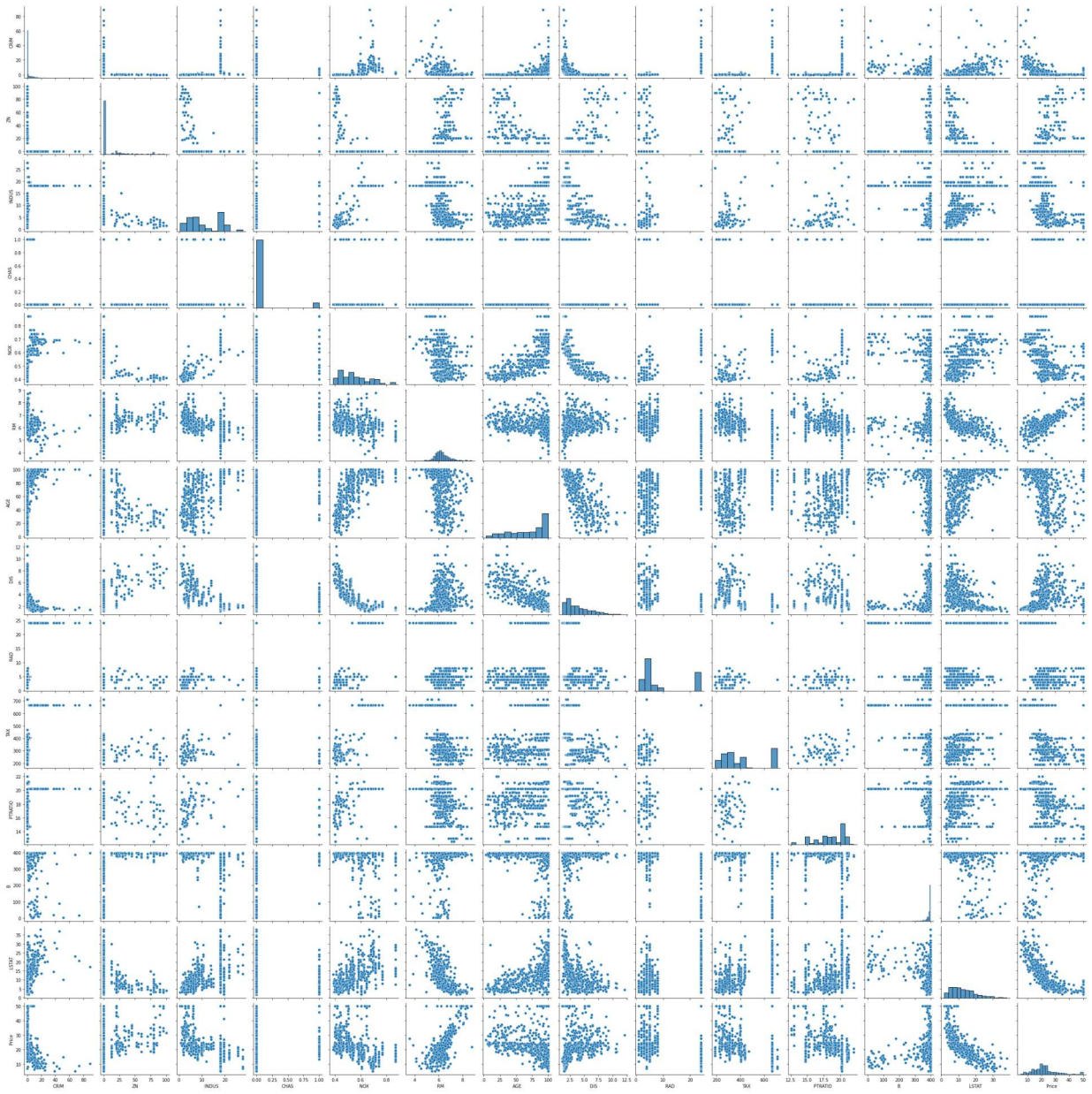
In [16]:
```
### EXploratory Data Analysis
## Correlation
dataset.corr()
```

Out[16]:

	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 [17]:
```
1 import seaborn as sns
2 sns.pairplot(dataset)
```

Out[17]: <seaborn.axisgrid.PairGrid at 0x2344ef6de08>



Analyzing The Correlated Features

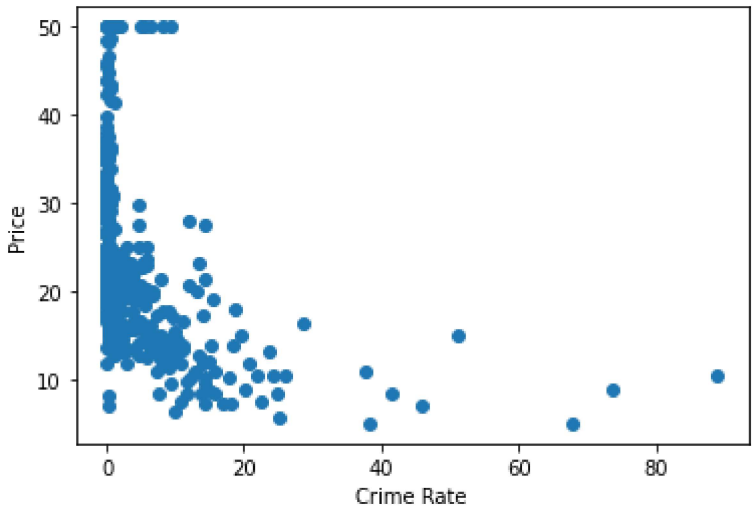
In [18]:
```
1 dataset.corr()
```

Out[18]:

	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.

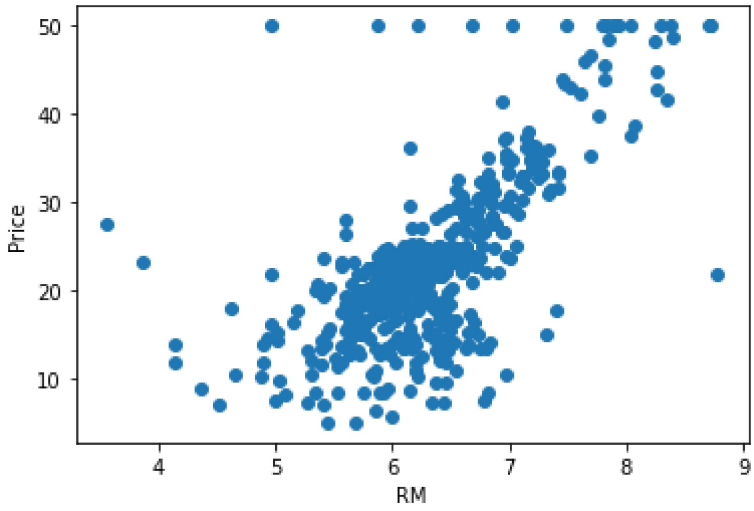
In [19]:
```
1 plt.scatter(dataset['CRIM'],dataset['Price'])
2 plt.xlabel("Crime Rate")
3 plt.ylabel("Price")
```

Out[19]: Text(0, 0.5, 'Price')



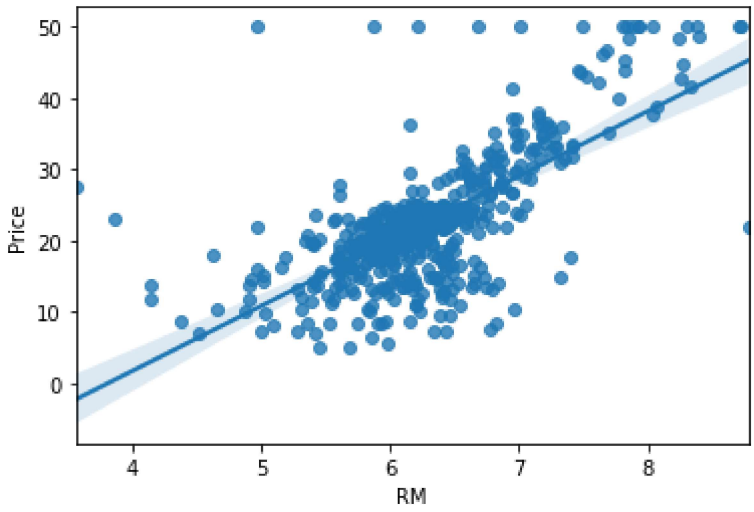
In [20]:
```
1 plt.scatter(dataset['RM'],dataset['Price'])
2 plt.xlabel("RM")
3 plt.ylabel("Price")
```

Out[20]: Text(0, 0.5, 'Price')



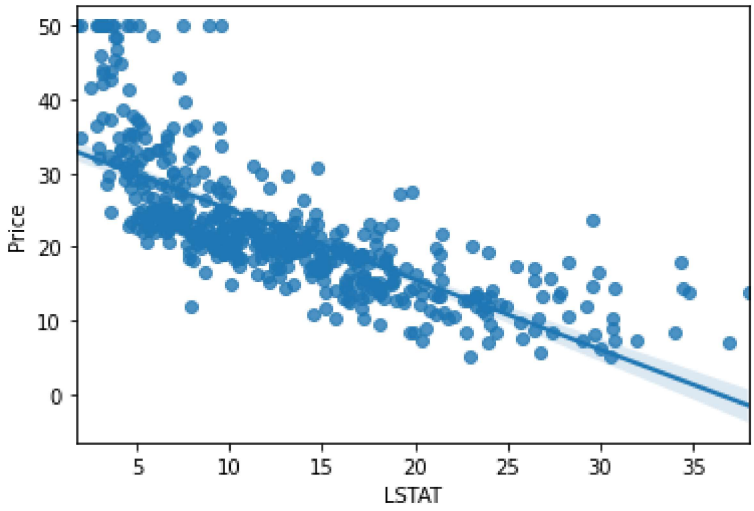
In [21]:
```
import seaborn as sns
sns.regplot(x="RM",y="Price",data=dataset)
```

Out[21]: <AxesSubplot:xlabel='RM', ylabel='Price'>



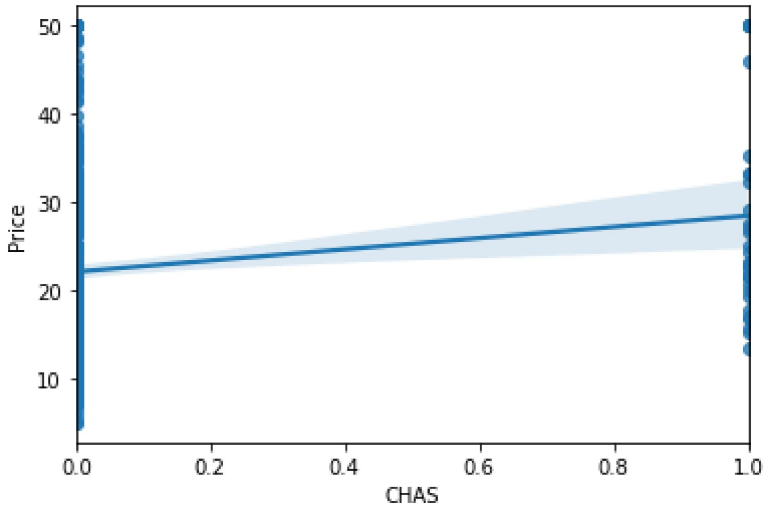
In [22]:
```
sns.regplot(x="LSTAT",y="Price",data=dataset)
```

Out[22]: <AxesSubplot:xlabel='LSTAT', ylabel='Price'>



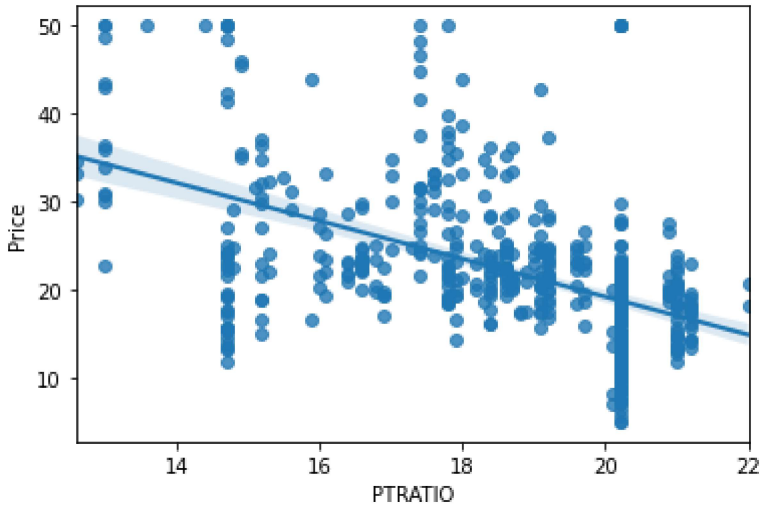
In [23]:
```
1 sns.regplot(x="CHAS",y="Price",data=dataset)
```

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



In [24]:
```
1 sns.regplot(x="PTRATIO",y="Price",data=dataset)
```

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



In [25]:
```
## Independent and Dependent features

X=dataset.iloc[:,:-1]
y=dataset.iloc[:,-1]
```

In [26]:
```
X.head()
```

Out[26]:

	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 [27]:
```
y
```

Out[27]:
```
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 [28]:
```
##Train Test Split
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_stat
```

In [29]:
```
1 X_train
```

Out[29]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3.0	222.0	18.7	394.12	5
116	0.13158	0.0	10.01	0.0	0.547	6.176	72.5	2.7301	6.0	432.0	17.8	393.30	12
45	0.17142	0.0	6.91	0.0	0.448	5.682	33.8	5.1004	3.0	233.0	17.9	396.90	10
16	1.05393	0.0	8.14	0.0	0.538	5.935	29.3	4.4986	4.0	307.0	21.0	386.85	6
468	15.57570	0.0	18.10	0.0	0.580	5.926	71.0	2.9084	24.0	666.0	20.2	368.74	18
...	...	...	...	...	...	...	...	...	...	...	...	...	
106	0.17120	0.0	8.56	0.0	0.520	5.836	91.9	2.2110	5.0	384.0	20.9	395.67	18
270	0.29916	20.0	6.96	0.0	0.464	5.856	42.1	4.4290	3.0	223.0	18.6	388.65	13
348	0.01501	80.0	2.01	0.0	0.435	6.635	29.7	8.3440	4.0	280.0	17.0	390.94	5
435	11.16040	0.0	18.10	0.0	0.740	6.629	94.6	2.1247	24.0	666.0	20.2	109.85	23
102	0.22876	0.0	8.56	0.0	0.520	6.405	85.4	2.7147	5.0	384.0	20.9	70.80	10

354 rows × 13 columns

In [30]:
```
1 X_test
```

Out[30]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
173	0.09178	0.0	4.05	0.0	0.510	6.416	84.1	2.6463	5.0	296.0	16.6	395.50	9
274	0.05644	40.0	6.41	1.0	0.447	6.758	32.9	4.0776	4.0	254.0	17.6	396.90	3
491	0.10574	0.0	27.74	0.0	0.609	5.983	98.8	1.8681	4.0	711.0	20.1	390.11	18
72	0.09164	0.0	10.81	0.0	0.413	6.065	7.8	5.2873	4.0	305.0	19.2	390.91	5
452	5.09017	0.0	18.10	0.0	0.713	6.297	91.8	2.3682	24.0	666.0	20.2	385.09	17
...	...	...	...	...	...	...	...	...	...	...	...	...	
441	9.72418	0.0	18.10	0.0	0.740	6.406	97.2	2.0651	24.0	666.0	20.2	385.96	19
23	0.98843	0.0	8.14	0.0	0.538	5.813	100.0	4.0952	4.0	307.0	21.0	394.54	19
225	0.52693	0.0	6.20	0.0	0.504	8.725	83.0	2.8944	8.0	307.0	17.4	382.00	4
433	5.58107	0.0	18.10	0.0	0.713	6.436	87.9	2.3158	24.0	666.0	20.2	100.19	16
447	9.92485	0.0	18.10	0.0	0.740	6.251	96.6	2.1980	24.0	666.0	20.2	388.52	16

152 rows × 13 columns

In [31]:
```
1 ## Standardize the dataset
2 from sklearn.preprocessing import StandardScaler
3 scaler=StandardScaler()
```

In [32]:
```
X_train=scaler.fit_transform(X_train)
```

In [33]:
```
X_test=scaler.transform(X_test)
```

In [34]:
```
import pickle
pickle.dump(scaler,open('scaling.pkl','wb'))
```

In [34]:
```
X_train
```

Out[34]:
```
array([[-0.41425879, -0.50512499, -1.29214218, ...,  0.18727079,
         0.39651419, -1.01531611],
       [-0.40200818, -0.50512499, -0.16208345, ..., -0.21208981,
         0.3870674 , -0.05366252],
       [-0.39721053, -0.50512499, -0.60948856, ..., -0.16771641,
         0.42854113, -0.31132373],
       ...,
       [-0.41604586,  3.03838247, -1.3166773 , ..., -0.56707702,
         0.35987906, -0.90549329],
       [ 0.92611293, -0.50512499,  1.00549958, ...,  0.8528718 ,
        -2.87841346,  1.52750437],
       [-0.39030549, -0.50512499, -0.37135358, ...,  1.16348561,
        -3.32828832, -0.25218837]])
```

In [35]:
```
X_test
```

Out[35]:
```
array([[-0.406801  , -0.50512499, -1.02225586, ..., -0.74457062,
         0.41241246, -0.47605794],
       [-0.41105674,  1.26662874, -0.68165068, ..., -0.30083661,
         0.42854113, -1.25185755],
       [-0.4051199 , -0.50512499,  2.39678516, ...,  0.8084984 ,
         0.35031705,  0.79535229],
       ...,
       [-0.35439903, -0.50512499, -0.71195877, ..., -0.38958342,
         0.25688594, -1.09697922],
       [ 0.25423453, -0.50512499,  1.00549958, ...,  0.8528718 ,
        -2.98970133,  0.53487511],
       [ 0.77732457, -0.50512499,  1.00549958, ...,  0.8528718 ,
         0.33199949,  0.56585078]])
```

Model Training

In [36]:
```
from sklearn.linear_model import LinearRegression
```

In [37]:
```
regression=LinearRegression()
```

In [38]:
```
regression.fit(X_train,y_train)
```

Out[38]:
```
LinearRegression()
```

In [39]:
```
## print the coefficients and the intercept
print(regression.coef_)
```

```
[-1.10834602  0.80843998  0.34313466  0.81386426 -1.79804295  2.913858
 -0.29893918 -2.94251148  2.09419303 -1.44706731 -2.05232232  1.02375187
 -3.88579002]
```

In [40]:
```
print(regression.intercept_)
```

```
23.01581920903955
```

In [41]:
```
## on which parameters the model has been trained
regression.get_params()
```

Out[41]:
```
{'copy_X': True,
 'fit_intercept': True,
 'n_jobs': None,
 'normalize': False,
 'positive': False}
```

In [42]:
```
### Prediction With Test Data
reg_pred=regression.predict(X_test)
```

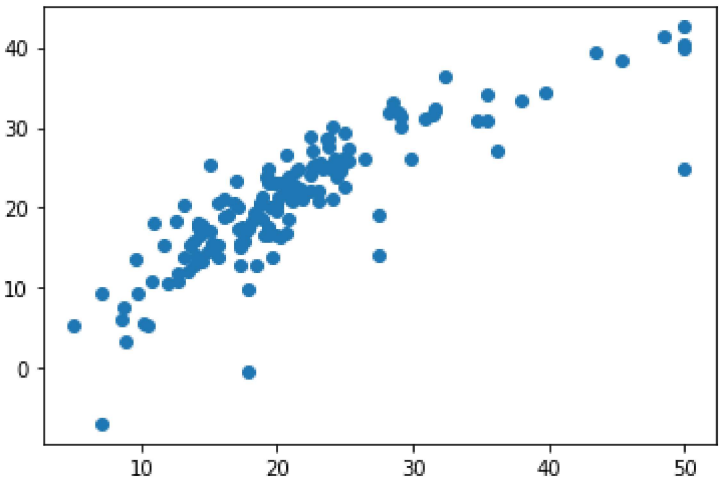
In [43]:
```
1 reg_pred
```

Out[43]:
```
array([28.64896005, 36.49501384, 15.4111932 , 25.40321303, 18.85527988,
       23.14668944, 17.3921241 , 14.07859899, 23.03692679, 20.59943345,
       24.82286159, 18.53057049, -6.86543527, 21.80172334, 19.22571177,
       26.19191985, 20.27733882,  5.61596432, 40.44887974, 17.57695918,
       27.44319095, 30.1715964 , 10.94055823, 24.02083139, 18.07693812,
       15.934748  , 23.12614028, 14.56052142, 22.33482544, 19.3257627 ,
       22.16564973, 25.19476081, 25.31372473, 18.51345025, 16.6223286 ,
       17.50268505, 30.94992991, 20.19201752, 23.90440431, 24.86975466,
       13.93767876, 31.82504715, 42.56978796, 17.62323805, 27.01963242,
       17.19006621, 13.80594006, 26.10356557, 20.31516118, 30.08649576,
       21.3124053 , 34.15739602, 15.60444981, 26.11247588, 39.31613646,
       22.99282065, 18.95764781, 33.05555669, 24.85114223, 12.91729352,
       22.68101452, 30.80336295, 31.63522027, 16.29833689, 21.07379993,
       16.57699669, 20.36362023, 26.15615896, 31.06833034, 11.98679953,
       20.42550472, 27.55676301, 10.94316981, 16.82660609, 23.92909733,
        5.28065815, 21.43504661, 41.33684993, 18.22211675,  9.48269245,
       21.19857446, 12.95001331, 21.64822797,  9.3845568 , 23.06060014,
       31.95762512, 19.16662892, 25.59942257, 29.35043558, 20.13138581,
       25.57297369,  5.42970803, 20.23169356, 15.1949595 , 14.03241742,
       20.91078077, 24.82249135, -0.47712079, 13.70520524, 15.69525576,
       22.06972676, 24.64152943, 10.7382866 , 19.68622564, 23.63678009,
       12.07974981, 18.47894211, 25.52713393, 20.93461307, 24.6955941 ,
        7.59054562, 19.01046053, 21.9444339 , 27.22319977, 32.18608828,
       15.27826455, 34.39190421, 12.96314168, 21.01681316, 28.57880911,
       15.86300844, 24.85124135,  3.37937111, 23.90465773, 25.81792146,
       23.11020547, 25.33489201, 33.35545176, 20.60724498, 38.4772665 ,
       13.97398533, 25.21923987, 17.80946626, 20.63437371,  9.80267398,
       21.07953576, 22.3378417 , 32.32381854, 31.48694863, 15.46621287,
       16.86242766, 28.99330526, 24.95467894, 16.73633557,  6.12858395,
       26.65990044, 23.34007187, 17.40367164, 13.38594123, 39.98342478,
       16.68286302, 18.28561759])
```

Assumptions

In [44]:
```
## plot a scatter plot for the prediction
plt.scatter(y_test,reg_pred)
```

Out[44]: <matplotlib.collections.PathCollection at 0x21810ccb248>



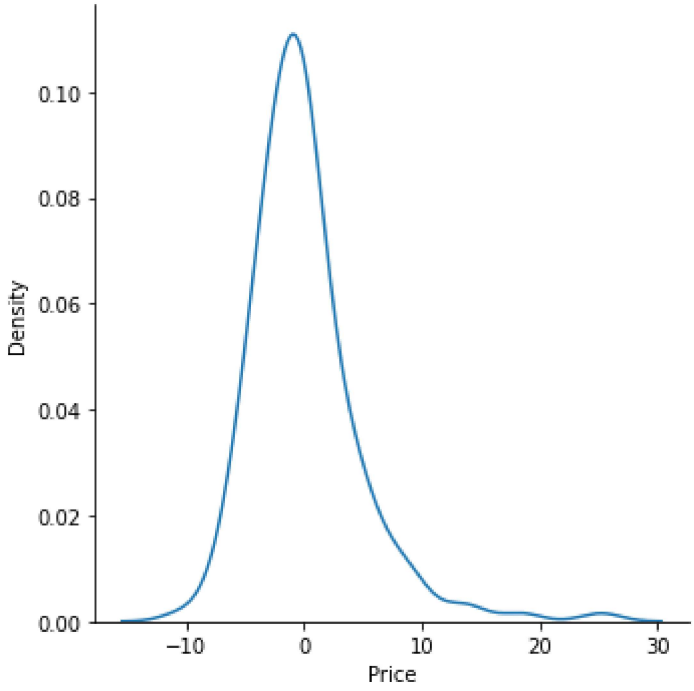
In [45]:
```
## Residuals
residuals=y_test-reg_pred
```

In [46]:
```
residuals
```

Out[46]:
```
173    -5.048960
274    -4.095014
491    -1.811193
72     -2.603213
452    -2.755280
          ...
441    -0.303672
23      1.114059
225    10.016575
433    -2.382863
447    -5.685618
Name: Price, Length: 152, dtype: float64
```

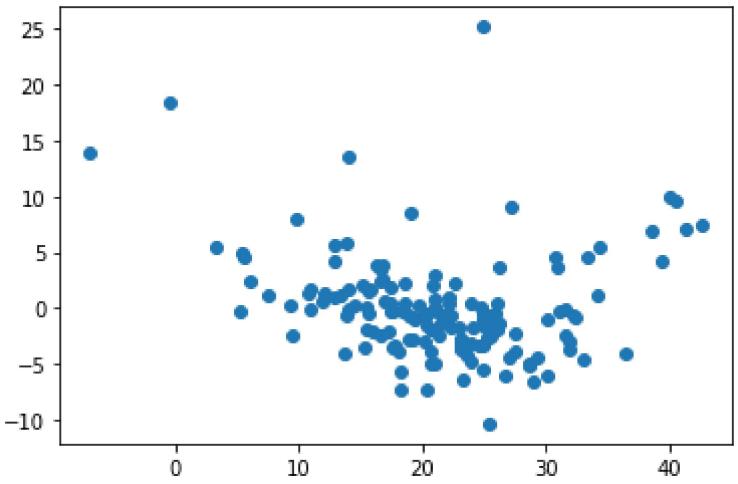
In [47]:
```
## Plot this residuals

sns.displot(residuals,kind="kde")
```

Out[47]: <seaborn.axisgrid.FacetGrid at 0x21810fde788>



In [48]:
```
## Scatter plot with respect to prediction and residuals
## uniform distribution
plt.scatter(reg_pred,residuals)
```

Out[48]: <matplotlib.collections.PathCollection at 0x21810facec8>



In [49]:
```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error

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

```
3.162709871457405
21.517444231177205
4.6386899261728205
```

R square and adjusted R square

Formula

R^2 = 1 - SSR/SST

R^2 = coefficient of determination SSR = sum of squares of residuals SST = total sum of squares

In [50]:
```
from sklearn.metrics import r2_score
score=r2_score(y_test,reg_pred)
print(score)
```

```
0.7112260057484933
```

In [ ]:
```

```

Adjusted R2 = 1 – [(1-R2)*(n-1)/(n-k-1)]

where:

R2: The R2 of the model n: The number of observations k: The number of predictor variables

In [51]:
```
#display adjusted R-squared
1 - (1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[51]:
```
0.6840226584639311
```

New Data Prediction

In [52]:
```
boston.data[0].reshape(1,-1)
```

Out[52]:
```
array([[6.320e-03, 1.800e+01, 2.310e+00, 0.000e+00, 5.380e-01, 6.575e+00,
        6.520e+01, 4.090e+00, 1.000e+00, 2.960e+02, 1.530e+01, 3.969e+02,
        4.980e+00]])
```

In [53]:
```
##transformation of new data
scaler.transform(boston.data[0].reshape(1,-1))
```

Out[53]:
```
array([[-0.41709233,  0.29216419, -1.27338003, -0.28154625, -0.16513629,
         0.34715902, -0.13030059,  0.15267164, -0.97798895, -0.66777595,
        -1.32142483,  0.42854113, -1.04769976]])
```

In [54]:
```
regression.predict(scaler.transform(boston.data[0].reshape(1,-1)))
```

Out[54]:
```
array([30.08649576])
```

Pickling The Model file For Deployment

In [55]:
```
import pickle
```

In [56]:
```
pickle.dump(regression,open('regmodel.pkl','wb'))
```

In [57]:
```
pickled_model=pickle.load(open('regmodel.pkl','rb'))
```

In [58]:
```
## Prediction
pickled_model.predict(scaler.transform(boston.data[0].reshape(1,-1)))
```

Out[58]:
```
array([30.08649576])
```

In [ ]:
```

```