Linear Regression

Linear Regression Practical implementation on Boston dataset

Life cycle of Machine learning Project

```
1.Understanding the Problem Statement
2.Data Collection
3.Exploratory data analysis
4.Data Cleaning
5.Data Pre-Processing
6.Model Training
7.Choose best model
```

Data Collection

importing required libraries

In [1]:

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

importing data

In [2]:

```
from sklearn.datasets import load_boston
```

In [3]:

```
boston = load_boston()
boston
```

Out[3]:

```
{'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690
e+02,
         4.9800e+00],
        [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
         9.1400e+00],
        [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
         4.0300e+00],
        ...,
        [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         5.6400e+00],
        [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
         6.4800e+00],
        [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         7.8800e+00]]),
 'target': array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.
9, 15. ,
        18.9, 21.7, 20.4, 18.2, 19.9, 23.1, 17.5, 20.2, 18.2, 13.6, 19.6,
        15.2, 14.5, 15.6, 13.9, 16.6, 14.8, 18.4, 21. , 12.7, 14.5, 13.2,
        13.1, 13.5, 18.9, 20. , 21. , 24.7, 30.8, 34.9, 26.6, 25.3, 24.7,
        21.2, 19.3, 20. , 16.6, 14.4, 19.4, 19.7, 20.5, 25. , 23.4, 18.9,
        35.4, 24.7, 31.6, 23.3, 19.6, 18.7, 16. , 22.2, 25. , 33. , 23.5,
        19.4, 22. , 17.4, 20.9, 24.2, 21.7, 22.8, 23.4, 24.1, 21.4, 20. ,
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        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. ,
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        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,
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        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,
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        42.8, 21.9, 20.9, 44. , 50. , 36. , 30.1, 33.8, 43.1, 48.8, 31. ,
        36.5, 22.8, 30.7, 50. , 43.5, 20.7, 21.1, 25.2, 24.4, 35.2, 32.4,
        32. , 33.2, 33.1, 29.1, 35.1, 45.4, 35.4, 46. , 50. , 32.2, 22. ,
        20.1, 23.2, 22.3, 24.8, 28.5, 37.3, 27.9, 23.9, 21.7, 28.6, 27.1,
        20.3, 22.5, 29. , 24.8, 22. , 26.4, 33.1, 36.1, 28.4, 33.4, 28.2,
        22.8, 20.3, 16.1, 22.1, 19.4, 21.6, 23.8, 16.2, 17.8, 19.8, 23.1,
        21. , 23.8, 23.1, 20.4, 18.5, 25. , 24.6, 23. , 22.2, 19.3, 22.6,
        19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
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        18.6, 30.1, 18.2, 20.6, 17.8, 21.7, 22.7, 22.6, 25. , 19.9, 20.8,
        16.8, 21.9, 27.5, 21.9, 23.1, 50. , 50. , 50. , 50. , 50. , 13.8,
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         7.2, 10.5,  7.4, 10.2, 11.5, 15.1, 23.2,  9.7, 13.8, 12.7, 13.1,
        12.5,  8.5,  5. ,  6.3,  5.6,  7.2, 12.1,  8.3,  8.5,  5. , 11.9,
        27.9, 17.2, 27.5, 15. , 17.2, 17.9, 16.3,  7. ,  7.2,  7.5, 10.4,
         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,
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 'feature_names': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE',
'DIS', 'RAD',
        'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'),
 'DESCR': ".. _boston_dataset:\n\nBoston house prices dataset\n-------------
--------------\n\n**Data Set Characteristics:**  \n\n    :Number of Instance
s: 506 \n\n    :Number of Attributes: 13 numeric/categorical predictive. Med
ian Value (attribute 14) is usually the target.\n\n    :Attribute Informatio
n (in order):\n        - CRIM     per capita crime rate by town\n        - Z
N       proportion of residential land zoned for lots over 25,000 sq.ft.\n
- INDUS    proportion of non-retail business acres per town\n        - CHAS
Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)\n
- NOX      nitric oxides concentration (parts per 10 million)\n        - RM
average number of rooms per dwelling\n        - AGE      proportion of owner
-occupied units built prior to 1940\n        - DIS      weighted distances t
o five Boston employment centres\n        - RAD      index of accessibility
to radial highways\n        - TAX      full-value property-tax rate per $10,
000\n        - PTRATIO  pupil-teacher ratio by town\n        - B        1000
(Bk - 0.63)^2 where Bk is the proportion of black people by town\n        -
LSTAT    % lower status of the population\n        - MEDV     Median value o
f owner-occupied homes in $1000's\n\n    :Missing Attribute Values: None\n\n
:Creator: Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housi
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& Welsch, 'Regression diagnostics\n...', Wiley, 1980.   N.B. Various transfo
rmations are used in the table on\npages 244-261 of the latter.\n\nThe Bosto
n house-price data has been used in many machine learning papers that addres
s regression\nproblems.   \n     \n.. topic:: References\n\n   - Belsley, Ku
h & Welsch, 'Regression diagnostics: Identifying Influential Data and Source
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Instance-Based and Model-Based Learning. In Proceedings on the Tenth Interna
tional Conference of Machine Learning, 236-243, University of Massachusetts,
Amherst. Morgan Kaufmann.\n",
 'filename': 'C:\\Users\\DHARAVATH RAMDAS\\Anaconda3\\lib\\site-packages\\sk
learn\\datasets\\data\\boston_house_prices.csv'}
```

In [4]:

```
print(boston)
```

```
{'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690
e+02,
         4.9800e+00],
        [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
         9.1400e+00],
        [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
         4.0300e+00],
        ...,
        [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         5.6400e+00],
        [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
         6.4800e+00],
        [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         7.8800e+00]]), 'target': array([24. , 21.6, 34.7, 33.4, 36.2, 28.7,
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       13.1, 13.5, 18.9, 20. , 21. , 24.7, 30.8, 34.9, 26.6, 25.3, 24.7,
       21.2, 19.3, 20. , 16.6, 14.4, 19.4, 19.7, 20.5, 25. , 23.4, 18.9,
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       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,
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       20.3, 22.5, 29. , 24.8, 22. , 26.4, 33.1, 36.1, 28.4, 33.4, 28.2,
       22.8, 20.3, 16.1, 22.1, 19.4, 21.6, 23.8, 16.2, 17.8, 19.8, 23.1,
       21. , 23.8, 23.1, 20.4, 18.5, 25. , 24.6, 23. , 22.2, 19.3, 22.6,
       19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
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       13.8, 15. , 13.9, 13.3, 13.1, 10.2, 10.4, 10.9, 11.3, 12.3,  8.8,
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        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,
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       29.8, 13.8, 13.3, 16.7, 12. , 14.6, 21.4, 23. , 23.7, 25. , 21.8,
       20.6, 21.2, 19.1, 20.6, 15.2,  7. ,  8.1, 13.6, 20.1, 21.8, 24.5,
       23.1, 19.7, 18.3, 21.2, 17.5, 16.8, 22.4, 20.6, 23.9, 22. , 11.9]),
'feature_names': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE',
'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'), 'DESCR': ".. _boston_d
ataset:\n\nBoston house prices dataset\n---------------------------\n\n**Dat
a Set Characteristics:**  \n\n    :Number of Instances: 506 \n\n    :Number
of Attributes: 13 numeric/categorical predictive. Median Value (attribute 1
4) is usually the target.\n\n    :Attribute Information (in order):\n
- CRIM     per capita crime rate by town\n        - ZN       proportion of r
esidential land zoned for lots over 25,000 sq.ft.\n        - INDUS    propor
tion 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       avera
ge number of rooms per dwelling\n        - AGE      proportion of owner-occu
pied units built prior to 1940\n        - DIS      weighted distances to fiv
e Boston employment centres\n        - RAD      index of accessibility to ra
dial 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    % low
er status of the population\n        - MEDV     Median value of owner-occupi
ed homes in $1000's\n\n    :Missing Attribute Values: None\n\n    :Creator:
Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing datase
t.\nhttps://archive.ics.uci.edu/ml/machine-learning-databases/housing/\n\n\n
This dataset was taken from the StatLib library which is maintained at Carne
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re used in the table on\npages 244-261 of the latter.\n\nThe Boston house-pr
ice data has been used in many machine learning papers that address regressi
on\nproblems.   \n     \n.. topic:: References\n\n   - Belsley, Kuh & Welsc
h, 'Regression diagnostics: Identifying Influential Data and Sources of Coll
inearity', Wiley, 1980. 244-261.\n   - Quinlan,R. (1993). Combining Instance
-Based and Model-Based Learning. In Proceedings on the Tenth International C
onference of Machine Learning, 236-243, University of Massachusetts, Amhers
t. Morgan Kaufmann.\n", 'filename': 'C:\\Users\\DHARAVATH RAMDAS\\Anaconda3
\\lib\\site-packages\\sklearn\\datasets\\data\\boston_house_prices.csv'}
```

In [5]:

```
boston.keys()
```

Out[5]:

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

In [6]:

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

```
.. _boston_dataset:

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

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value
(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 river;
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 peo
ple by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

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

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


This dataset was taken from the StatLib library which is maintained at Carne
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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 diagnostic
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...', 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 th
at address regression
problems.

.. topic:: References

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

In [7]:

```
print(boston.data)
```

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

In [8]:

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

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

In [9]:

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

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

lets prepare dataset

In [10]:

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

In [11]:

```
dataset.head()
```

Out[11]:

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

output feature adding

In [12]:

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

In [13]:

```
dataset.head()
```

Out[13]:

	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	

check datatype of features in dataset

In [14]:

```
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
```

describe is used for statistics analysis

In [15]:

```
dataset.describe()
```

Out[15]:

	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.

transpose the describe

In [16]:

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

Out[16]:

	count	mean	std	min	25%	50%	75%	ma
CRIM	506.0	3.613524	8.601545	0.00632	0.082045	0.25651	3.677083	88.976
ZN	506.0	11.363636	23.322453	0.00000	0.000000	0.00000	12.500000	100.000
INDUS	506.0	11.136779	6.860353	0.46000	5.190000	9.69000	18.100000	27.740
CHAS	506.0	0.069170	0.253994	0.00000	0.000000	0.00000	0.000000	1.000
NOX	506.0	0.554695	0.115878	0.38500	0.449000	0.53800	0.624000	0.871
RM	506.0	6.284634	0.702617	3.56100	5.885500	6.20850	6.623500	8.780
AGE	506.0	68.574901	28.148861	2.90000	45.025000	77.50000	94.075000	100.000
DIS	506.0	3.795043	2.105710	1.12960	2.100175	3.20745	5.188425	12.126
RAD	506.0	9.549407	8.707259	1.00000	4.000000	5.00000	24.000000	24.000
TAX	506.0	408.237154	168.537116	187.00000	279.000000	330.00000	666.000000	711.000
PTRATIO	506.0	18.455534	2.164946	12.60000	17.400000	19.05000	20.200000	22.000
B	506.0	356.674032	91.294864	0.32000	375.377500	391.44000	396.225000	396.900
LSTAT	506.0	12.653063	7.141062	1.73000	6.950000	11.36000	16.955000	37.970
Price	506.0	22.532806	9.197104	5.00000	17.025000	21.20000	25.000000	50.000

check the missing values

In [17]:

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

Out[17]:

```
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
```

relation betweeen independent and dependent feat

In [18]:

```
## EDA
```

In [19]:

```
dataset.corr()
```

Out[19]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670
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 [20]:

```
# we go with more 95%
```

corr visualization

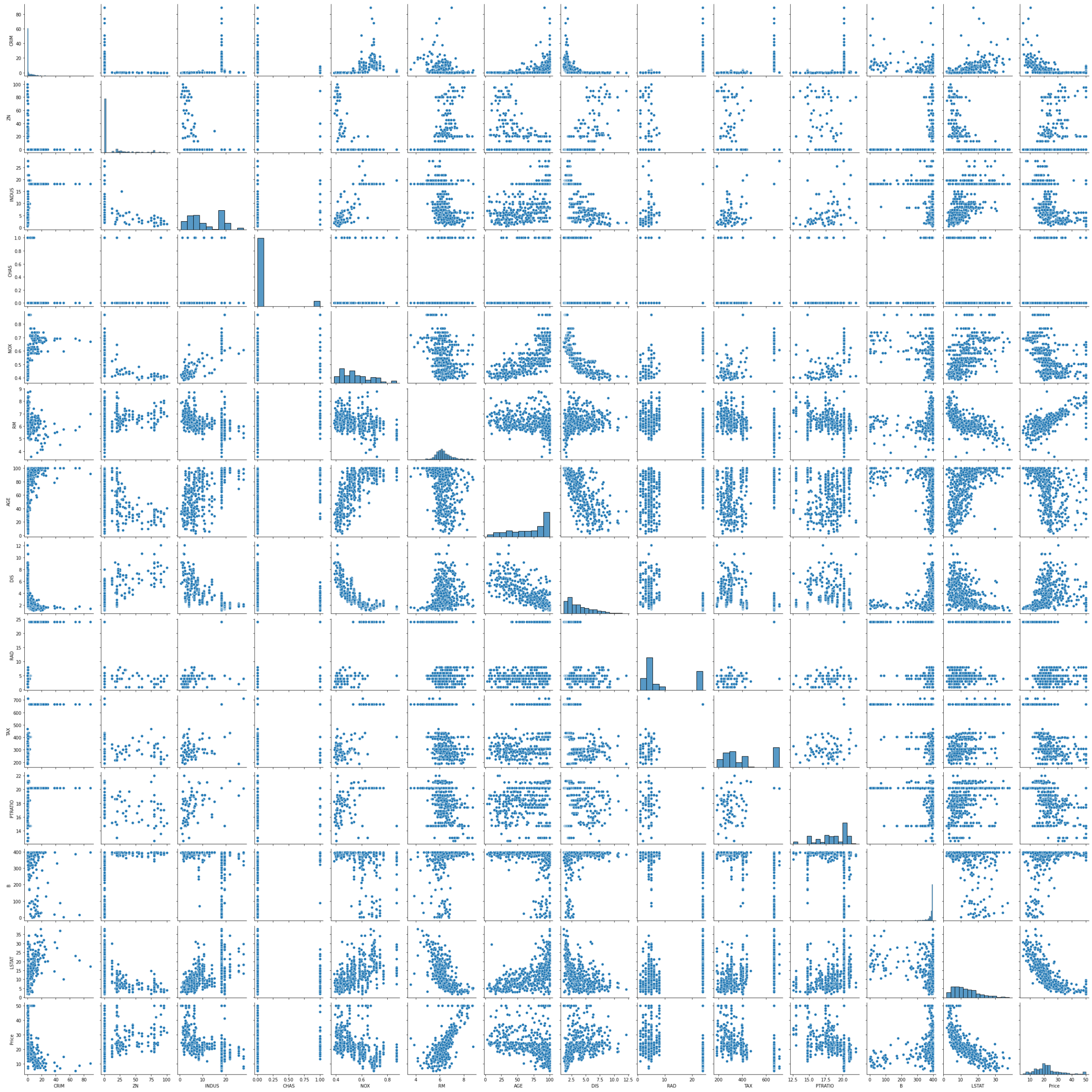
Pairplot

In [21]:

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

Out[21]:

```
<seaborn.axisgrid.PairGrid at 0x22674e599a0>
```



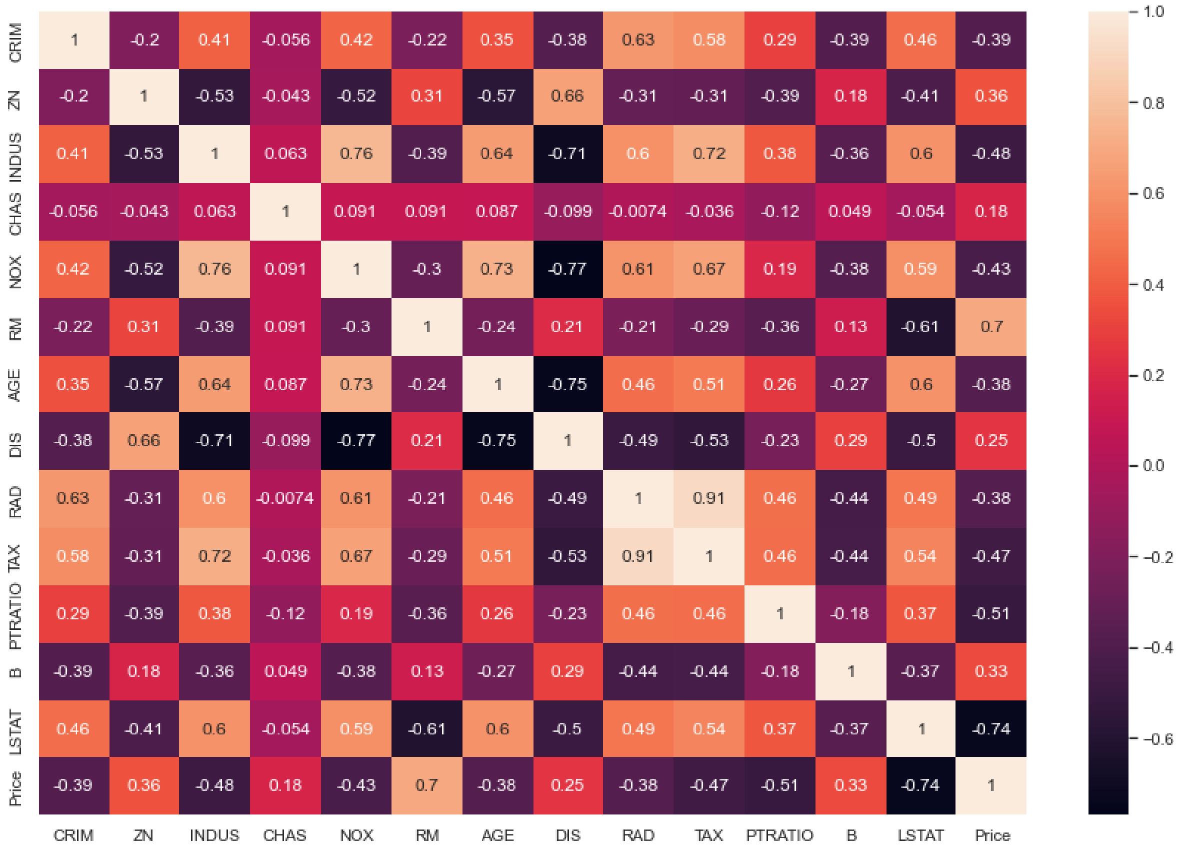
Heatmap

In [22]:

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

Out[22]:

```
<AxesSubplot:>
```



In [23]:

```
# price is dependent feature
```

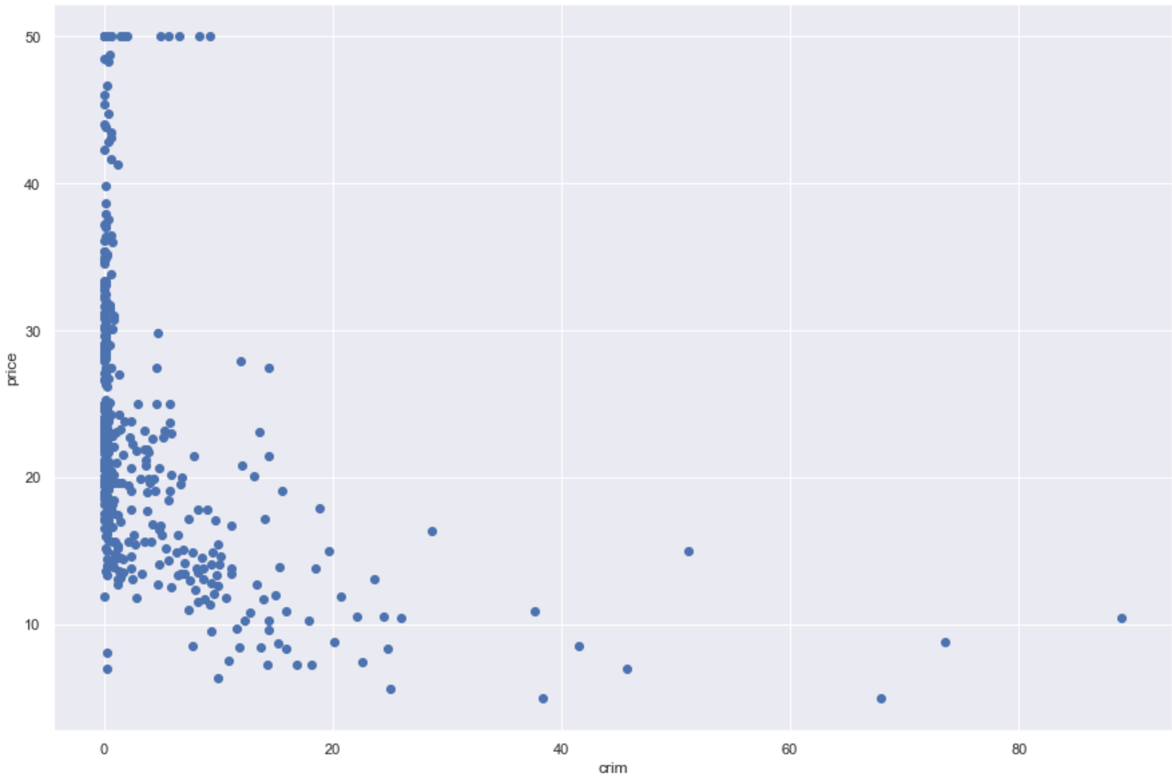
Scatter plot

In [24]:

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

Out[24]:

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

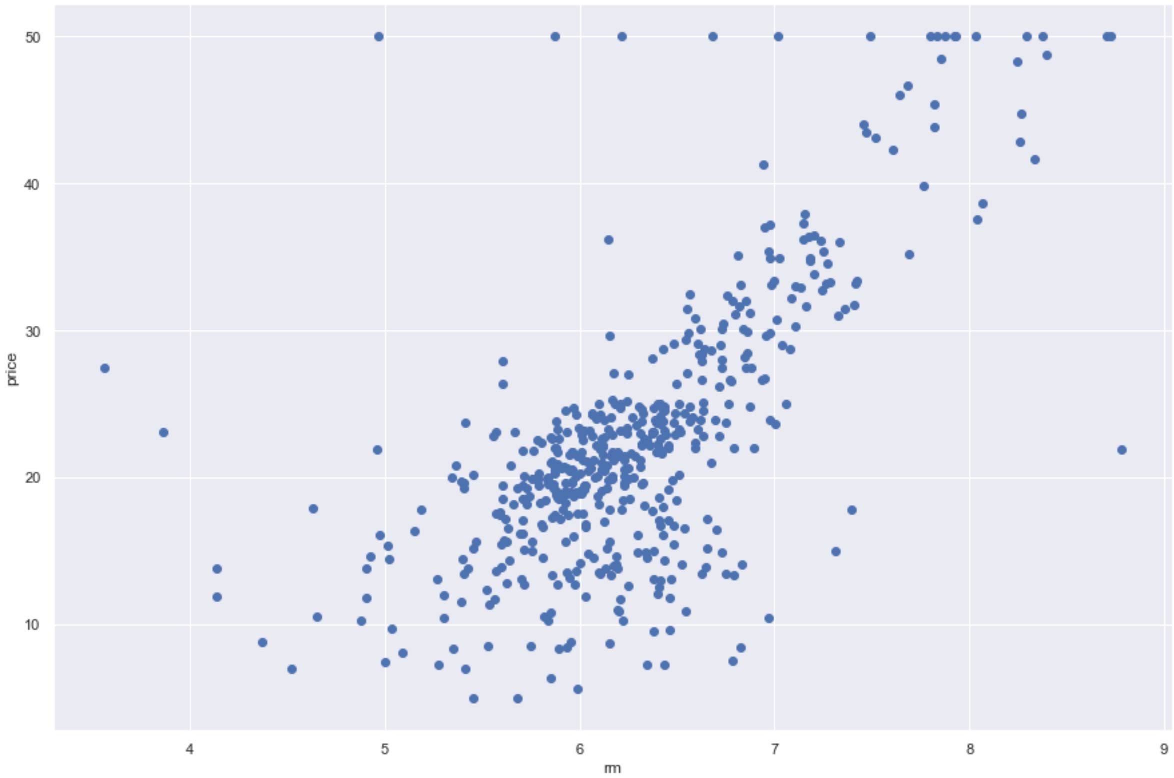


In [25]:

```
plt.scatter(dataset['RM'],dataset['Price'])
plt.xlabel("rm")
plt.ylabel("price")
```

Out[25]:

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



In [ ]:

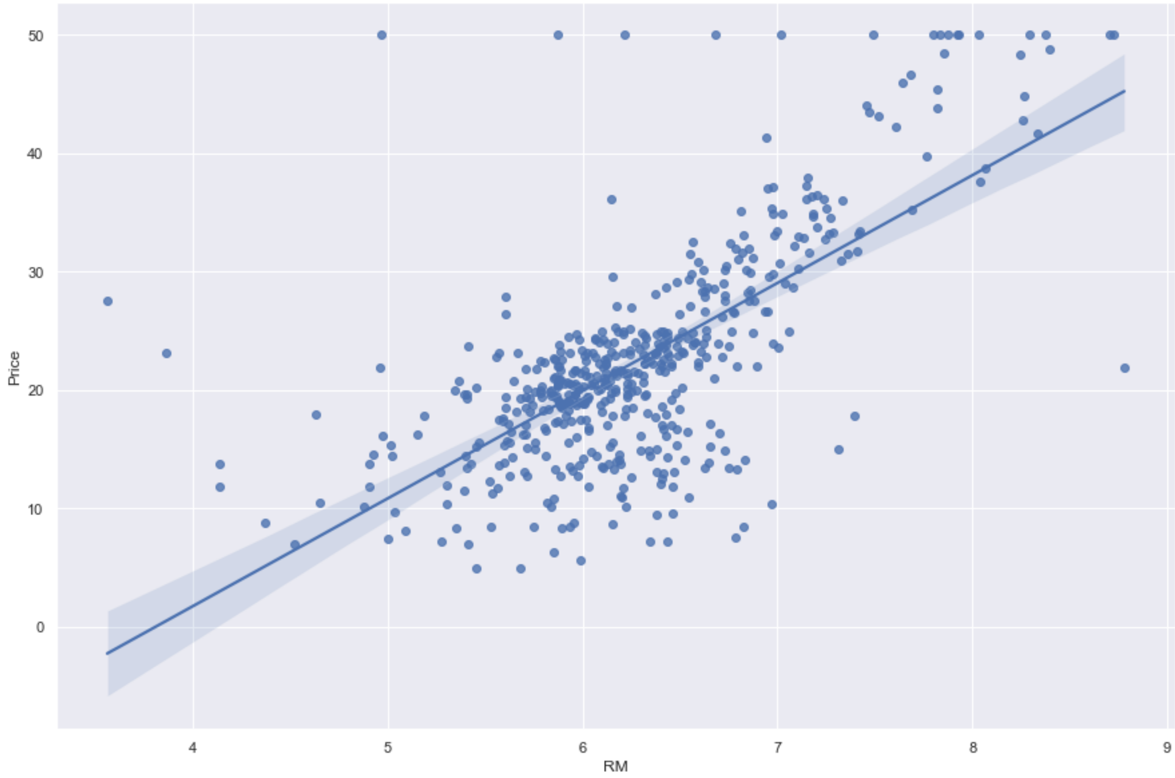
plot data in linear regression

In [26]:

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

Out[26]:

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



In [27]:

```
# shaded region  in plot  is redge and lasso
# we see more points is there not shaped mean gap
# other have
# point is more the shade region is less
# point is less the shade region is high
```

In [28]:

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

Out[28]:

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

Boxplot

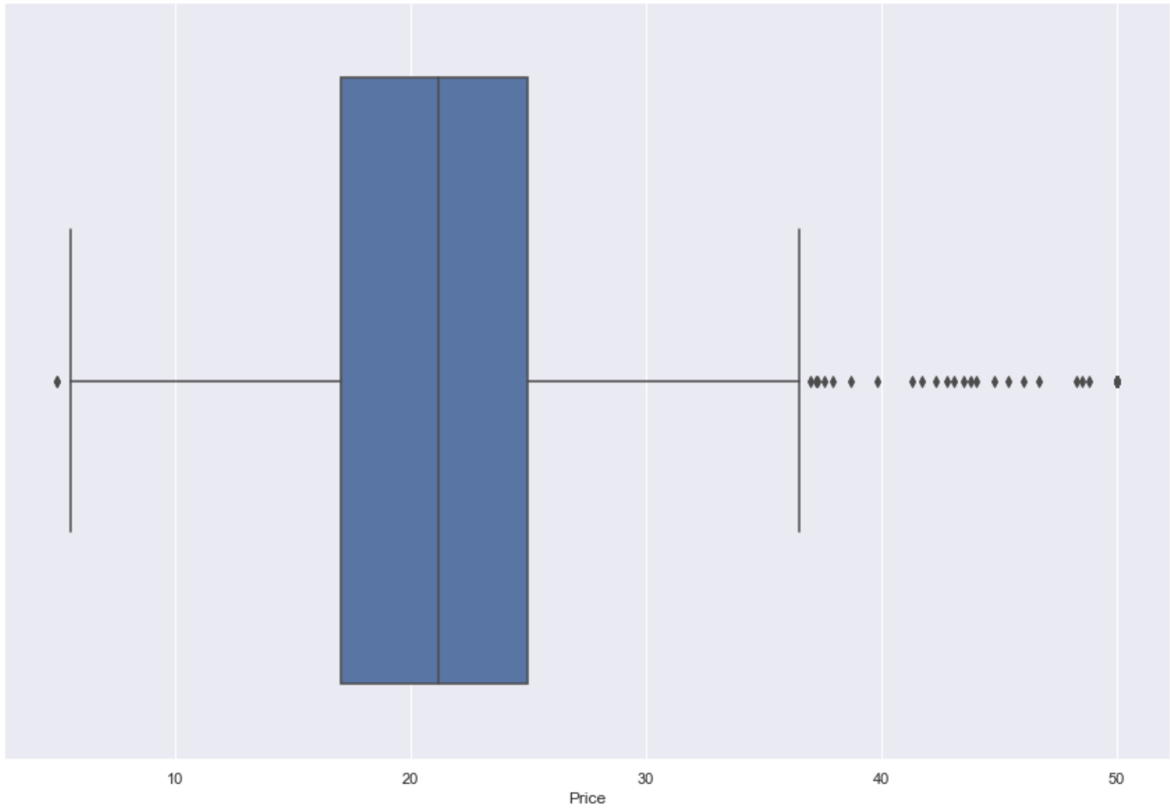
In [29]:

```
sns.boxplot(dataset["Price"])
```

```
C:\Users\DHARAVATH RAMDAS\Anaconda3\lib\site-packages\seaborn\_decorators.p
y:36: FutureWarning: Pass the following variable as a keyword arg: x. From v
ersion 0.12, the only valid positional argument will be `data`, and passing
other arguments without an explicit keyword will result in an error or misin
terpretation.
  warnings.warn(
```

Out[29]:

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



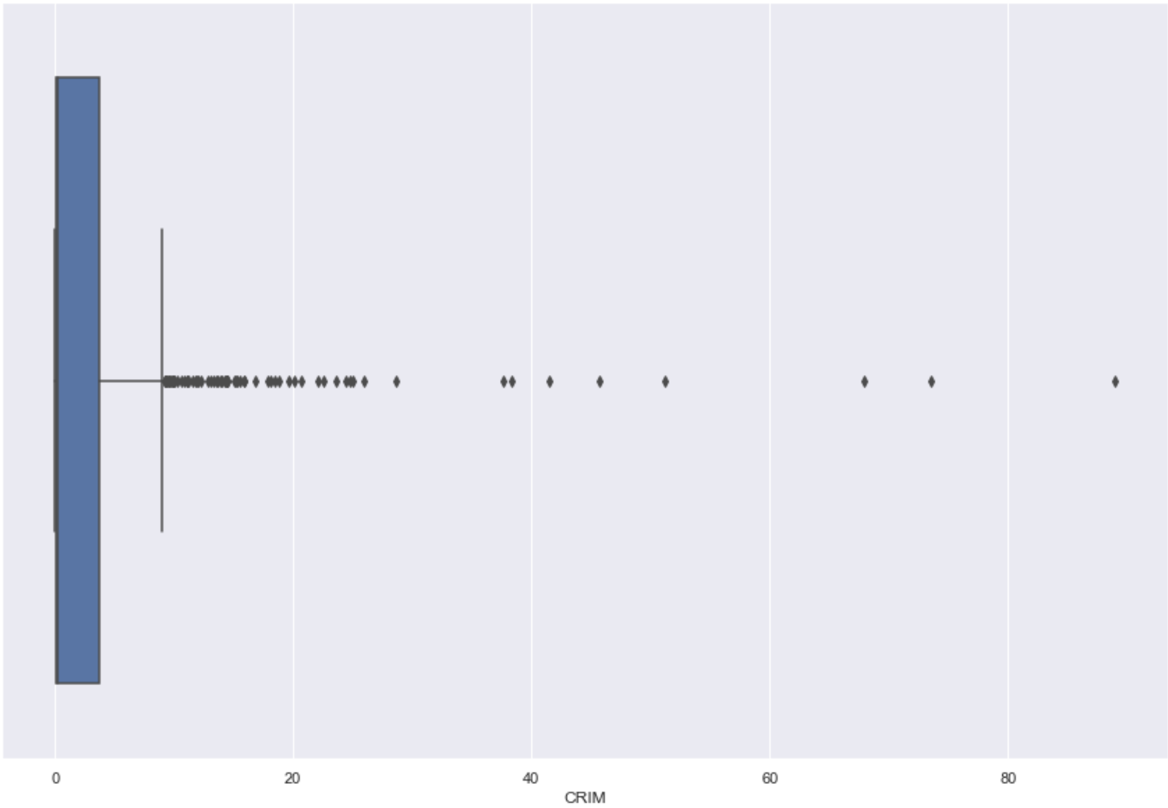
In [30]:

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

```
C:\Users\DHARAVATH RAMDAS\Anaconda3\lib\site-packages\seaborn\_decorators.p
y:36: FutureWarning: Pass the following variable as a keyword arg: x. From v
ersion 0.12, the only valid positional argument will be `data`, and passing
other arguments without an explicit keyword will result in an error or misin
terpretation.
  warnings.warn(
```

Out[30]:

<AxesSubplot:xlabel='CRIM'>



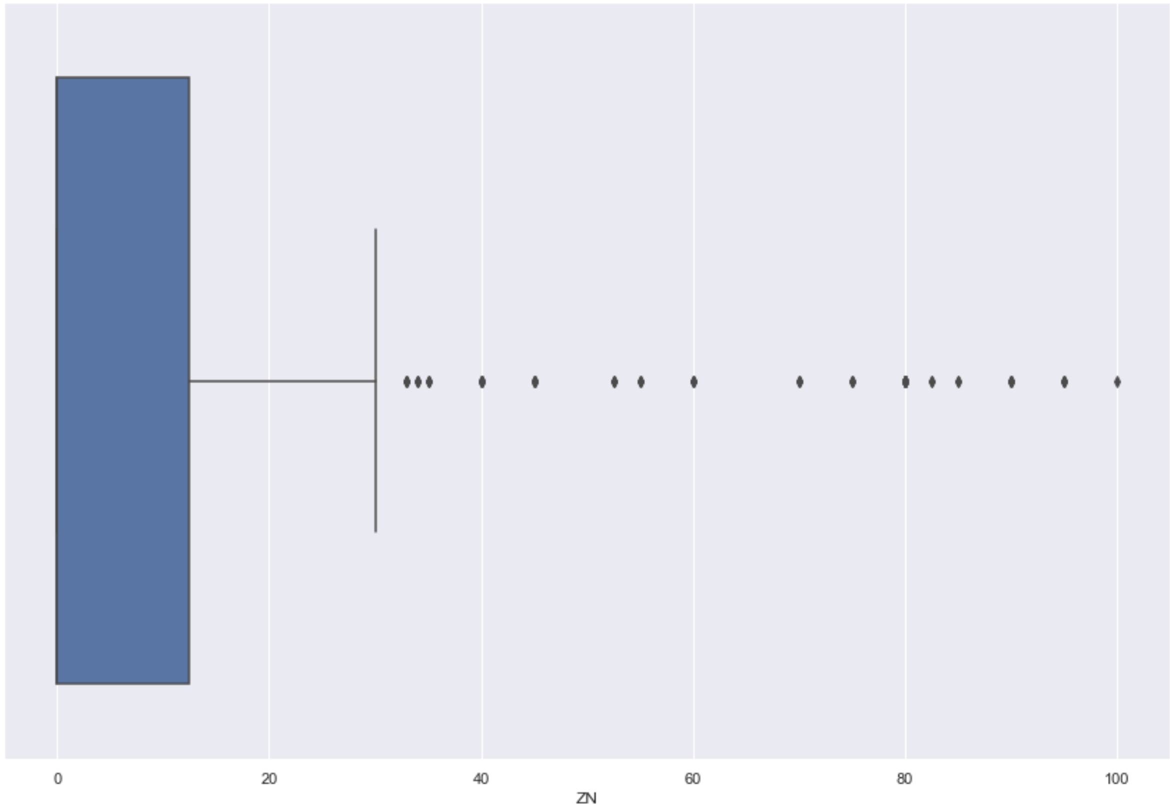
In [31]:

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

```
C:\Users\DHARAVATH RAMDAS\Anaconda3\lib\site-packages\seaborn\_decorators.p
y:36: FutureWarning: Pass the following variable as a keyword arg: x. From v
ersion 0.12, the only valid positional argument will be `data`, and passing
other arguments without an explicit keyword will result in an error or misin
terpretation.
  warnings.warn(
```

Out[31]:

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



In [32]:

```
dataset.head()
```

Out[32]:

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

independent and dependent feature seperation

independent col

In [33]:

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

dependent col

In [34]:

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

In [35]:

```
X.head()
```

Out[35]:

	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	4
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
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
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
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

In [36]:

```
y.head()
```

Out[36]:

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

spliting the data into train test split

In [37]:

```
# spliting the data into train test split
# it will return 4 different paremeters
# output feature of x train is y train and x test is y test
# test size = 0.25   if 1000 in 25% of data
# random state
```

In [38]:

```
from sklearn.model_selection import train_test_split
```

In [39]:

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

In [40]:

```
X_train.shape
```

Out[40]:

```
(339, 13)
```

In [41]:

```
y_train.shape
```

Out[41]:

```
(339,)
```

In [42]:

```
X_test.shape
```

Out[42]:

```
(167, 13)
```

In [43]:

```
y_test.shape
```

Out[43]:

```
(167,)
```

Standardize or featur scalling the datasets

In [44]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

In [45]:

```
scaler
```

Out[45]:

```
StandardScaler()
```

apply data

In [46]:

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

In [47]:

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

In [48]:

```
 #data lekage we dont need to leak the data of test to train data
#avoid datalekage use transform
#example :
#    is eaxm paper is x_train if you get before exam is called parer lekage
# f to f' we convert mean and std in fit and transform
```

In [49]:

```
X_test
```

Out[49]:

```
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 ]])
```

In [50]:

```
X_train
```

Out[50]:

```
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]])
```

Model Training

In [51]:

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

In [52]:

```
regression=LinearRegression()
```

In [53]:

```
regression
```

Out[53]:

```
LinearRegression()
```

In [54]:

```
# fit data and transform
# only fir only apply
# x trian indepe y tai n is dependent
```

In [55]:

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

Out[55]:

```
LinearRegression()
```

Coefficient and intercept

In [56]:

```
## print the coefficient and the intercept
## price 1 unit is increse crime is decrease relation
```

coefficient

In [57]:

```
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]
```

intercept

In [58]:

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

```
22.077286135693214
```

prediction for the test data

In [59]:

```
reg_pred = regression.predict(X_test)
```

In [60]:

```
reg_pred
```

Out[60]:

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

Assumption of linear regression

In [61]:

```
## assumption of linear regression
# we used to check model is good or not
# 1.linear relation between y test and
# 2.residuals we get normal distribution
# 3 get uniform distribution
```

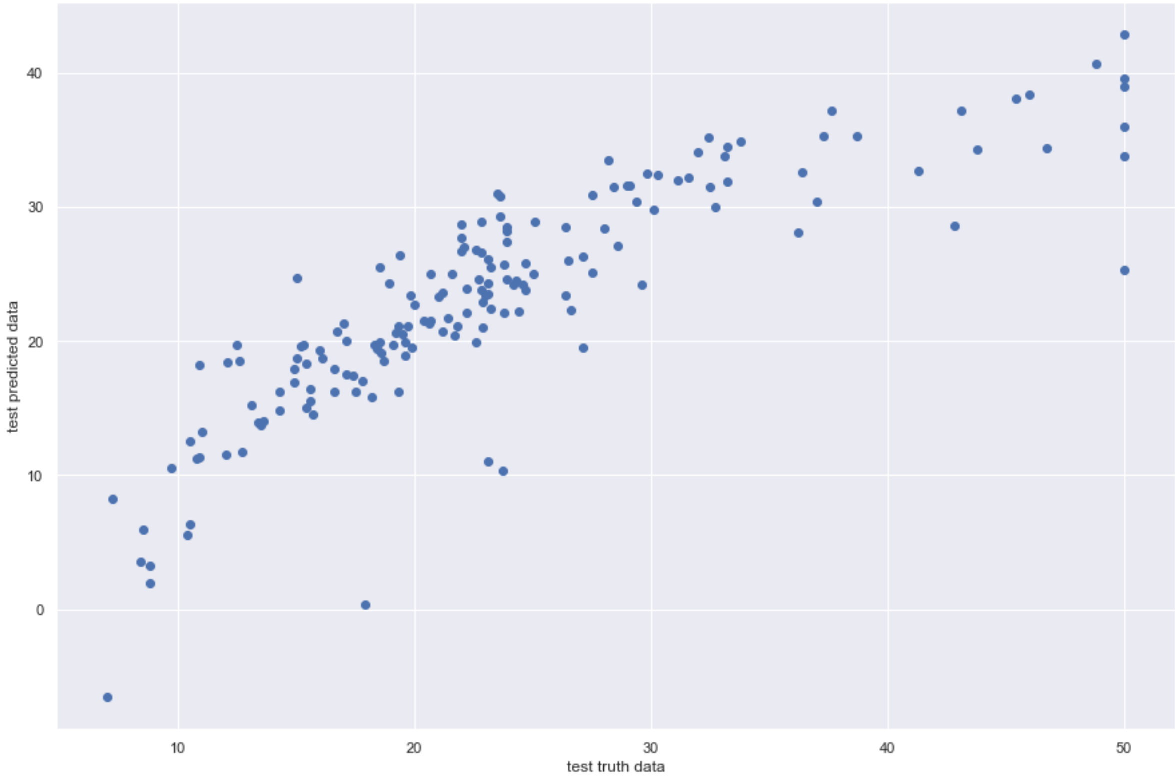
1.linear relationship between y_test and reg_prediction

In [62]:

```
plt.scatter(y_test,reg_pred)
plt.xlabel("test truth data")
plt.ylabel("test predicted data")
```

Out[62]:

```
Text(0, 0.5, 'test predicted data')
```



2.residual we get normal distributin

In [63]:

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

Out[63]:

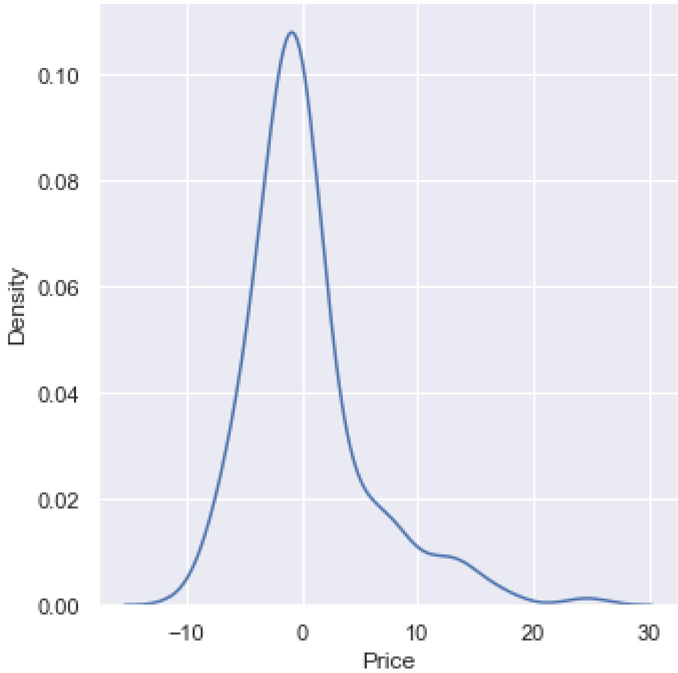
```
305   -3.038496
193   -0.887944
65    -7.498956
349    4.286033
151    0.705072
         ...
442   -1.004380
451   -4.387684
188   -2.638009
76    -2.661709
314   -1.885761
Name: Price, Length: 167, dtype: float64
```

In [64]:

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

Out[64]:

<seaborn.axisgrid.FacetGrid at 0x226021f9b80>



3.uniform distributin

In [65]:

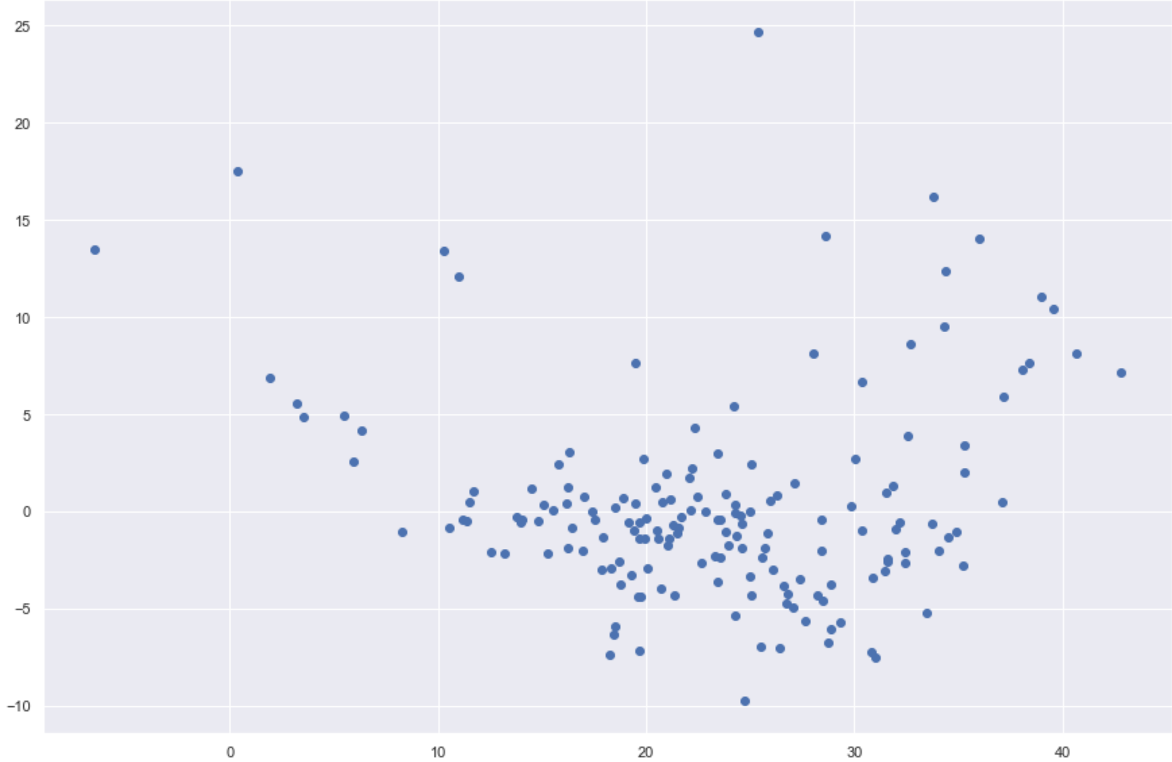
```
## scatter plot with prediction and residual
## uniform distribution  called below plot
```

In [66]:

```
plt.scatter(reg_pred,residuals)
```

Out[66]:

```
<matplotlib.collections.PathCollection at 0x226062aabe0>
```



Mean_squared_error, Mean_absolute_error

In [67]:

```
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
```

Performance metrics

R squared and adjusted R square

R squared

In [68]:

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

```
0.7165219393967555
```

Adjusted R Squared

In [69]:

```
#### adjusted R square
#### display adjusted R-squared
```

In [70]:

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

Out[70]:

```
0.6924355682343882
```

Ridge Regression:-

In [71]:

```
# importing ridge regression from sklearn library
from sklearn.linear_model import Ridge
```

Train the Model

In [72]:

```
# Train the model
ridgeR = Ridge(alpha=.99)
ridgeR.fit(X_train,y_train)
```

Out[72]:

```
Ridge(alpha=0.99)
```

Coefficients and intercepts

In [73]:

```
# coefficient
```

In [74]:

```
print(ridgeR.coef_)
```

```
[-1.27580076  1.5822088  -0.16122045  0.37668477 -1.72424166  2.24417936
  0.30969509 -3.26445939  2.60370907 -2.00010928 -1.75207382  1.25004819
 -3.81475273]
```

In [75]:

```
# intercepts

print(ridgeR.intercept_)
```

```
22.077286135693214
```

prediction for test data

In [76]:

```
ridgeR_pred = ridgeR.predict(X_test)
ridgeR_pred
```

Out[76]:

```
array([31.33057488, 31.98187113, 30.96557336, 22.44979345, 18.93136096,
       16.21766097, 35.9695201 , 14.84502334, 25.00681679, 37.08865709,
       21.49611307, 30.86418833, 27.98870994, 33.98311439, 33.72761124,
       40.61765149, 24.27260265, 23.3396092 , 25.52874965, 21.42633474,
       32.687195  , 17.88580074, 25.50287525, 25.01789638, 32.58713523,
       20.48525253, 19.5157083 , 16.94085284, 38.35830043,  0.3359304 ,
       32.44395443, 32.10396125, 26.13535705, 23.81366531, 20.64418441,
       19.71806618,  3.56120622, 35.17406836, 27.02047743, 27.65050098,
       34.34092247, 29.77294057, 18.39839475, 31.55299939, 17.92572438,
       28.51396241, 19.49629399, 21.65556993, 38.03647563, 16.4768963 ,
       24.5632252 , 19.66078388, 24.49101977, 34.33486274, 26.74628864,
       34.83754441, 21.08503023, 19.88392682, 18.65848344, 24.71541141,
       20.00211437, 23.58561577, 39.60661267, 42.79568807, 30.35504889,
       17.07390321, 23.8441424 ,  3.23179317, 31.42616831, 28.74993352,
       18.49735122, 27.14661903, 19.64645914, 25.29002063, 25.07848511,
       10.32184217, 38.9403347 ,  8.26852687, 18.50639148, 30.38981337,
       22.88691963, 21.08700275, 20.09017432, 28.70320022, 30.81536523,
       28.22571459, 26.28192393, 31.61825054, 22.15757652, -6.42202444,
       21.55921162, 19.89796163, 24.96572959, 23.47335755, 19.25735742,
       18.80337634, 27.37974341, 22.19215481, 26.7827143 , 23.40775675,
       23.92752519, 19.18837687, 21.09793011, 10.90980367, 13.8055226 ,
       20.78564836, 23.49703861, 14.19539174, 28.86460768, 15.85507771,
       15.26390265, 22.39393371, 26.63582763, 28.87665175, 24.26013291,
       18.26466894, 16.26560094, 17.44890671, 15.58548959, 21.24110535,
       33.72653107, 30.07040403, 21.17355072, 14.04499134, 16.21814707,
       29.26687873, 13.18723962, 22.07244012, 24.34914885, 31.88218013,
       33.34343802,  5.95890004, 35.14783652, 24.25615242, 17.5551893 ,
       24.27003373, 28.42163323, 34.47570069,  6.32390404,  2.03811704,
       28.40133687, 12.59053332, 18.32099701, 19.75868378,  5.51544542,
       14.42225083, 37.15224879, 25.86016615, 23.29905211, 26.39564847,
       11.41964159, 20.48864901, 35.29511598, 20.61583808, 11.45806067,
       16.36323857, 24.57009605, 10.51061694, 15.13764409, 26.01127654,
       11.22970807, 11.70173265, 19.39461107, 19.59202899, 32.42958757,
       22.67089926, 25.68378556])
```

Asumptions for ridgeRegression

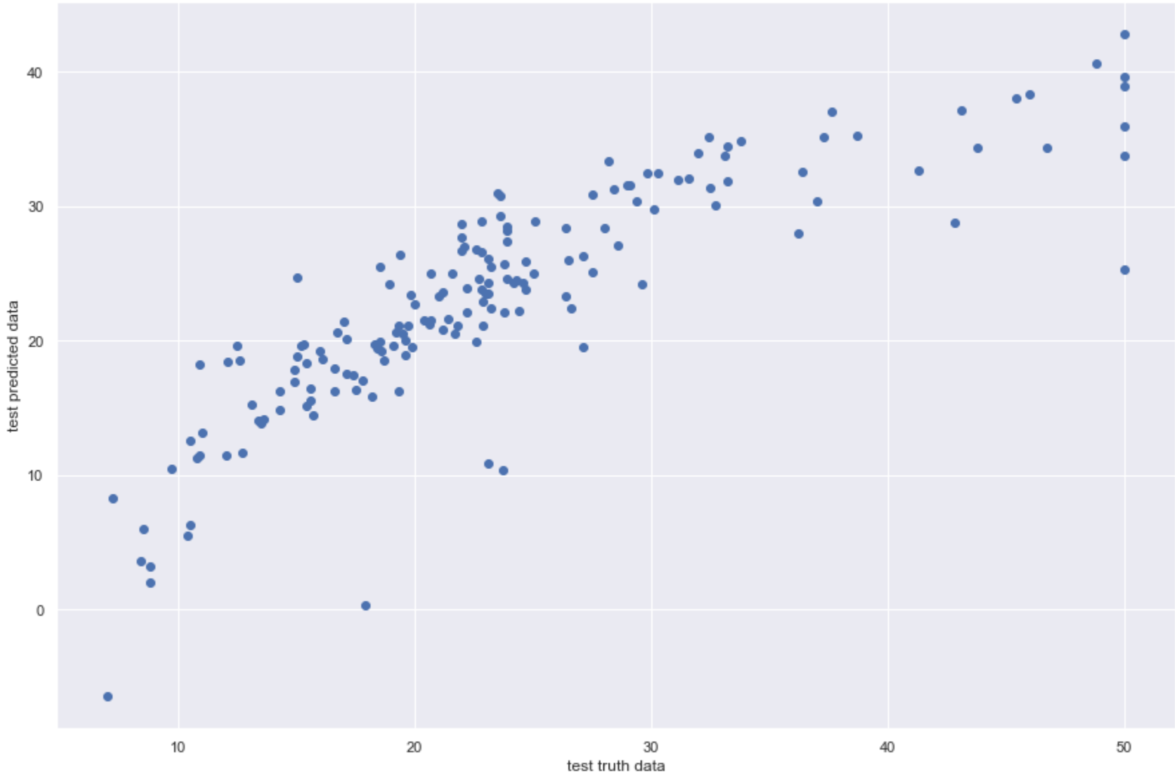
1.linear relationship between y_test and reg_prediction

In [77]:

```
plt.scatter(y_test,ridgeR_pred)
plt.xlabel("test truth data")
plt.ylabel("test predicted data")
```

Out[77]:

```
Text(0, 0.5, 'test predicted data')
```



2.residual we get normal distributin

In [78]:

```
residuals=y_test-ridgeR_pred
residuals
```

Out[78]:

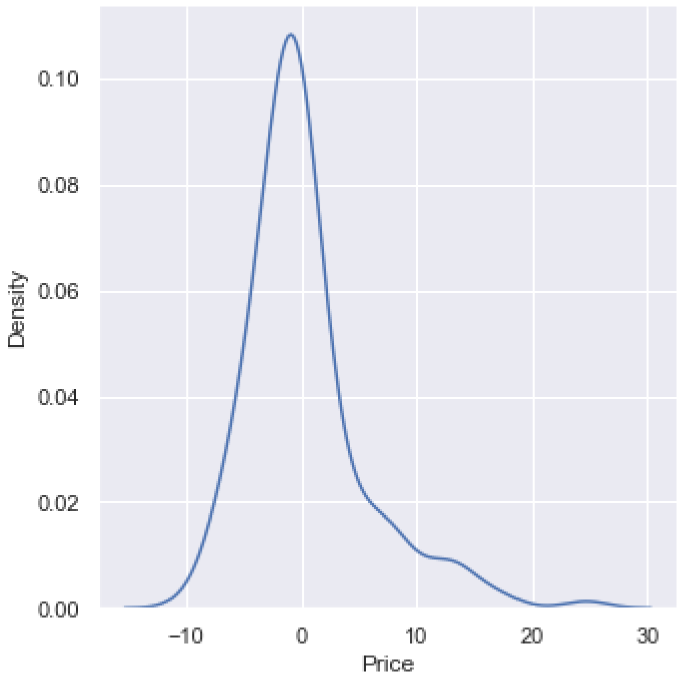
```
305   -2.930575
193   -0.881871
65    -7.465573
349    4.150207
151    0.668639
         ...
442   -0.994611
451   -4.392029
188   -2.629588
76    -2.670899
314   -1.883786
Name: Price, Length: 167, dtype: float64
```

In [79]:

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

Out[79]:

```
<seaborn.axisgrid.FacetGrid at 0x226065fd6a0>
```



3.uniform distributin

scatter plot with prediction and residual

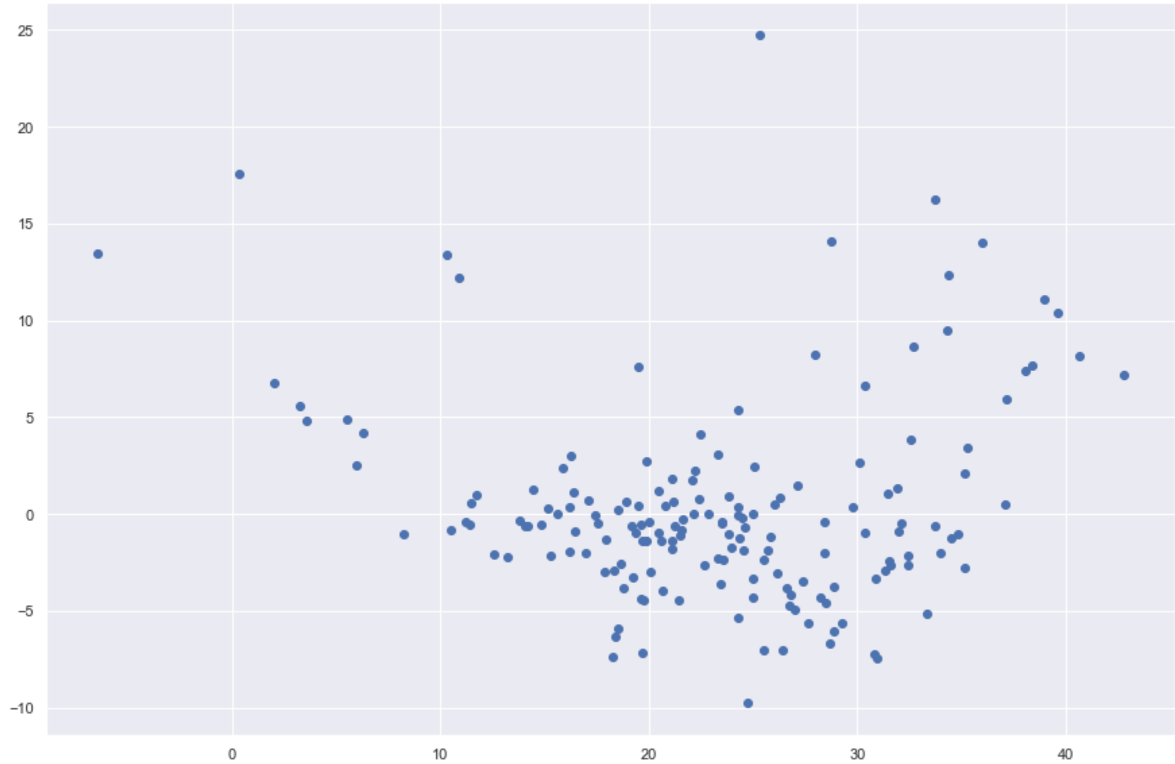
uniform distribution called below plot

In [80]:

```
plt.scatter(ridgeR_pred,residuals)
```

Out[80]:

```
<matplotlib.collections.PathCollection at 0x2260657ad00>
```



Performance Matrics

In [81]:

```
# mean squared error , mean absolute error , root mean square error
```

In [82]:

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

```
27.076711766488984
3.516149635367478
5.203528780211462
```

R Square

In [83]:

```
from sklearn.metrics import r2_score
ridgeR_score = r2_score(y_test,ridgeR_pred)
print(ridgeR_score)
```

```
0.7167759091171659
```

Adjusted R Square

In [84]:

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

Out[84]:

```
0.6927111170813696
```

Lasso Regression:-

In [85]:

```
# import lasso regression from sklearn library
```

In [86]:

```
from sklearn.linear_model import Lasso
```

Train the model

In [87]:

```
lasso = Lasso(alpha = 0.05)
lasso.fit(X_train,y_train)
```

Out[87]:

```
Lasso(alpha=0.05)
```

coefficient and intercept

In [88]:

```
# coefficient
```

In [89]:

```
print(lasso.coef_)
```

```
[-1.1362951   1.39694799 -0.15032956  0.36283533 -1.44054618  2.34832732
  0.08736711 -2.99867466  1.97095926 -1.50608266 -1.68128859  1.21430748
 -3.76284248]
```

In [90]:

```
# intercept
```

In [91]:

```
print(lasso.intercept_)
```

```
22.077286135693214
```

predict lasso

In [92]:

```
lasso_pred = lasso.predict(X_test)
lasso_pred
```

Out[92]:

```
array([30.57855402, 32.04704681, 30.7836755 , 23.22473341, 19.31928679,
       16.31947881, 36.04756378, 15.14089993, 24.54690088, 36.75657835,
       21.40934745, 30.42914651, 27.51095643, 33.62846912, 33.51369108,
       40.35412747, 24.74380038, 22.64379453, 25.44641771, 21.94003238,
       32.63731951, 17.88286672, 25.46744211, 25.20808824, 32.88728015,
       20.51622533, 19.37852914, 17.08461594, 38.00682559,  0.06256954,
       32.39077209, 31.71723378, 26.30318902, 24.1901777 , 20.3564376 ,
       19.84503741,  3.86980824, 34.72575591, 27.02264842, 27.47090983,
       34.53116392, 29.31157273, 18.25916767, 31.51857148, 17.73102663,
       28.47466208, 19.54285003, 21.45175703, 37.5908217 , 16.49354151,
       24.5126893 , 19.48032315, 24.10857748, 34.59994156, 26.81233855,
       34.46731518, 21.20314923, 19.9936519 , 18.68266087, 24.75076636,
       20.37856907, 23.69939752, 39.77095878, 42.55019349, 30.379202  ,
       17.38116342, 24.21711232,  3.12416695, 30.75349905, 29.62345485,
       18.5192404 , 27.43236171, 19.47599315, 24.87019176, 25.17221038,
       10.64908788, 38.71843785,  8.15059193, 18.23414632, 30.71384341,
       22.85932785, 21.71206893, 20.38635835, 28.48894474, 30.65193988,
       28.27081287, 26.39867762, 31.80294712, 22.44882748, -6.01035538,
       21.85415236, 19.74998054, 24.86417911, 23.82224106, 18.77079303,
       18.77446874, 27.12552809, 22.12906624, 26.39563297, 23.30345555,
       23.81399841, 19.31351717, 21.04216569, 10.31196755, 13.84686945,
       21.08101131, 22.93217687, 15.20995347, 28.78083174, 16.28804803,
       15.31957849, 22.18278963, 26.74002085, 28.51768319, 23.98128081,
       18.18916848, 15.86212965, 17.71706915, 16.10038338, 21.16042723,
       33.25045535, 30.33820105, 21.33745138, 14.45015516, 16.27700171,
       28.83292852, 13.26778624, 22.1853298 , 24.41571998, 31.899553  ,
       32.49621638,  6.4042328 , 34.77744249, 24.93811797, 17.60029616,
       24.71900332, 28.36594981, 34.16829719,  6.20786078,  3.03375677,
       28.44099918, 12.78225953, 18.34434928, 20.10835996,  5.67421836,
       14.00955543, 36.75926849, 25.9811435 , 23.28347761, 26.07126116,
       11.97748528, 20.67267473, 35.29400398, 20.97321467, 11.16644946,
       17.03938045, 24.60074646, 10.28030585, 15.66517757, 26.17739514,
       11.31085536, 11.80389692, 19.28696647, 19.56361505, 32.38793789,
       22.69205019, 25.6203023 ])
```

Assumption of LassoRegression

In [93]:

```
## assumption of linear regression
# we used to check model is good or not
# 1.linear relation between y test and
# 2.residuals we get normal distribution
# 3 get uniform distribution
```

In [94]:

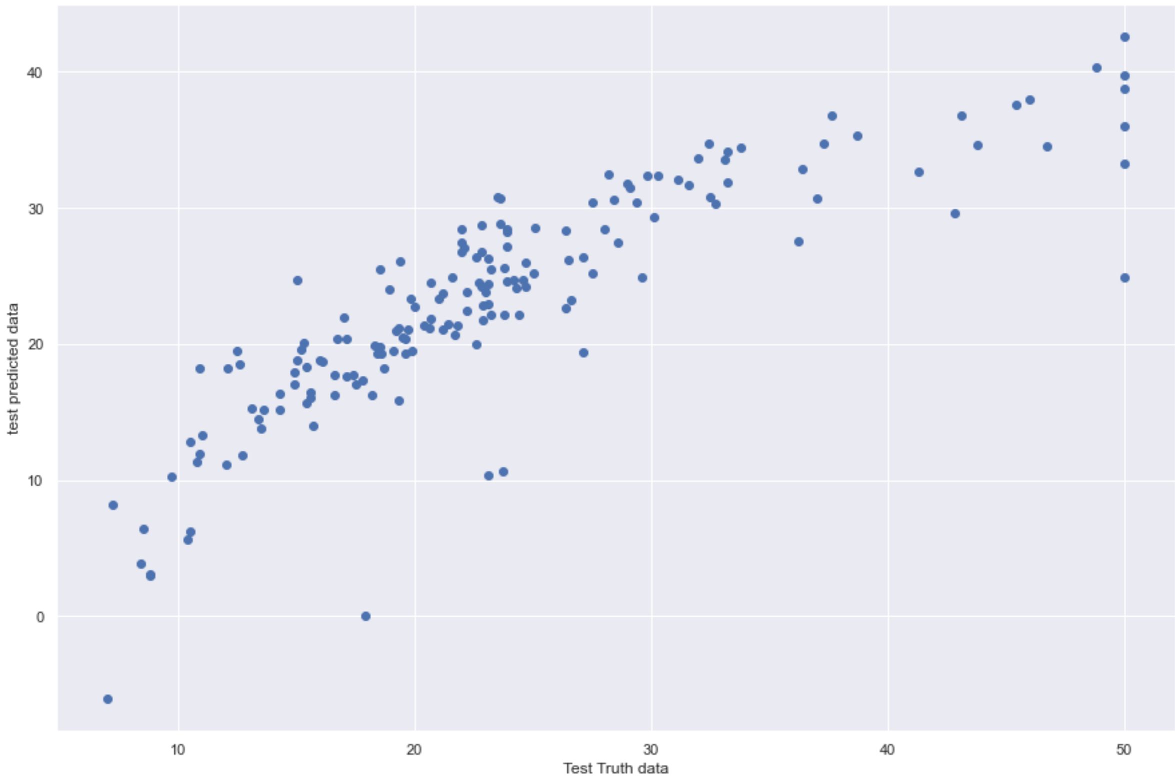
```
# 1.relationship between real data and predict data
```

In [95]:

```
plt.scatter(y_test,lasso_pred)
plt.xlabel("Test Truth data")
plt.ylabel("test predicted data")
```

Out[95]:

```
Text(0, 0.5, 'test predicted data')
```



In [96]:

```
# 2.calculate the residual
```

In [127]:

```
residuals = y_test-lasso_pred
residuals
```

Out[127]:

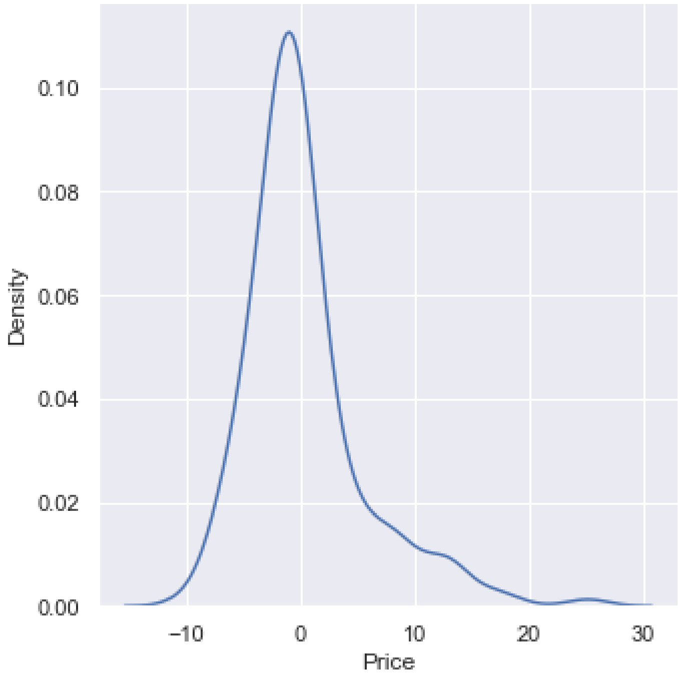
```
305   -2.178554
193   -0.947047
65    -7.283676
349    3.375267
151    0.280713
         ...
442   -0.886966
451   -4.363615
188   -2.587938
76    -2.692050
314   -1.820302
Name: Price, Length: 167, dtype: float64
```

In [128]:

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

Out[128]:

<seaborn.axisgrid.FacetGrid at 0x2260191bc70>



In [129]:

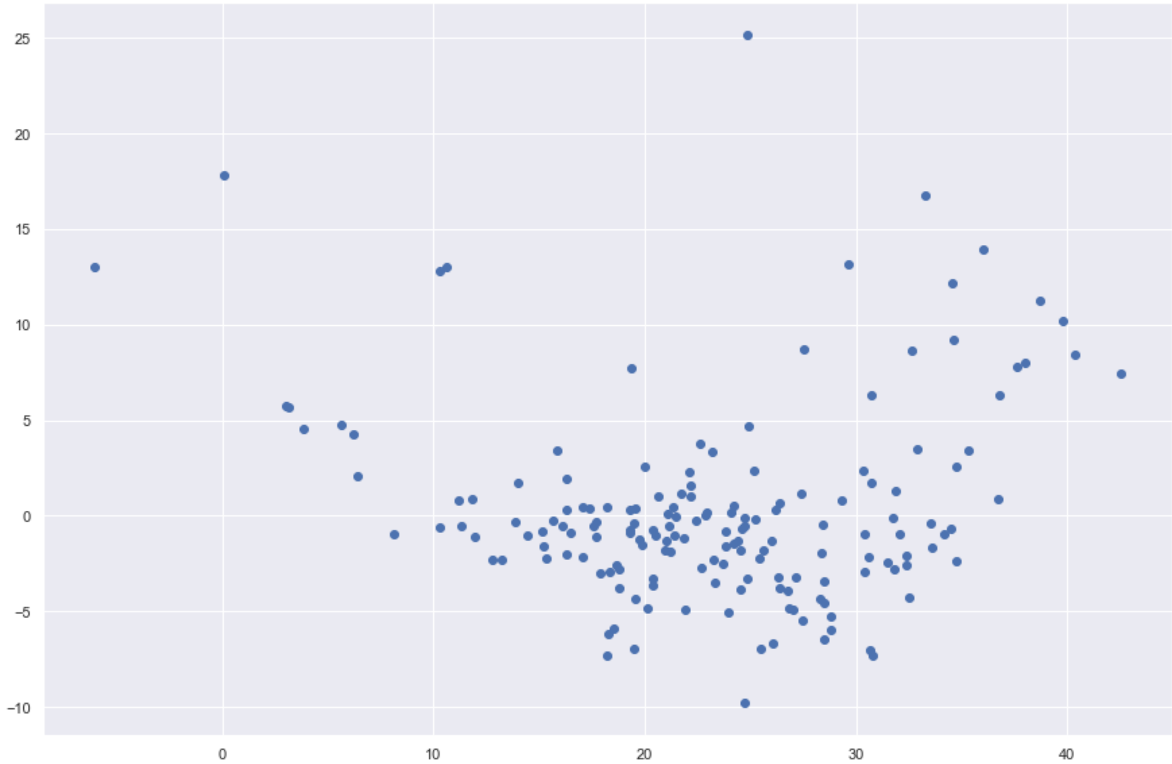
```
# 3 get uniform distribution
```

In [130]:

```
plt.scatter(lasso_pred,residuals)
```

Out[130]:

<matplotlib.collections.PathCollection at 0x226075444c0>



Performance Matrics

In [103]:

```
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)))
```

```
26.891235686064327
3.4901509037901235
5.185676010518236
```

R Square

In [104]:

```
from sklearn.metrics import r2_score
lasso_score = r2_score(y_test,lasso_pred)
print(lasso_score)
```

```
0.7187160004662122
```

Adjusted R Square

In [105]:

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

Out[105]:

```
0.6948160527934066
```

ElasticNet Regression

In [106]:

```
# import model
```

In [107]:

```
from sklearn.linear_model import ElasticNet
```

Train the model

In [108]:

```
el_net = ElasticNet(alpha=.02,l1_ratio=.2)
el_net.fit(X_train,y_train)
```

Out[108]:

```
ElasticNet(alpha=0.02, l1_ratio=0.2)
```

coefficient and intercept

In [109]:

```
#coefficient
```

In [110]:

```
print(el_net.coef_)
```

```
[-1.20552262  1.46094793 -0.23215955  0.393075   -1.55138849  2.31437091
  0.24113825 -3.04649334  2.19062072 -1.64162732 -1.71126882  1.23818913
 -3.72782837]
```

In [111]:

```
# intercept
```

In [112]:

```
print(el_net.intercept_)
```

```
22.077286135693214
```

prediction

In [113]:

```
elastic_pred = el_net.predict(X_test)
elastic_pred
```

Out[113]:

```
array([30.85320392, 31.95227044, 30.80930105, 23.0311917 , 19.10356298,
       16.24600244, 35.87472708, 14.9895382 , 24.82885226, 36.89115631,
       21.4886189 , 30.73150696, 27.67922031, 33.66227778, 33.58606909,
       40.49230464, 24.43871474, 23.00271234, 25.46496544, 21.7949502 ,
       32.5439557 , 17.8971736 , 25.50064893, 25.06306784, 32.76489368,
       20.48825102, 19.63035066, 17.00997366, 38.22052183,  0.23782986,
       32.49185944, 31.87233767, 26.27375723, 23.9223078 , 20.50068616,
       19.81219508,  3.81973163, 34.78789885, 26.9037553 , 27.57428463,
       34.30221555, 29.5059595 , 18.34458072, 31.47505857, 17.96071003,
       28.54751586, 19.50966375, 21.47597087, 37.76635394, 16.61030726,
       24.46653295, 19.57476414, 24.27600651, 34.43751694, 26.73386342,
       34.63692279, 21.16421431, 19.90817887, 18.5488929 , 24.69397623,
       20.16910225, 23.67112496, 39.70500876, 42.65458117, 30.27897294,
       17.23152662, 23.90157845,  3.20344734, 31.05847458, 29.26237067,
       18.51704129, 27.20011652, 19.53951402, 25.03664031, 25.15562111,
       10.48286187, 38.81108622,  8.27808334, 18.45239416, 30.58459273,
       22.93337851, 21.5974977 , 20.28893043, 28.565945  , 30.77233786,
       28.19443256, 26.28702801, 31.72552797, 22.30323027, -6.12234331,
       21.7164113 , 19.85502516, 24.95600212, 23.60608907, 19.13739826,
       19.0018081 , 27.27646041, 22.24833325, 26.55664574, 23.41604877,
       23.9377974 , 19.2681326 , 21.11856869, 10.45988909, 13.96044739,
       20.95875649, 23.24409298, 14.81422861, 28.77838171, 16.21533207,
       15.31662352, 22.2359584 , 26.72672259, 28.80489302, 24.08783381,
       18.24286485, 16.23716435, 17.66088454, 15.84254868, 21.0864064 ,
       33.4322881 , 30.31853999, 21.22010083, 14.43501547, 16.36111989,
       29.04857322, 13.20498662, 22.03277638, 24.36696995, 31.91173178,
       32.82389714,  6.2106213 , 34.89766179, 24.63421167, 17.61283799,
       24.3831644 , 28.31977492, 34.3449386 ,  6.3004853 ,  2.52616545,
       28.37535208, 12.71389456, 18.36495297, 19.97264189,  5.6008522 ,
       14.08147588, 36.94100142, 26.03286818, 23.23068726, 26.22291905,
       11.61054969, 20.61949156, 35.33646245, 20.7753819 , 11.32969665,
       16.90317482, 24.59243041, 10.42467596, 15.44611433, 26.10104352,
       11.31065451, 11.74673149, 19.34759372, 19.60773469, 32.36160995,
       22.69729411, 25.6655162 ])
```

Assumptions of ElasticsNetRegression

In [114]:

```
## assumption of linear regression
# we used to check model is good or not
# 1.linear relation between y test and predicted
# 2.residuals we get normal distribution
# 3 get uniform distribution
```

In [115]:

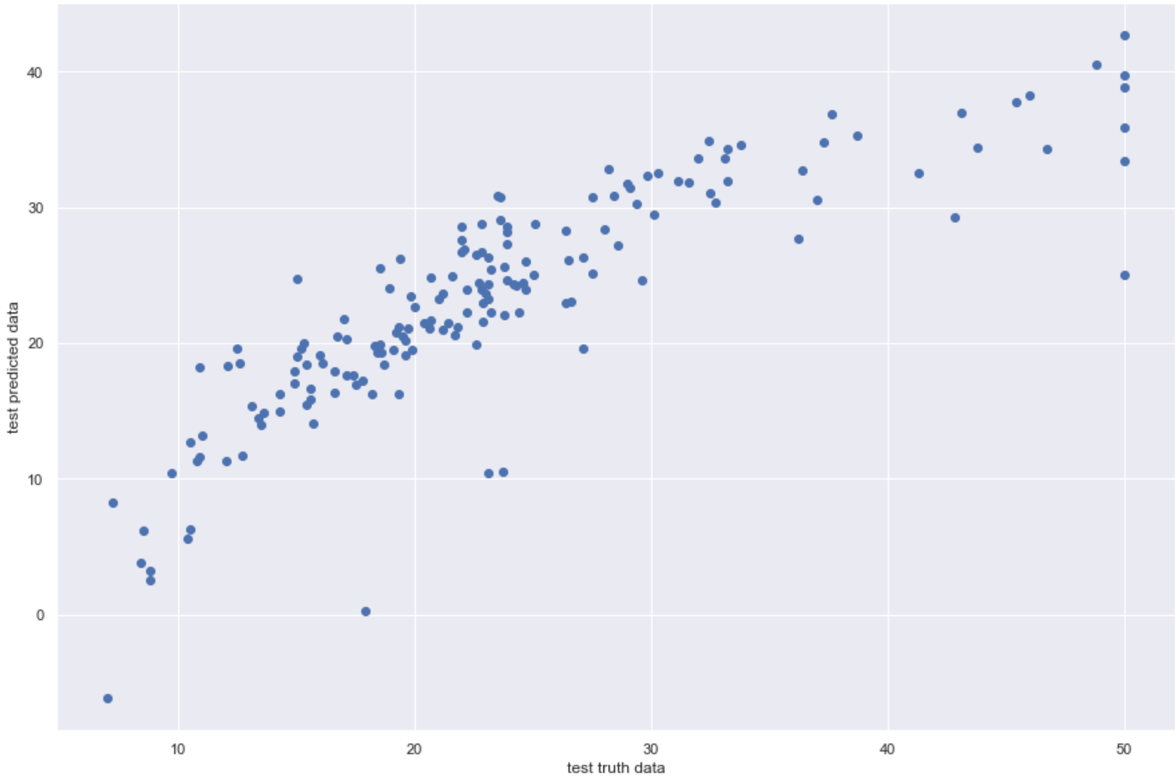
```
# 1.relationship between actual y test and predicted
```

In [116]:

```
plt.scatter(y_test,elastic_pred)
plt.xlabel("test truth data")
plt.ylabel("test predicted data")
```

Out[116]:

```
Text(0, 0.5, 'test predicted data')
```



In [117]:

```
# 2.residual
```

In [118]:

```
residuals = y_test - elastic_pred
residuals
```

Out[118]:

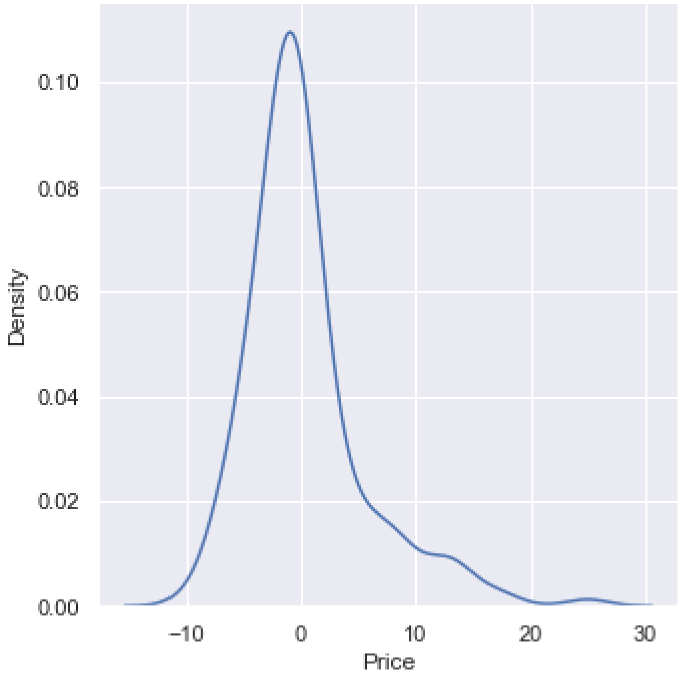
```
305   -2.453204
193   -0.852270
65    -7.309301
349    3.568808
151    0.496437
         ...
442   -0.947594
451   -4.407735
188   -2.561610
76    -2.697294
314   -1.865516
Name: Price, Length: 167, dtype: float64
```

In [119]:

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

Out[119]:

<seaborn.axisgrid.FacetGrid at 0x22606a99f70>



In [120]:

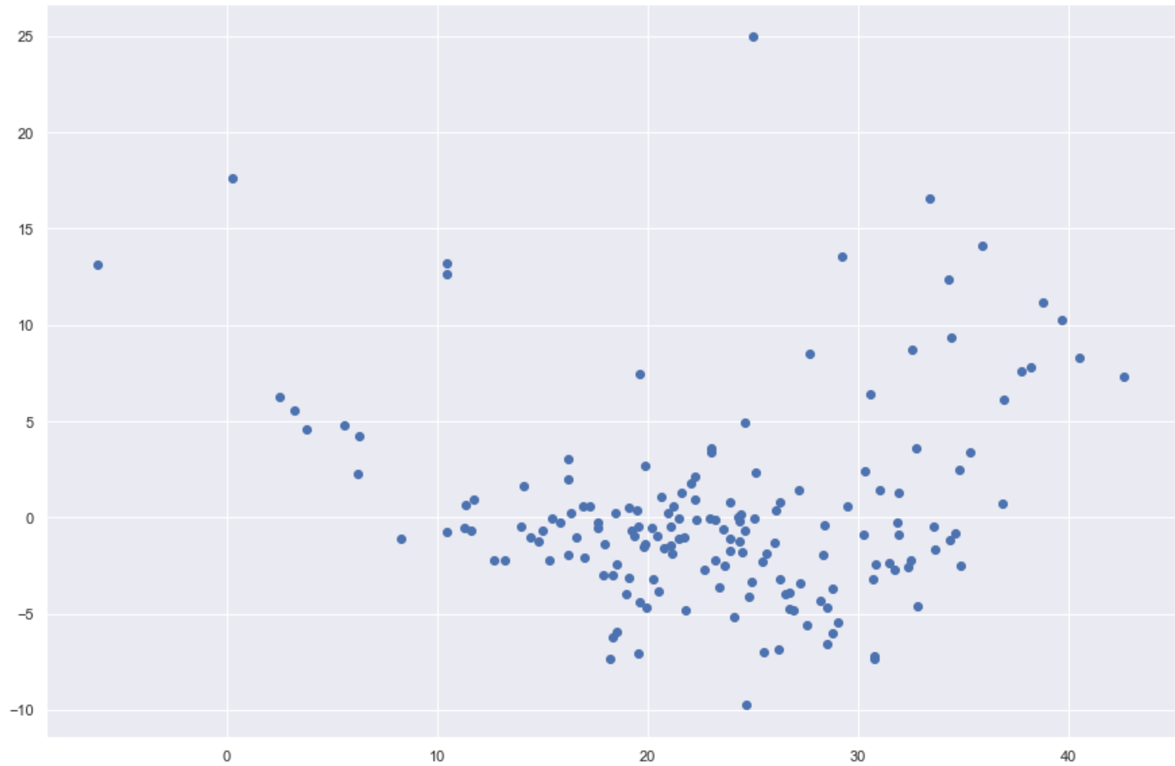
```
# 3.uniform distribution
```

In [126]:

```
plt.scatter(elastic_pred,residuals)
```

Out[126]:

```
<matplotlib.collections.PathCollection at 0x22607272670>
```



Performance Matrics

In [122]:

```
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)))
```

```
27.000688509169624
3.498561559790622
5.196218674110013
```

R Square

In [131]:

```
from sklearn.metrics import r2_score
elastic_score = r2_score(y_test,elastic_pred)
print(elastic_score)
```

```
0.7175711171219605
```

Adjusted R Square

In [132]:

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

Out[132]:

```
0.693573891779382
```

In [ ]: