In [1]:

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

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]:

```
print(boston.DESCR)
```

```
.. _boston_dataset:

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

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Valu
e (attribute 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 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds rive
r; 0 otherwise)
        - 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/ (http
s://archive.ics.uci.edu/ml/machine-learning-databases/housing/)


This dataset was taken from the StatLib library which is maintained at Ca
rnegie 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 diagnos
tics
...', Wiley, 1980.   N.B. Various transformations are used in the table o
n
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 Influent
ial Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learnin
g. In Proceedings on the Tenth International Conference of Machine Learni
ng, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.
```

In [6]:

```
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]:

```
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]:

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

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

In [9]:

```
## Lets prepare the dataframe
```

In [10]:

```
dataset=pd.DataFrame(boston.data,columns=boston.feature_names)
dataset.head()
```

Out[10]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
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	[illegible]
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	[illegible]
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	[illegible]
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	[illegible]
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	[illegible]

In [11]:

```
dataset['Price']=boston.target
```

In [12]:

```
dataset.head()
```

Out[12]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
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	[illegible]
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	[illegible]
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	[illegible]
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	[illegible]
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	[illegible]

In [13]:

```
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]:

```
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	50
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	1.

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]:

```
## EDA
dataset.corr()
```

Out[16]:

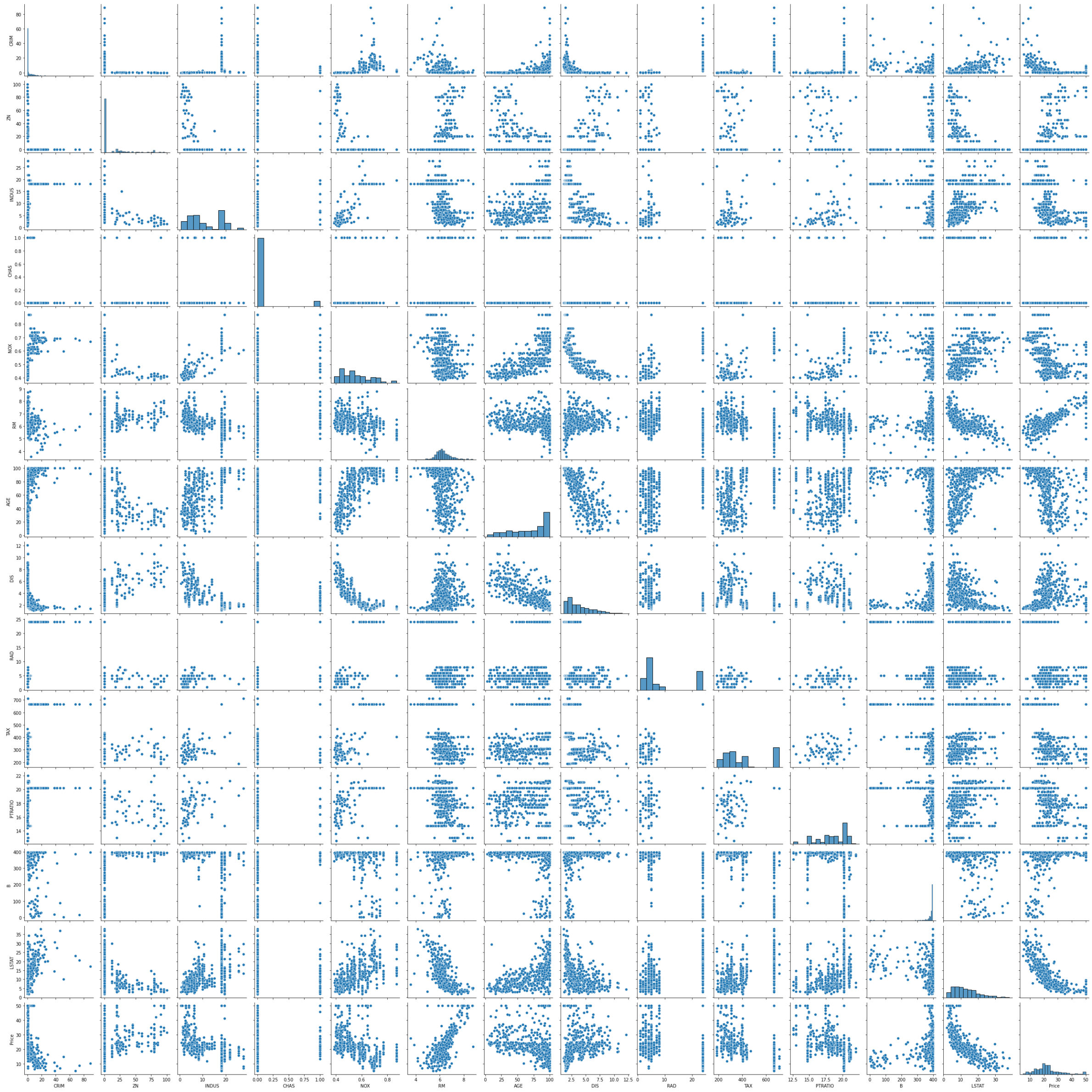
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027
CHAS	-0.055892	-0.042697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

In [17]:

```
import seaborn as sns
sns.pairplot(dataset)
```

Out[17]:

<seaborn.axisgrid.PairGrid at 0x180f666e5e0>



In [18]:

```
sns.set(rc={'figure.figsize':(10,8)})

sns.heatmap(dataset.corr(),annot=True)
```

Out[18]:

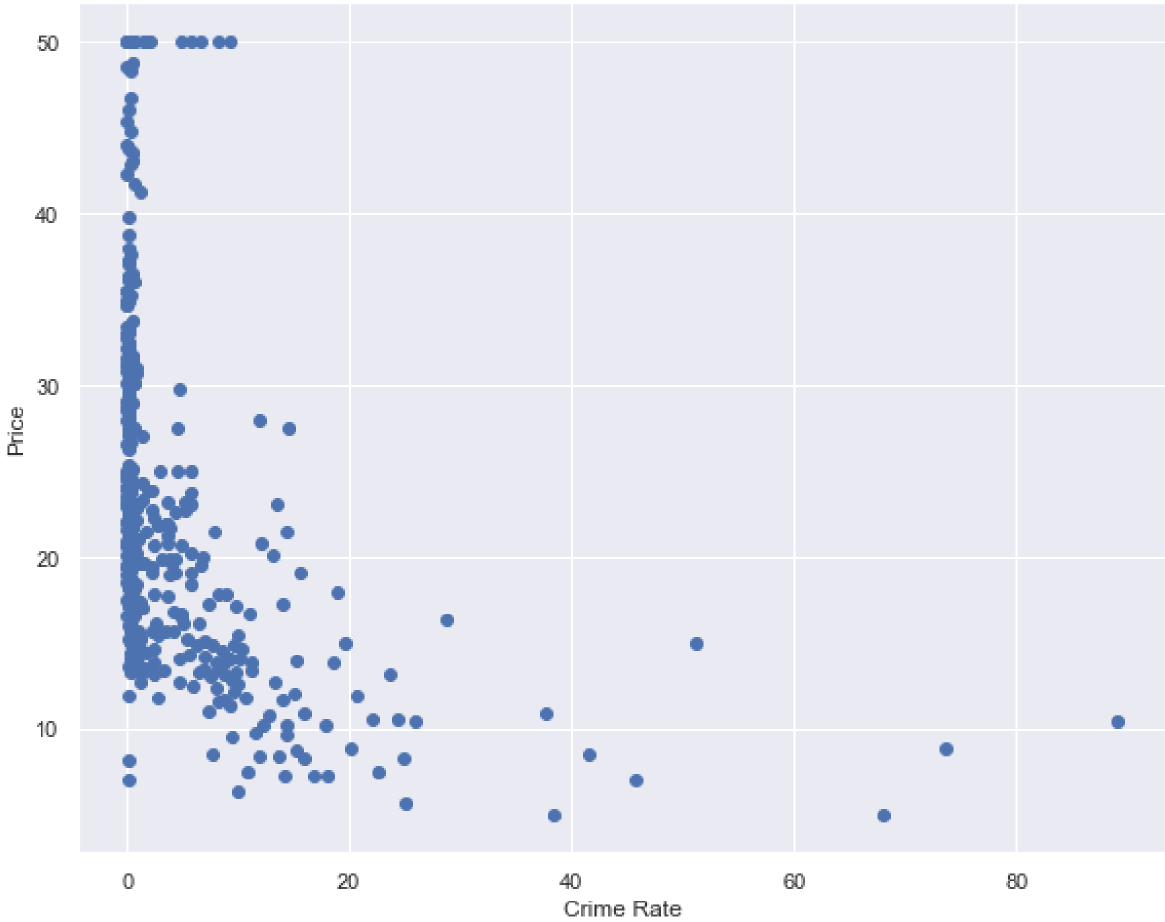
<AxesSubplot:>

In [19]:

```
plt.scatter(dataset['CRIM'],dataset['Price'])
plt.xlabel("Crime Rate")
plt.ylabel("Price")
```

Out[19]:

```
Text(0, 0.5, 'Price')
```

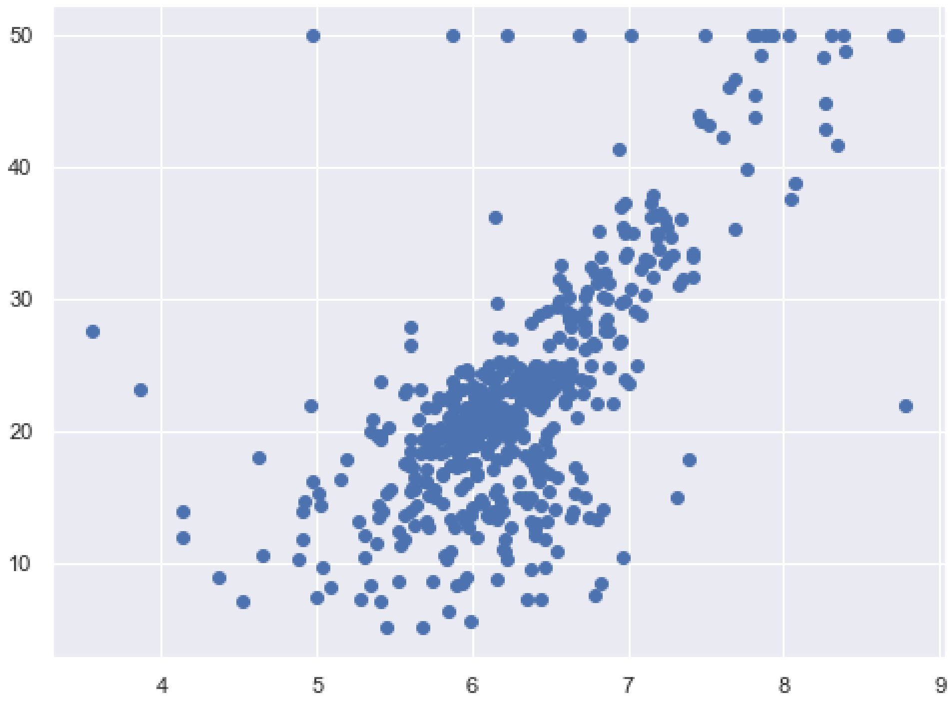


In [20]:

```
sns.set(rc={'figure.figsize':(8,6)})
plt.scatter(dataset['RM'],dataset['Price'])
```

Out[20]:

```
<matplotlib.collections.PathCollection at 0x18081c8ce80>
```

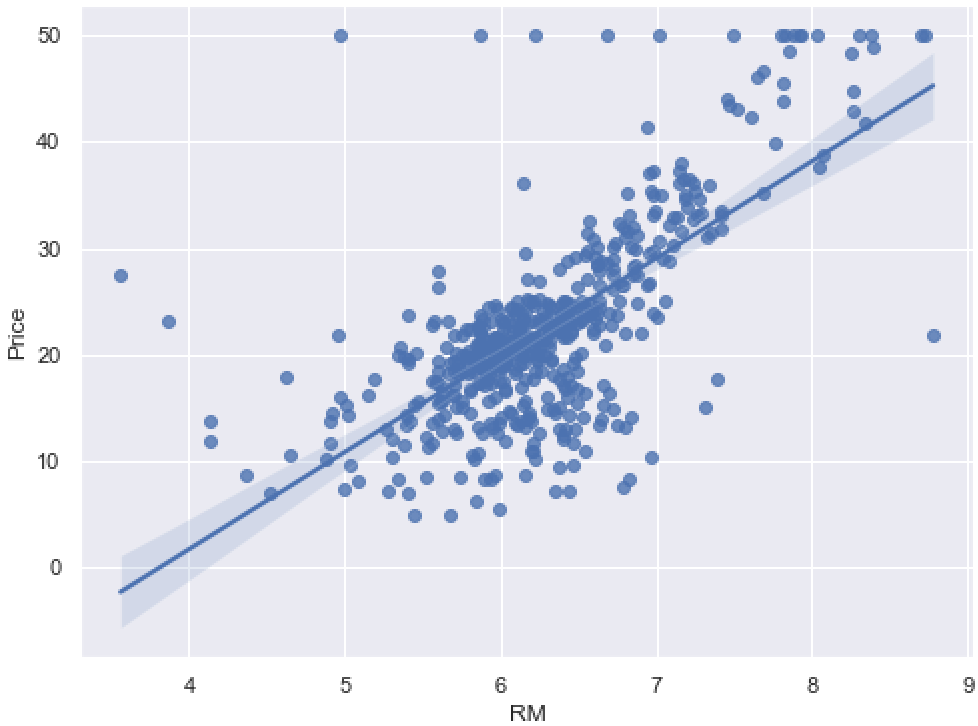


In [21]:

```
sns.regplot(x='RM',y='Price',data=dataset)
```

Out[21]:

```
<AxesSubplot:xlabel='RM', ylabel='Price'>
```

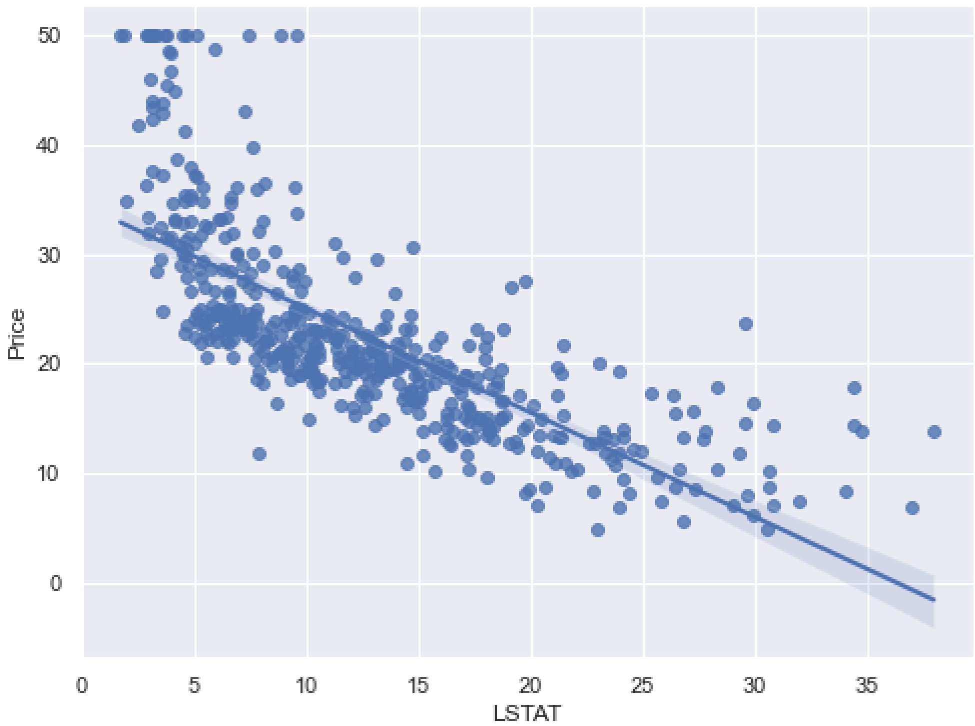


In [22]:

```
sns.regplot(x="LSTAT",y="Price",data=dataset)
```

Out[22]:

```
<AxesSubplot:xlabel='LSTAT', ylabel='Price'>
```

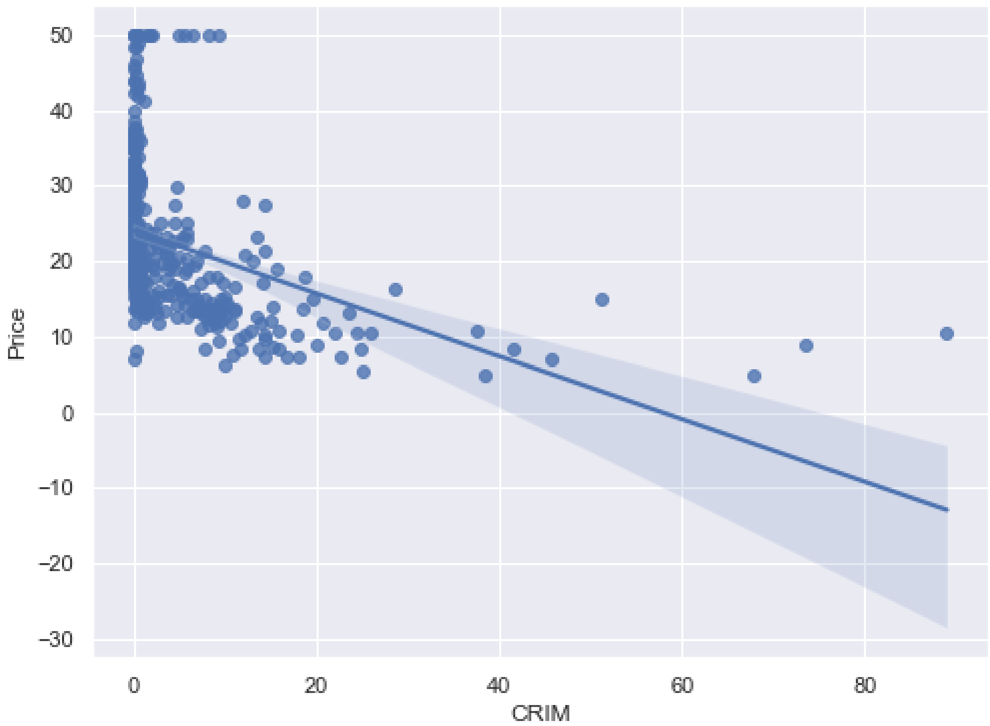


In [23]:

```
sns.regplot(x='CRIM',y='Price',data=dataset)
```

Out[23]:

```
<AxesSubplot:xlabel='CRIM', ylabel='Price'>
```



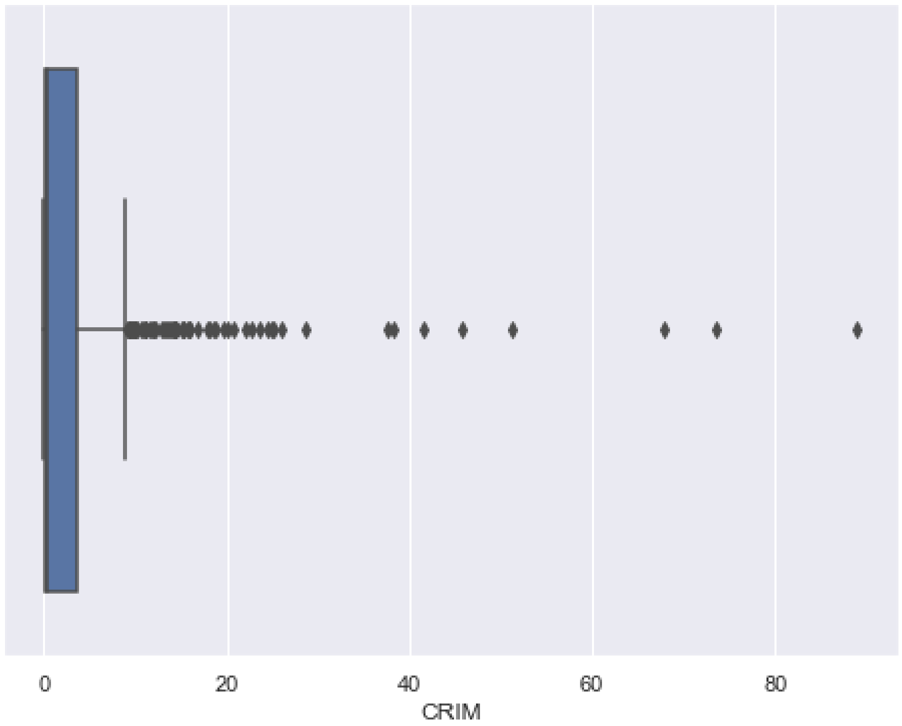
In [24]:

```
sns.boxplot(dataset['CRIM'])
```

```
C:\Users\sekar\anaconda3\lib\site-packages\seaborn\_decorators.py:36: Future
Warning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[24]:

```
<AxesSubplot:xlabel='CRIM'>
```



In [25]:

```
dataset.head()
```

Out[25]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
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	
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	
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	
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	
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	

In [26]:

```
## Independent and Dependent Features
X = dataset.iloc[:,:-1]
y = dataset.iloc[:,-1]
```

In [27]:

```
X.head()
```

Out[27]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
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	
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	
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	
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	
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	

In [28]:

```
y
```

Out[28]:

```
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 [29]:

```
from sklearn.model_selection import train_test_split  #test data validating the data
```

In [30]:

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.33,random_state=10)
```

In [31]:

```
X_train.shape
```

Out[31]:

```
(339, 13)
```

In [32]:

```
y_train.shape
```

Out[32]:

```
(339,)
```

In [33]:

```
X_test.shape
```

Out[33]:

```
(167, 13)
```

In [34]:

```
y_test.shape
```

Out[34]:

```
(167,)
```

In [35]:

```
y_test.shape
```

Out[35]:

```
(167,)
```

In [36]:

```
## Standardize or feature scaling the datasets
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
```

In [37]:

```
scaler
```

Out[37]:

```
StandardScaler()
```

In [38]:

```
X_train = scaler.fit_transform(X_train)
```

In [39]:

```
X_test=scaler.transform(X_test)
```

In [40]:

```
X_train
```

Out[40]:

```
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 [41]:

```
X_test
```

Out[41]:

```
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 [42]:

```
from sklearn.linear_model import LinearRegression
```

In [43]:

```
regression = LinearRegression()
```

In [44]:

```
regression
```

Out[44]:

```
LinearRegression()
```

In [45]:

```
regression.fit(X_train,y_train) #X train independet feature y train depfeaut
```

Out[45]:

```
LinearRegression()
```

In [46]:

```
##print the coefficents 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 [47]:

```
print(regression.intercept_)
```

```
22.077286135693214
```

In [48]:

```
## Prediction for the test data
reg_pred=regression.predict(X_test)
```

In [49]:

```
reg_pred
```

Out[49]:

```
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])
```

In [50]:

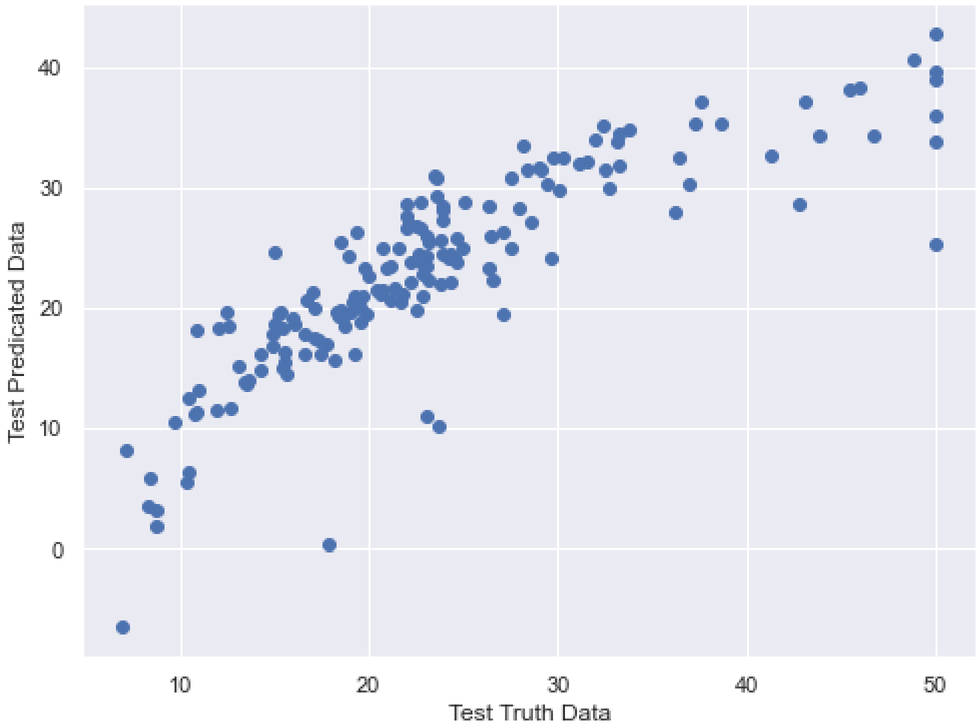
```
### Assumption of Linear Regression
```

In [51]:

```
plt.scatter(y_test,reg_pred)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predicated Data')
```

Out[51]:

```
Text(0, 0.5, 'Test Predicated Data')
```



In [52]:

```
##residuals
residuals=y_test-reg_pred
```

In [53]:

```
residuals
```

Out[53]:

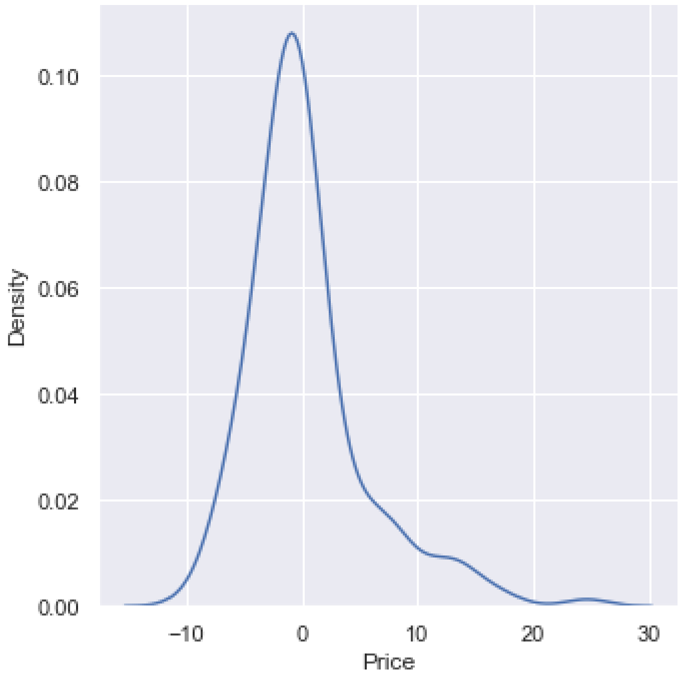
```
305   -3.038496
193   -0.887944
65    -7.498956
349    4.286033
151    0.705072
         ...
442   -1.004380
451   -4.387684
188   -2.638009
76    -2.661709
314   -1.885761
Name: Price, Length: 167, dtype: float64
```

In [54]:

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

Out[54]:

<seaborn.axisgrid.FacetGrid at 0x18083078fd0>

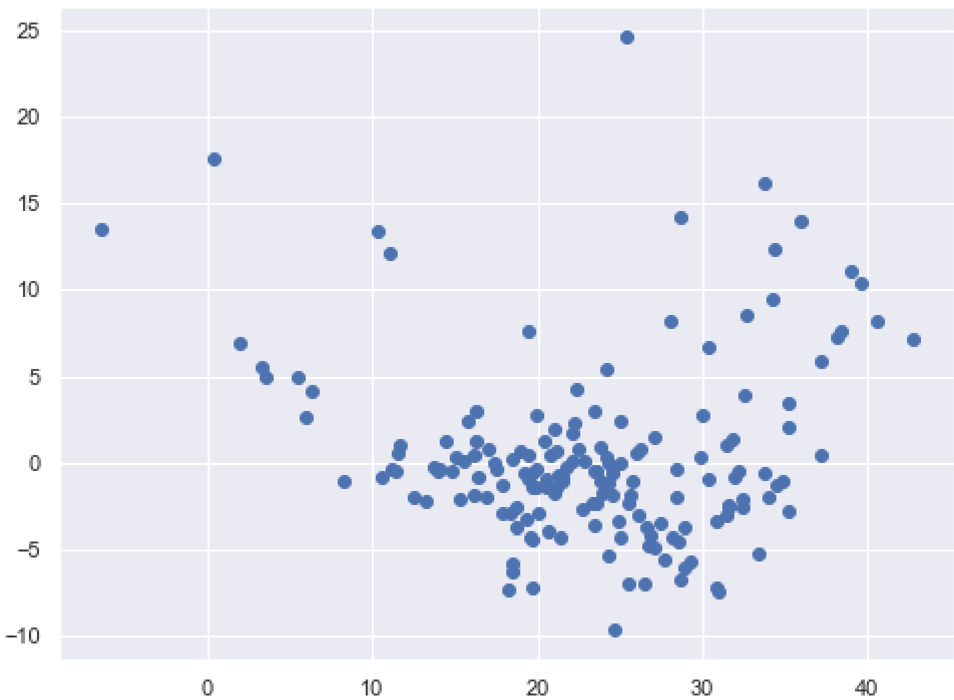


In [55]:

```
## Scattte plot  with preciction and residual
## uniform distribution
plt.scatter(reg_pred,residuals)  #Doubt Model is good or not
```

Out[55]:

<matplotlib.collections.PathCollection at 0x18083179fa0>



In [56]:

```
## performance Metrics
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)))
```

```
27.100991709962482
3.520658529879791
5.205861284164464
```

R square and adjusted R square

In [57]:

```
from sklearn.metrics import r2_score
score = r2_score(y_test,reg_pred)
print(score)
```

```
0.7165219393967555
```

In [58]:

```
#Adjusted R2 square
#display adjusted R-squared
1-(1-score)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[58]:

```
0.6924355682343882
```

In [59]:

```
## Ridge
from sklearn.linear_model import Ridge
ridge=Ridge()
```

In [60]:

```
ridge.fit(X_train,y_train)
```

Out[60]:

```
Ridge()
```

In [61]:

```
ridge_pred = ridge.predict(X_test)
```

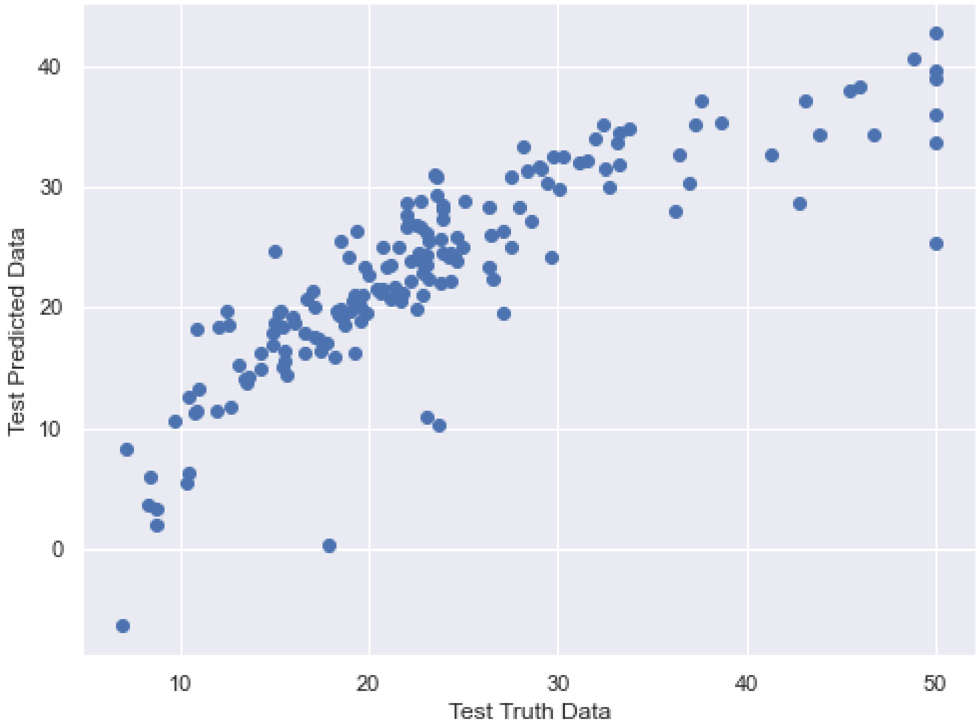
Assumptions of Ridge Regression

In [62]:

```
plt.scatter(y_test,ridge_pred)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predicted Data')
```

Out[62]:

```
Text(0, 0.5, 'Test Predicted Data')
```



In [63]:

```
## Residual
ridge_residuals = y_test-ridge_pred
ridge_residuals
```

Out[63]:

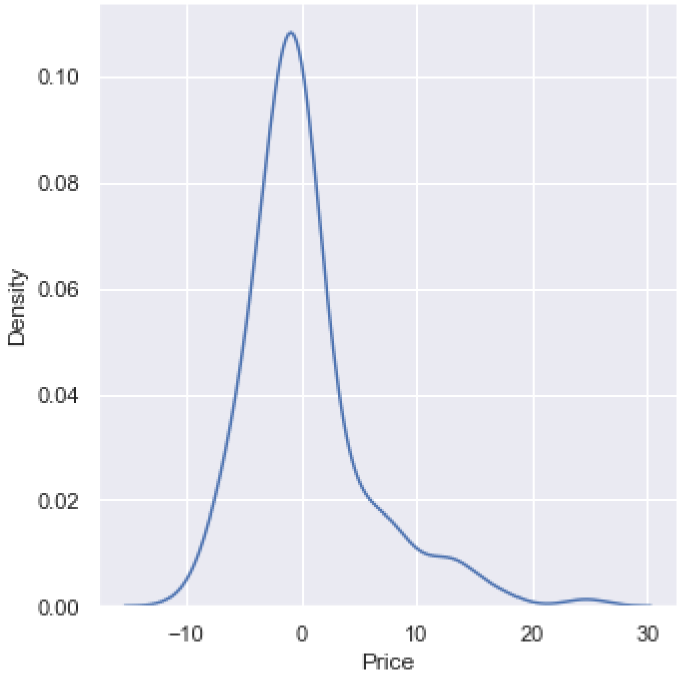
```
305   -2.929516
193   -0.881807
65    -7.465240
349    4.148877
151    0.668281
         ...
442   -0.994515
451   -4.392072
188   -2.629490
76    -2.670984
314   -1.883764
Name: Price, Length: 167, dtype: float64
```

In [64]:

```
## Normal distributed expected
sns.displot(ridge_residuals,kind='kde')
```

Out[64]:

```
<seaborn.axisgrid.FacetGrid at 0x1808316a280>
```

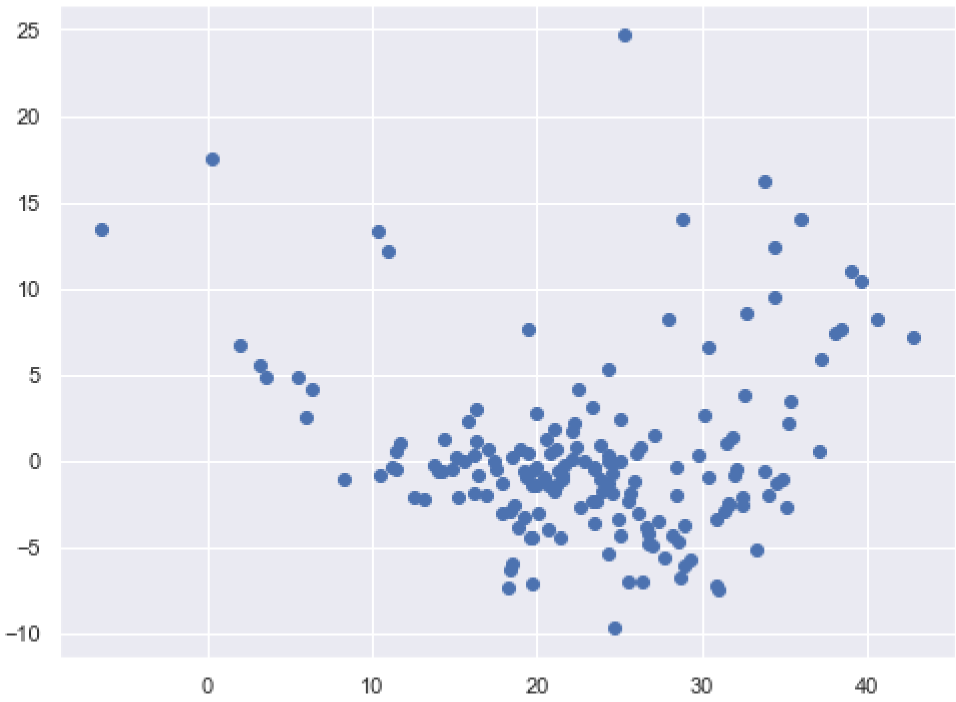


In [65]:

```
## Scatter plot with prediction and residual
## If it is Uniform distribution, model is good
plt.scatter(ridge_pred,ridge_residuals)
```

Out[65]:

<matplotlib.collections.PathCollection at 0x18085547be0>



In [67]:

```
## Performance Matrix
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
3.516104426348424
5.203507471066089
```

In [68]:

```
#R2 score
from sklearn.metrics import r2_score
r_score_ridge=r2_score(y_test,ridge_pred)
print(r_score_ridge)
```

```
0.716778228793379
```

In [69]:

```
## Adjusted R square
#display adjusted R-squared
1-(1-r_score_ridge)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[69]:

```
0.6927136338542543
```

Lasso Regression

In [72]:

```
## Lasso
from sklearn.linear_model import Lasso
lasso=Lasso()
```

In [73]:

```
lasso.fit(X_train,y_train)
```

Out[73]:

```
Lasso()
```

In [74]:

```
#Lasso Prediction
lasso_pred = lasso.predict(X_test)
```

In [75]:

```
lasso_pred
```

Out[75]:

```
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])
```

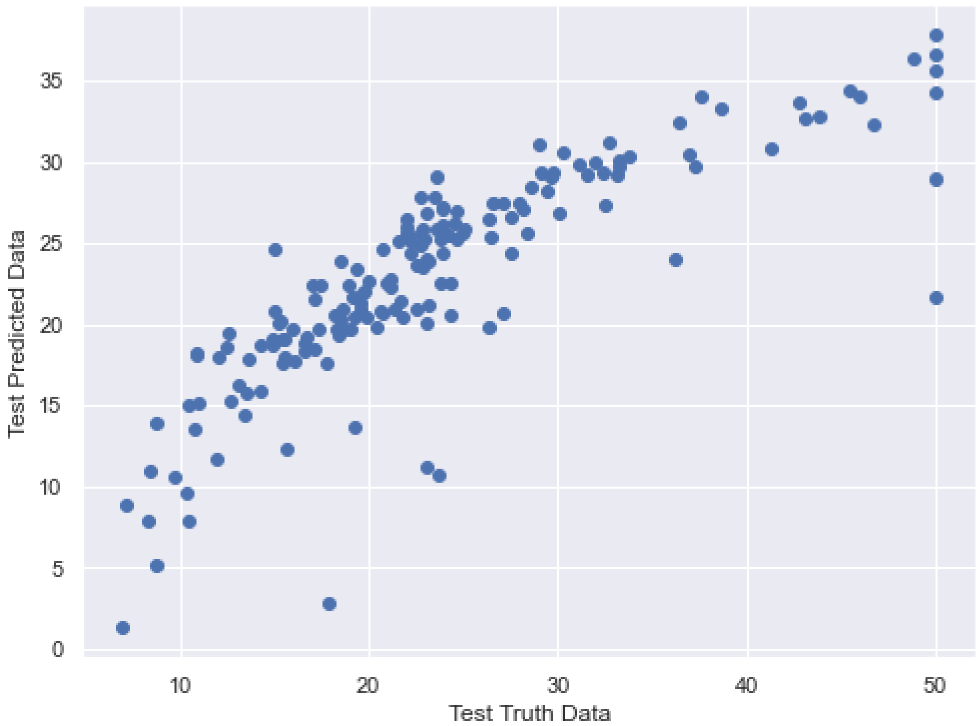
Assumptions of Lasso Regression

In [76]:

```
plt.scatter(y_test,lasso_pred)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predicted Data')
```

Out[76]:

```
Text(0, 0.5, 'Test Predicted Data')
```



In [77]:

```
## Residual
lasso_residuals = y_test-lasso_pred
lasso_residuals
```

Out[77]:

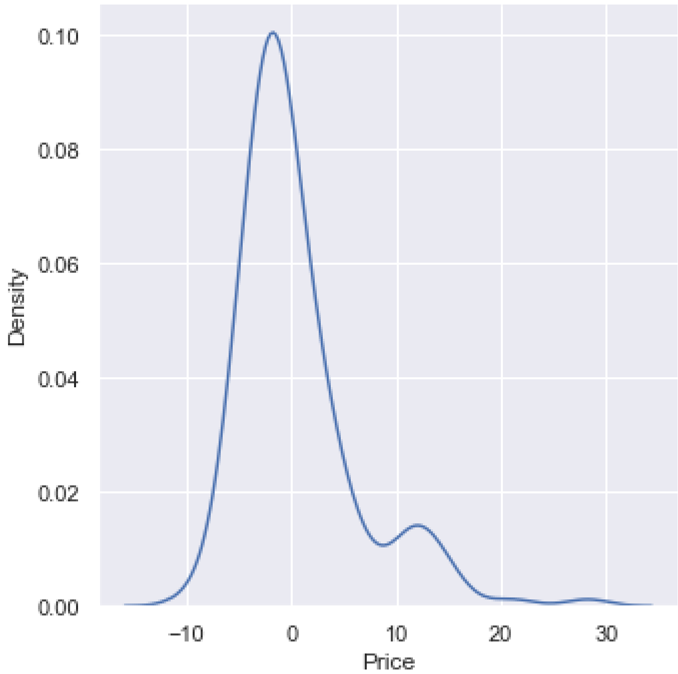
```
305    2.758056
193    1.285747
65    -4.443243
349   -0.952565
151   -1.396403
         ...
442   -0.975254
451   -4.919391
188    0.438910
76    -2.660821
314   -1.504938
Name: Price, Length: 167, dtype: float64
```

In [78]:

```
## Normal distribution expected
sns.displot(lasso_residuals,kind='kde')
```

Out[78]:

<seaborn.axisgrid.FacetGrid at 0x18087ac1640>

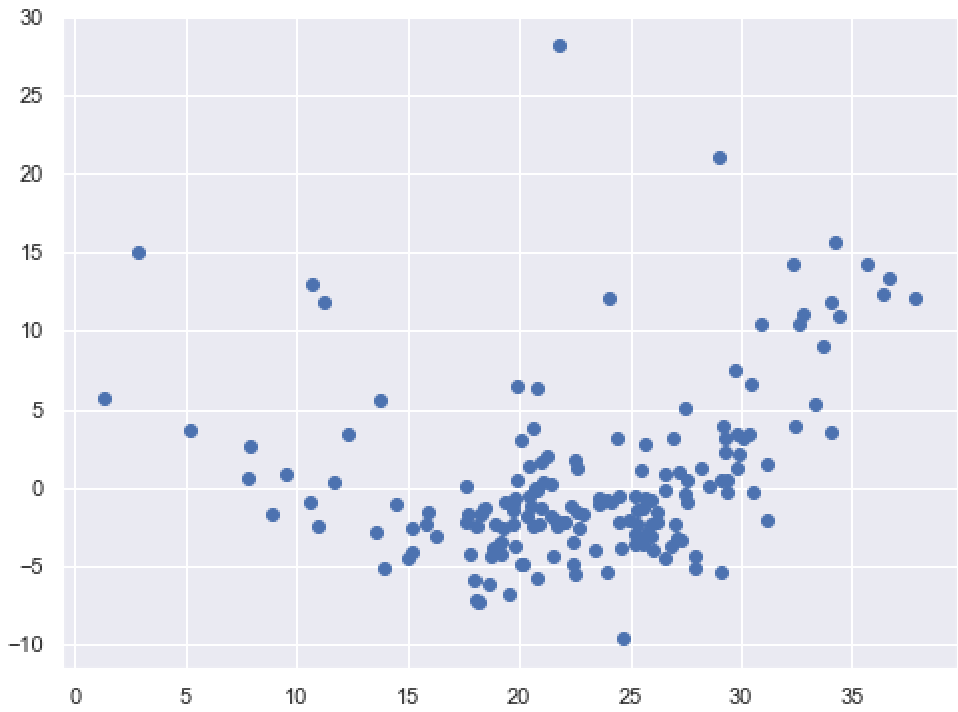


In [79]:

```
## Scatter plot with prediction and residual
## If it is Uniform distribution , model is good
plt.scatter(lasso_pred,lasso_residuals)
```

Out[79]:

```
<matplotlib.collections.PathCollection at 0x18088742b50>
```



In [80]:

```
## Performance Matrix
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,lasso_pred))
print(mean_absolute_error(y_test,lasso_pred))
print(np.sqrt(mean_squared_error(y_test,lasso_pred)))
```

```
32.16822537607397
3.9064325476573205
5.671703921757021
```

In [81]:

```
#R2 score
from sklearn.metrics import r2_score
r_score_lasso=r2_score(y_test,lasso_pred)
print(r_score_lasso)
```

```
0.6635183597615237
```

In [82]:

```
## Adjusted R square
#display adjusted R-squred
1-(1-r_score_lasso)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[82]:

```
0.6349284164732871
```

Elastic Net Regression

In [87]:

```
## Elastic Net
from sklearn.linear_model import ElasticNet
elasticnet = ElasticNet()
```

In [89]:

```
elasticnet.fit(X_train,y_train)
```

Out[89]:

```
ElasticNet()
```

In [91]:

```
## ElasticNet Prediction
elasticnet_pred = elasticnet.predict(X_test)
```

In [92]:

```
elasticnet_pred
```

Out[92]:

```
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])
```

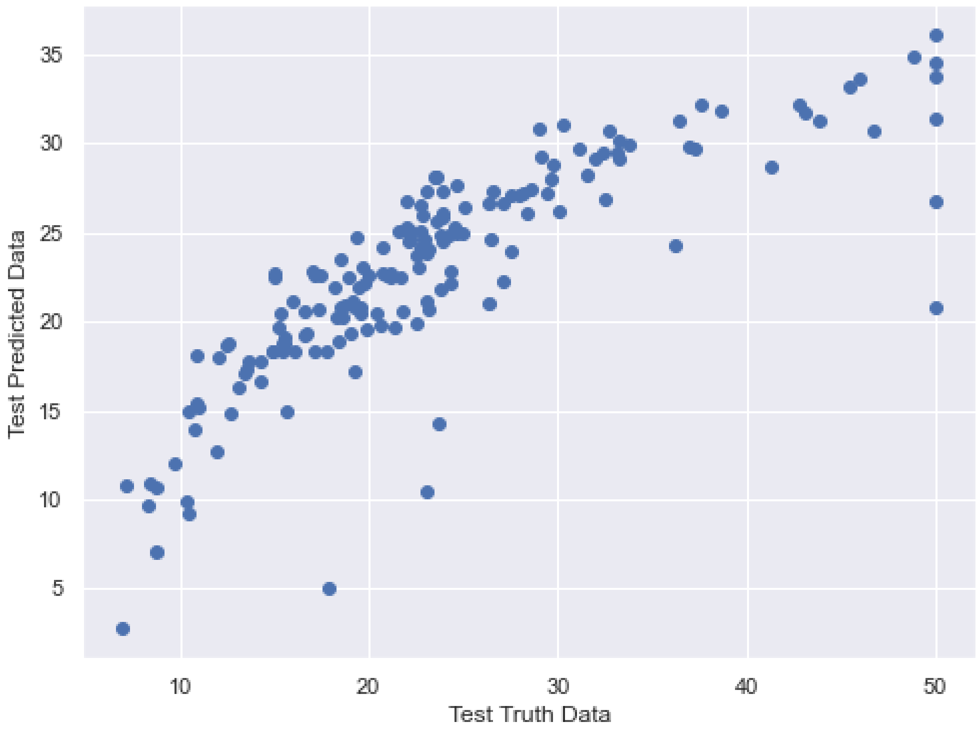
Assumptions of ElasticNet Regression

In [93]:

```
plt.scatter(y_test,elasticnet_pred)
plt.xlabel('Test Truth Data')
plt.ylabel('Test Predicted Data')
```

Out[93]:

```
Text(0, 0.5, 'Test Predicted Data')
```



In [94]:

```
## Residual
elasticnet_residuals = y_test-elasticnet_pred
elasticnet_residuals
```

Out[94]:

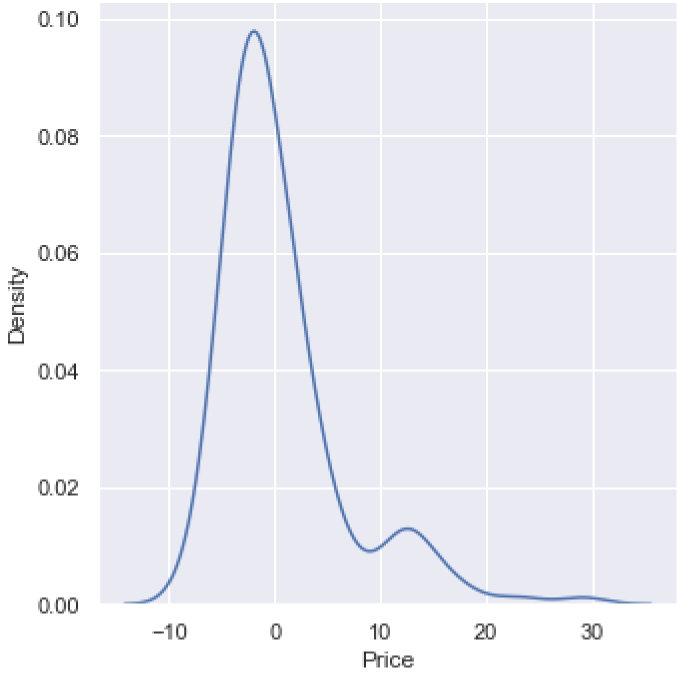
```
305    2.358247
193    1.371526
65    -4.632493
349   -0.731267
151   -0.828805
         ...
442   -0.527272
451   -4.495415
188    1.050616
76    -2.611671
314   -1.021046
Name: Price, Length: 167, dtype: float64
```

In [95]:

```
## Normal distribution expected
sns.displot(elasticnet_residuals,kind='kde')
```

Out[95]:

```
<seaborn.axisgrid.FacetGrid at 0x18087ac74f0>
```

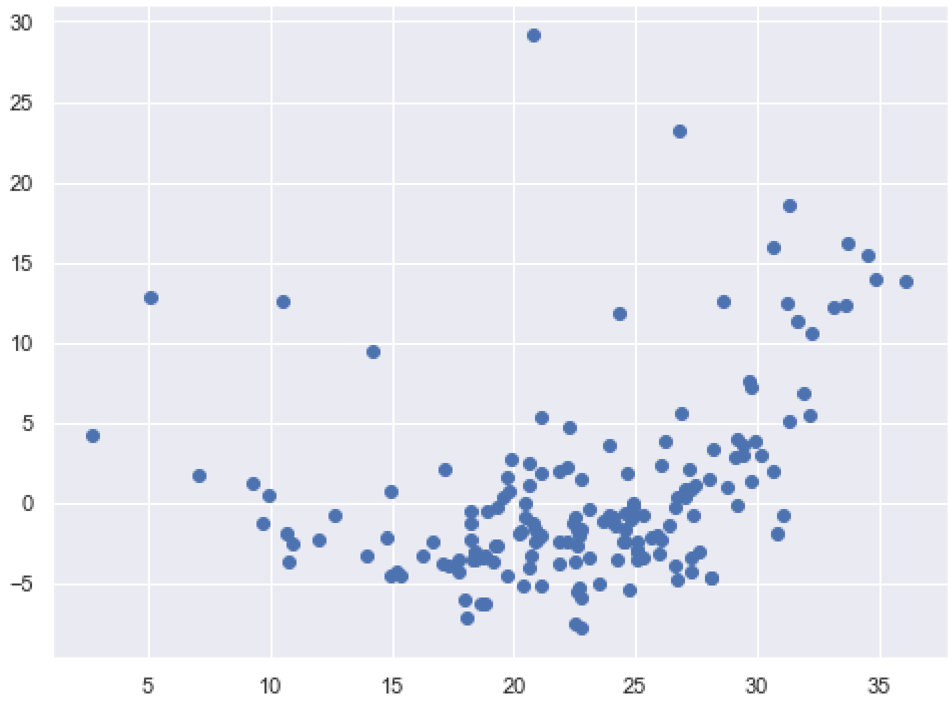


In [96]:

```
## Scatter plot with prediction and residual
## If it is uniform distribution , model is good
plt.scatter(elasticnet_pred,elasticnet_residuals)
```

Out[96]:

```
<matplotlib.collections.PathCollection at 0x180865df700>
```



In [98]:

```
## Performance Matrix
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
print(mean_squared_error(y_test,elasticnet_pred))
print(mean_absolute_error(y_test,elasticnet_pred))
print(np.sqrt(mean_squared_error(y_test,elasticnet_pred)))
```

```
35.341543853934674
4.035696708769101
5.944875427957652
```

In [99]:

```
#R2 Score
from sklearn.metrics import r2_score
r_score_elasticnet = r2_score(y_test,elasticnet_pred)
print(r_score_elasticnet)
```

0.6303252509112043

In [100]:

```
## Adjusted R sqaure
# display adjusted R-squared
1-(1-r_score_elasticnet)*(len(y_test)-1)/(len(y_test)-X_test.shape[1]-1)
```

Out[100]:

0.5989149781128098

In [101]:

```
!pip install nbconvert[webpdf]
```

```
Requirement already satisfied: nbconvert[webpdf] in c:\users\sekar\anacon
da3\lib\site-packages (6.1.0)
Requirement already satisfied: bleach in c:\users\sekar\anaconda3\lib\sit
e-packages (from nbconvert[webpdf]) (4.0.0)
Requirement already satisfied: traitlets>=5.0 in c:\users\sekar\anaconda3
\lib\site-packages (from nbconvert[webpdf]) (5.1.0)
Requirement already satisfied: nbformat>=4.4 in c:\users\sekar\anaconda3
\lib\site-packages (from nbconvert[webpdf]) (5.1.3)
Requirement already satisfied: nbclient<0.6.0,>=0.5.0 in c:\users\sekar\a
naconda3\lib\site-packages (from nbconvert[webpdf]) (0.5.3)
Requirement already satisfied: jinja2>=2.4 in c:\users\sekar\anaconda3\li
b\site-packages (from nbconvert[webpdf]) (2.11.3)
Requirement already satisfied: jupyterlab-pygments in c:\users\sekar\anac
onda3\lib\site-packages (from nbconvert[webpdf]) (0.1.2)
Requirement already satisfied: jupyter-core in c:\users\sekar\anaconda3\l
ib\site-packages (from nbconvert[webpdf]) (4.8.1)
Requirement already satisfied: pygments>=2.4.1 in c:\users\sekar\anaconda
3\lib\site-packages (from nbconvert[webpdf]) (2.10.0)
Requirement already satisfied: entrypoints>=0.2.2 in c:\users\sekar\anaco
nda3\lib\site-packages (from nbconvert[webpdf]) (0.3)
Requirement already satisfied: defusedxml in c:\users\sekar\anaconda3\lib
\site-packages (from nbconvert[webpdf]) (0.7.1)
Requirement already satisfied: mistune<2,>=0.8.1 in c:\users\sekar\anacon
da3\lib\site-packages (from nbconvert[webpdf]) (0.8.4)
Requirement already satisfied: testpath in c:\users\sekar\anaconda3\lib\s
ite-packages (from nbconvert[webpdf]) (0.5.0)
Requirement already satisfied: pandocfilters>=1.4.1 in c:\users\sekar\ana
conda3\lib\site-packages (from nbconvert[webpdf]) (1.4.3)
Collecting pyppeteer==0.2.2
  Downloading pyppeteer-0.2.2-py3-none-any.whl (145 kB)
Collecting websockets<9.0,>=8.1
  Downloading websockets-8.1.tar.gz (58 kB)
Requirement already satisfied: appdirs<2.0.0,>=1.4.3 in c:\users\sekar\an
aconda3\lib\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (1.
4.4)
Requirement already satisfied: urllib3<2.0.0,>=1.25.8 in c:\users\sekar\a
naconda3\lib\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (1.
26.7)
Requirement already satisfied: tqdm<5.0.0,>=4.42.1 in c:\users\sekar\anac
onda3\lib\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (4.62.
3)
Collecting pyee<8.0.0,>=7.0.1
  Downloading pyee-7.0.4-py2.py3-none-any.whl (12 kB)
Requirement already satisfied: MarkupSafe>=0.23 in c:\users\sekar\anacond
a3\lib\site-packages (from jinja2>=2.4->nbconvert[webpdf]) (2.0.1)
Requirement already satisfied: nest-asyncio in c:\users\sekar\anaconda3\l
ib\site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (1.5.1)
Requirement already satisfied: jupyter-client>=6.1.5 in c:\users\sekar\an
aconda3\lib\site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert[webpd
f]) (6.1.12)
Requirement already satisfied: async-generator in c:\users\sekar\anaconda
3\lib\site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (1.1
0)
Requirement already satisfied: pyzmq>=13 in c:\users\sekar\anaconda3\lib
\site-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbcon
vert[webpdf]) (22.2.1)
```

```
Requirement already satisfied: tornado>=4.1 in c:\users\sekar\anaconda3\l
ib\site-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbc
onvert[webpdf]) (6.1)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\sekar\ana
conda3\lib\site-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.
5.0->nbconvert[webpdf]) (2.8.2)
Requirement already satisfied: pywin32>=1.0 in c:\users\sekar\anaconda3\l
ib\site-packages (from jupyter-core->nbconvert[webpdf]) (228)
Requirement already satisfied: ipython-genutils in c:\users\sekar\anacond
a3\lib\site-packages (from nbformat>=4.4->nbconvert[webpdf]) (0.2.0)
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in c:\users\sekar
\anaconda3\lib\site-packages (from nbformat>=4.4->nbconvert[webpdf]) (3.
2.0)
Requirement already satisfied: pyrsistent>=0.14.0 in c:\users\sekar\anaco
nda3\lib\site-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbco
nvert[webpdf]) (0.18.0)
Requirement already satisfied: setuptools in c:\users\sekar\anaconda3\lib
\site-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert[we
bpdf]) (58.0.4)
Requirement already satisfied: six>=1.11.0 in c:\users\sekar\anaconda3\li
b\site-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert[w
ebpdf]) (1.16.0)
Requirement already satisfied: attrs>=17.4.0 in c:\users\sekar\anaconda3
\lib\site-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconver
t[webpdf]) (21.2.0)
Requirement already satisfied: colorama in c:\users\sekar\anaconda3\lib\s
ite-packages (from tqdm<5.0.0,>=4.42.1->pyppeteer==0.2.2->nbconvert[webpd
f]) (0.4.4)
Requirement already satisfied: webencodings in c:\users\sekar\anaconda3\l
ib\site-packages (from bleach->nbconvert[webpdf]) (0.5.1)
Requirement already satisfied: packaging in c:\users\sekar\anaconda3\lib
\site-packages (from bleach->nbconvert[webpdf]) (21.0)
Requirement already satisfied: pyparsing>=2.0.2 in c:\users\sekar\anacond
a3\lib\site-packages (from packaging->bleach->nbconvert[webpdf]) (3.0.4)
Building wheels for collected packages: websockets
  Building wheel for websockets (setup.py): started
  Building wheel for websockets (setup.py): finished with status 'done'
  Created wheel for websockets: filename=websockets-8.1-cp39-cp39-win_amd
64.whl size=62758 sha256=816b4578c8e95e0d6f2b3a6b9e7080b64752f253a001ab39
f959f01974efac18
  Stored in directory: c:\users\sekar\appdata\local\pip\cache\wheels\d8\b
9\a0\b97b211aeda2ebd6ac2e43fc300d308dbf1f9df520ed390cae
Successfully built websockets
Installing collected packages: websockets, pyee, pyppeteer
Successfully installed pyee-7.0.4 pyppeteer-0.2.2 websockets-8.1
```

In [ ]: