Our Target here to check how the different features effect the pricing of houses in "Boston"

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
%matplotlib  inline
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

load boston data set

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

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

In [4]:
```
type(boston)
```

Out[4]:
```
sklearn.utils.Bunch
```

In [5]:
```
boston.keys()
```

Out[5]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename', 'data_module'])
```

check description of dataset

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 people by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

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

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


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

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

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

.. topic:: References

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

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)  # which is price of house.
```

```
[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]
```

preparing our data set

In [9]:
```
dataset =pd.DataFrame(boston.data,columns =boston.feature_names)  #to add the column name we use boston.feature_names
```

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

Out[10]:

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

In [11]:
```
dataset['price']=boston.target
```

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

Out[12]:

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

In [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
```

summarizing stats of data

In [14]:
```
dataset.describe()
```

Out[14]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	price
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534	356.674032	12.653063	22.532806
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946	91.294864	7.141062	9.197104
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.320000	1.730000	5.000000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000	375.377500	6.950000	17.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000	391.440000	11.360000	21.200000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000	396.225000	16.955000	25.000000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.900000	37.970000	50.000000

check the missing values

In [15]:
```
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
```

Exploratory data analysis

Correlation

In [16]:
```
dataset.corr()
```

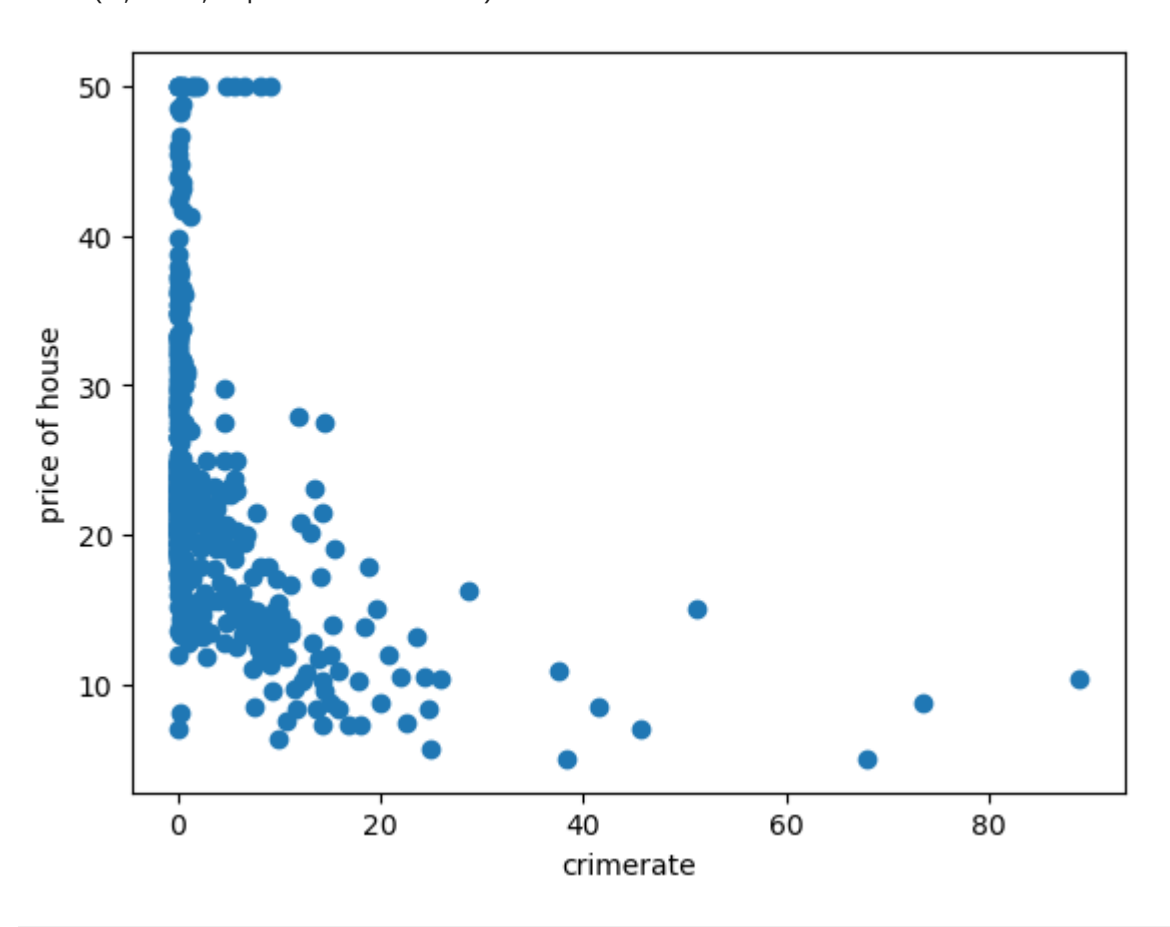
Out[16]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	price
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670	0.625505	0.582764	0.289946	-0.385064	0.455621	-0.388305
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408	-0.311948	-0.314563	-0.391679	0.175520	-0.412995	0.360445
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.595129	0.720760	0.383248	-0.356977	0.603800	-0.483725
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.099176	-0.007368	-0.035587	-0.121515	0.048788	-0.053929	0.175260
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.769230	0.611441	0.668023	0.188933	-0.380051	0.590879	-0.427321
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.205246	-0.209847	-0.292048	-0.355501	0.128069	-0.613808	0.695360
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.747881	0.456022	0.506456	0.261515	-0.273534	0.602339	-0.376955
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.000000	-0.494588	-0.534432	-0.232471	0.291512	-0.496996	0.249929
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.494588	1.000000	0.910228	0.464741	-0.444413	0.488676	-0.381626
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.534432	0.910228	1.000000	0.460853	-0.441808	0.543993	-0.468536
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	0.464741	0.460853	1.000000	-0.177383	0.374044	-0.507787
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.291512	-0.444413	-0.441808	-0.177383	1.000000	-0.366087	0.333461
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.496996	0.488676	0.543993	0.374044	-0.366087	1.000000	-0.737663
price	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.249929	-0.381626	-0.468536	-0.507787	0.333461	-0.737663	1.000000

analyse relationship b/w few of our fetures with target column

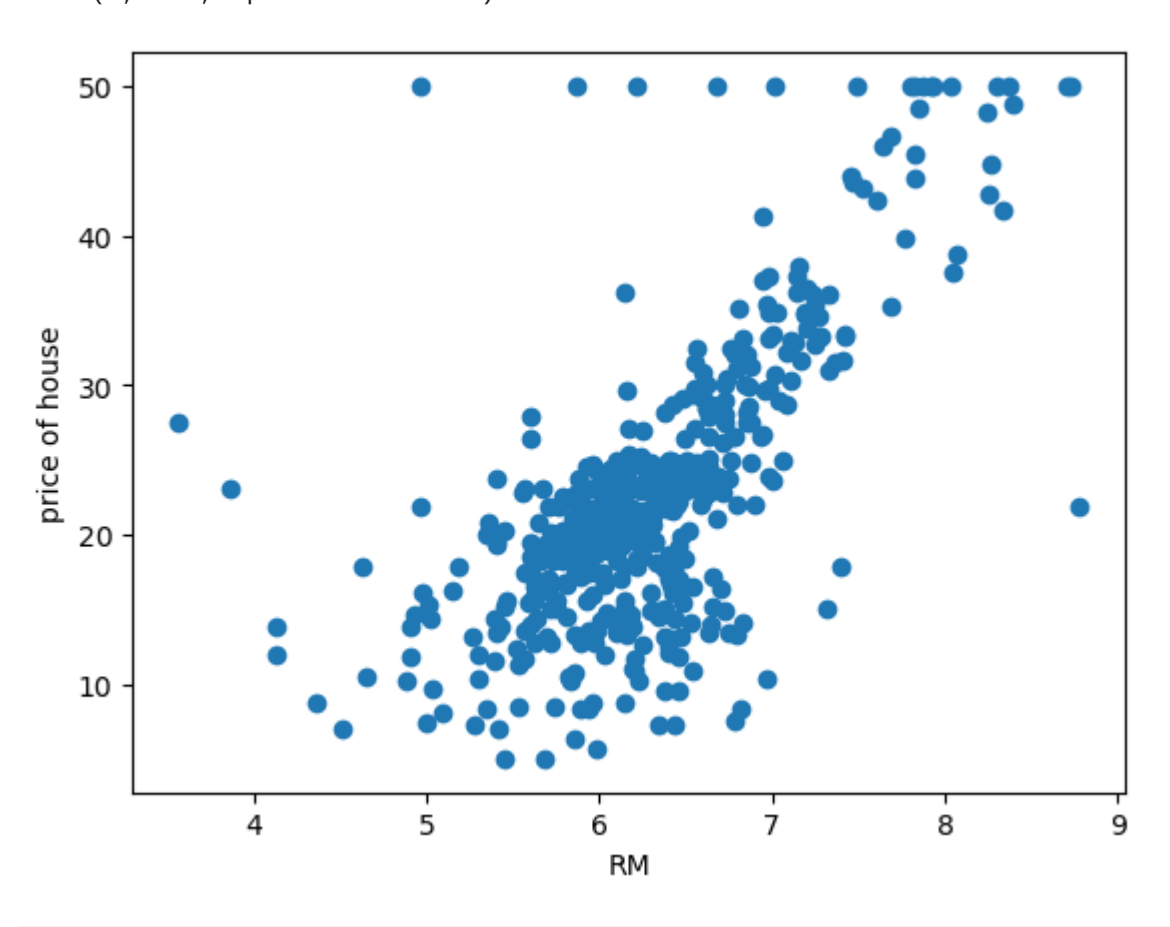
In [17]:
```
plt.scatter(dataset['CRIM'],dataset['price'])
plt.xlabel('crimerate')
plt.ylabel('price of house')                    # AS WE CAN SEE AS CRIMERATE INCREASE PRICE OF HOUSE WILL DECREASE
```

Out[17]:
```
Text(0, 0.5, 'price of house')
```



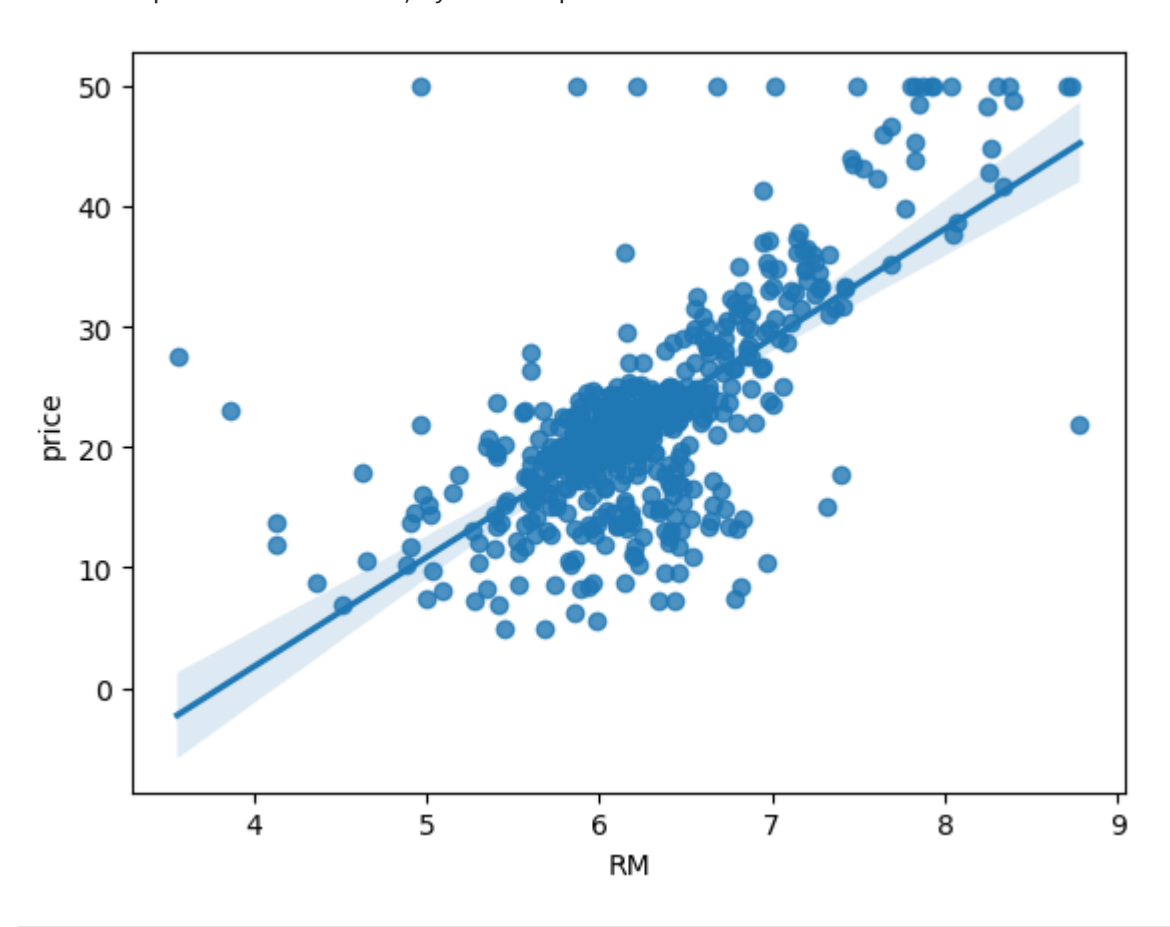
In [18]:
```
plt.scatter(dataset['RM'],dataset['price'])
plt.xlabel('RM')
plt.ylabel('price of house')
```

Out[18]:
```
Text(0, 0.5, 'price of house')
```



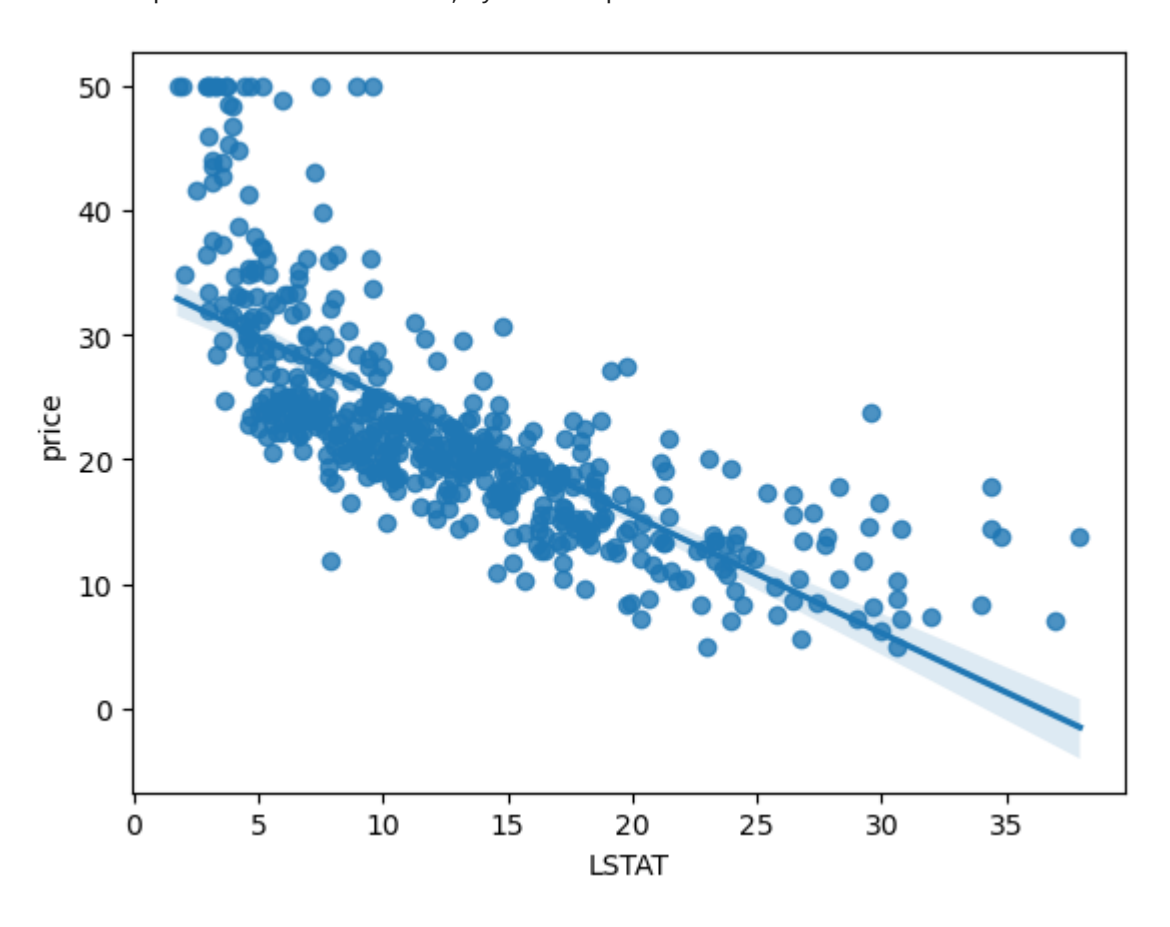
In [19]:
```
import seaborn  as sns                          #HERE WE CAN SEE POSTITVE COORELATION BETWEEN AVG ROOM AND PRICE
sns.regplot(x='RM',y='price',data=dataset)
```

Out[19]:
```
<AxesSubplot:xlabel='RM', ylabel='price'>
```



In [20]:
```
sns.regplot(x='LSTAT',y='price',data=dataset)  #HERE WE HAVE NEGATIVE RELATION
```

Out[20]:
```
<AxesSubplot:xlabel='LSTAT', ylabel='price'>
```



Now its time to split our dataset into dependent and independent features

In [21]:
```
dataset.head()
```

Out[21]:

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

In [22]:
```
x =dataset.iloc[:,:-1]
y =dataset.iloc[:,-1]
```

In [23]:
```
x.head()
```

Out[23]:

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

Train ,test split

In [24]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test =train_test_split(x,y,test_size =0.2,random_state =42)
```

In [25]:
```
x_train
```

Out[25]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
477	15.02340	0.0	18.10	0.0	0.6140	5.304	97.3	2.1007	24.0	666.0	20.2	349.48	24.91
15	0.62739	0.0	8.14	0.0	0.5380	5.834	56.5	4.4986	4.0	307.0	21.0	395.62	8.47
332	0.03466	35.0	6.06	0.0	0.4379	6.031	23.3	6.6407	1.0	304.0	16.9	362.25	7.83
423	7.05042	0.0	18.10	0.0	0.6140	6.103	85.1	2.0218	24.0	666.0	20.2	2.52	23.29
19	0.72580	0.0	8.14	0.0	0.5380	5.727	69.5	3.7965	4.0	307.0	21.0	390.95	11.28
...	...	...	...	...	...	...	...	...	...	...	...	...	...
106	0.17120	0.0	8.56	0.0	0.5200	5.836	91.9	2.2110	5.0	384.0	20.9	395.67	18.66
270	0.29916	20.0	6.96	0.0	0.4640	5.856	42.1	4.4290	3.0	223.0	18.6	388.65	13.00
348	0.01501	80.0	2.01	0.0	0.4350	6.635	29.7	8.3440	4.0	280.0	17.0	390.94	5.99
435	11.16040	0.0	18.10	0.0	0.7400	6.629	94.6	2.1247	24.0	666.0	20.2	109.85	23.27
102	0.22876	0.0	8.56	0.0	0.5200	6.405	85.4	2.7147	5.0	384.0	20.9	70.80	10.63

404 rows × 13 columns

In [26]:
```
x_test
```

Out[26]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
173	0.09178	0.0	4.05	0.0	0.510	6.416	84.1	2.6463	5.0	296.0	16.6	395.50	9.04
274	0.05644	40.0	6.41	1.0	0.447	6.758	32.9	4.0776	4.0	254.0	17.6	396.90	3.53
491	0.10574	0.0	27.74	0.0	0.609	5.983	98.8	1.8681	4.0	711.0	20.1	390.11	18.07
72	0.09164	0.0	10.81	0.0	0.413	6.065	7.8	5.2873	4.0	305.0	19.2	390.91	5.52
452	5.09017	0.0	18.10	0.0	0.713	6.297	91.8	2.3682	24.0	666.0	20.2	385.09	17.27
...	...	...	...	...	...	...	...	...	...	...	...	...	...
412	18.81100	0.0	18.10	0.0	0.597	4.628	100.0	1.5539	24.0	666.0	20.2	28.79	34.37
436	14.42080	0.0	18.10	0.0	0.740	6.461	93.3	2.0026	24.0	666.0	20.2	27.49	18.05
411	14.05070	0.0	18.10	0.0	0.597	6.657	100.0	1.5275	24.0	666.0	20.2	35.05	21.22
86	0.05188	0.0	4.49	0.0	0.449	6.015	45.1	4.4272	3.0	247.0	18.5	395.99	12.86
75	0.09512	0.0	12.83	0.0	0.437	6.286	45.0	4.5026	5.0	398.0	18.7	383.23	8.94

102 rows × 13 columns

standardize the dataset

In [27]:
```
from sklearn.preprocessing import StandardScaler
scaler =StandardScaler()
```

In [28]:
```
x_train =scaler.fit_transform(x_train)
```

In [29]:
```
x_train
```

Out[29]:
```
array([[ 1.28770177, -0.50032012,  1.03323679, ...,  0.84534281,
        -0.07433689,  1.75350503],
       [-0.33638447, -0.50032012, -0.41315956, ...,  1.20474139,
         0.4301838 , -0.5614742 ],
       [-0.40325332,  1.01327135, -0.71521823, ..., -0.63717631,
         0.06529747, -0.65159505],
       ...,
       [-0.40547014,  2.95931752, -1.30336132, ..., -0.59225149,
         0.37901005, -0.91069248],
       [ 0.85189733, -0.50032012,  1.03323679, ...,  0.84534281,
        -2.69458597,  1.52257036],
       [-0.38135592, -0.50032012, -0.35216694, ...,  1.15981657,
        -3.12158061, -0.25731635]])
```

In [30]:
```
x_test=scaler.transform(x_test)
```

In [31]:
```
x_test
```

Out[31]:
```
array([[-0.39680933, -0.50032012, -1.00711147, ..., -0.77195078,
         0.42887165, -0.48121032],
       [-0.40079621,  1.2294987 , -0.66439105, ..., -0.32270256,
         0.44418004, -1.25709448],
       [-0.39523443, -0.50032012,  2.43316256, ...,  0.80041799,
         0.36993437,  0.79033849],
       ...,
       [ 1.1779666 , -0.50032012,  1.03323679, ...,  0.84534281,
        -3.5124912 ,  1.23390203],
       [-0.40131065, -0.50032012, -0.94321444, ...,  0.08162084,
         0.43422959,  0.05669848],
       [-0.39643252, -0.50032012,  0.26792466, ...,  0.17147048,
         0.29470458, -0.49529171]])
```

Train model

In [32]:
```
 from sklearn.linear_model import LinearRegression
```

In [33]:
```
reg =LinearRegression()
```

In [34]:
```
reg.fit(x_train,y_train)
```

Out[34]:
```
LinearRegression()
```

print the coefficients and the intercept

In [35]:
```
print(reg.coef_)
```

```
[-1.00213533  0.69626862  0.27806485  0.7187384  -2.0223194   3.14523956
 -0.17604788 -3.0819076   2.25140666 -1.76701378 -2.03775151  1.12956831
 -3.61165842]
```

In [36]:
```
print(reg.intercept_)
```

```
22.796534653465375
```

on which parameters the model has been trained

In [37]:
```
reg.get_params()
```

Out[37]:
```
{'copy_X': True,
 'fit_intercept': True,
 'n_jobs': None,
 'normalize': 'deprecated',
 'positive': False}
```

prediction with test data

In [38]:
```
reg_pred =reg.predict(x_test)
```

In [39]:
```
reg_pred
```

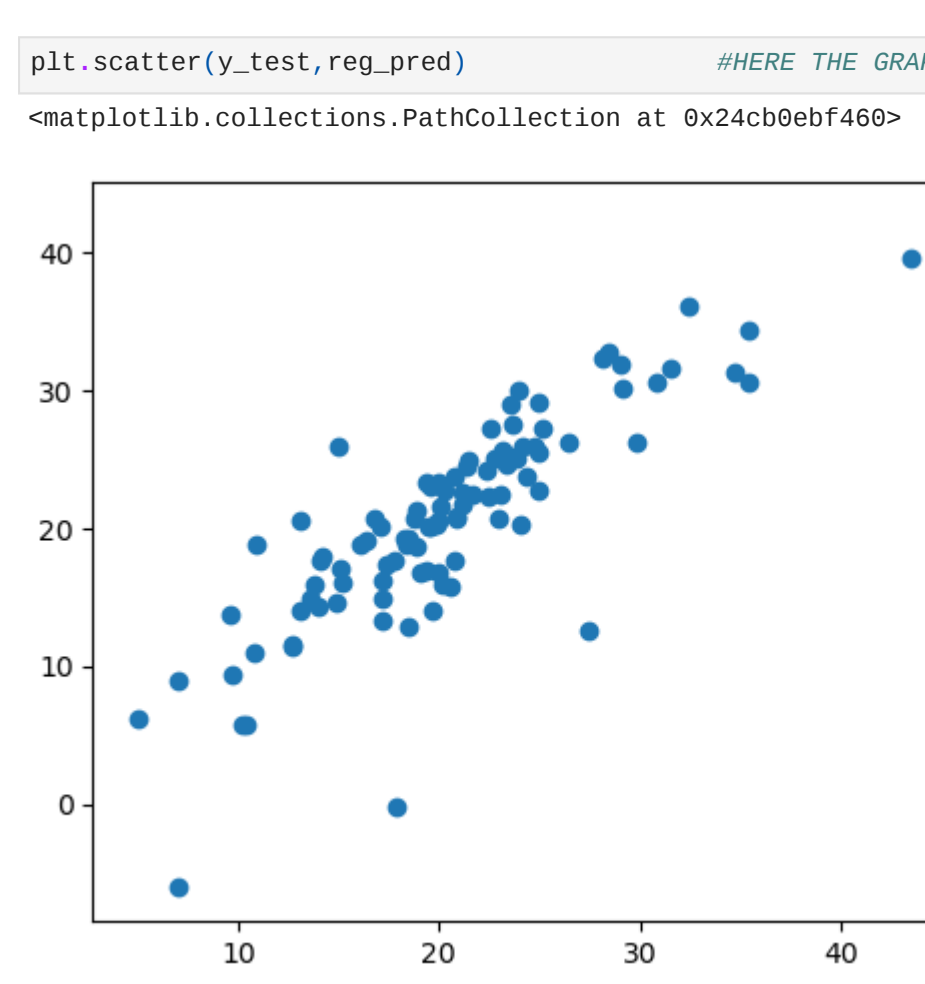
Out[39]:
```
array([28.99672362, 36.02556534, 14.81694405, 25.03197915, 18.76987992,
       23.25442929, 17.66253818, 14.34119   , 23.01320703, 20.63245597,
       24.90850512, 18.63883645, -6.08842184, 21.75834668, 19.23922576,
       26.19319733, 20.64773313,  5.79472718, 40.50033966, 17.61289074,
       27.24909479, 30.06625441, 11.34179277, 24.16077616, 17.86058499,
       15.83609765, 22.78148106, 14.57704449, 22.43626052, 19.19631835,
       22.43383455, 25.21979081, 25.93909562, 17.70162434, 16.76911711,
       16.95125411, 31.23340153, 20.13246729, 23.76579011, 24.6322925 ,
       13.94204955, 32.25576301, 42.67251161, 17.32745046, 27.27618614,
       16.99310991, 14.07009109, 25.90341861, 20.29485982, 29.95339638,
       21.28860173, 34.34451856, 16.04739105, 26.22562412, 39.53939798,
       22.57950697, 18.84531367, 32.72531661, 25.0673037 , 12.88628956,
       22.68221908, 30.48287757, 31.52626806, 15.90148607, 20.22094826,
       16.71089812, 20.52384893, 25.96356264, 30.61607978, 11.59783023,
       20.51232627, 27.48111878, 11.01962332, 15.68096344, 23.79316251,
        6.19929359, 21.6039073 , 41.41377225, 18.76548695,  8.87931901,
       20.83076916, 13.25620627, 20.73963699,  9.36482222, 23.22444271,
       31.9155003 , 19.10228271, 25.51579303, 29.04256769, 20.14358566,
       25.5859787 ,  5.70159447, 20.09474756, 14.95069156, 12.50395648,
       20.72635294, 24.73957161, -0.164237  , 13.68486682, 16.18359697,
       22.27621999, 24.47902364])
```

plot scatter for prediction

Assumptions

In [40]:
```
plt.scatter(y_test,reg_pred)                #HERE THE GRAPH IS LINEAR WHICH MEANS OUR MODEL PERFORM FINE HERE
```

Out[40]:
```
<matplotlib.collections.PathCollection at 0x24cb0ebf460>
```



calculation of residuals or we can say error

In [41]:
```
residuals =y_test-reg_pred
```

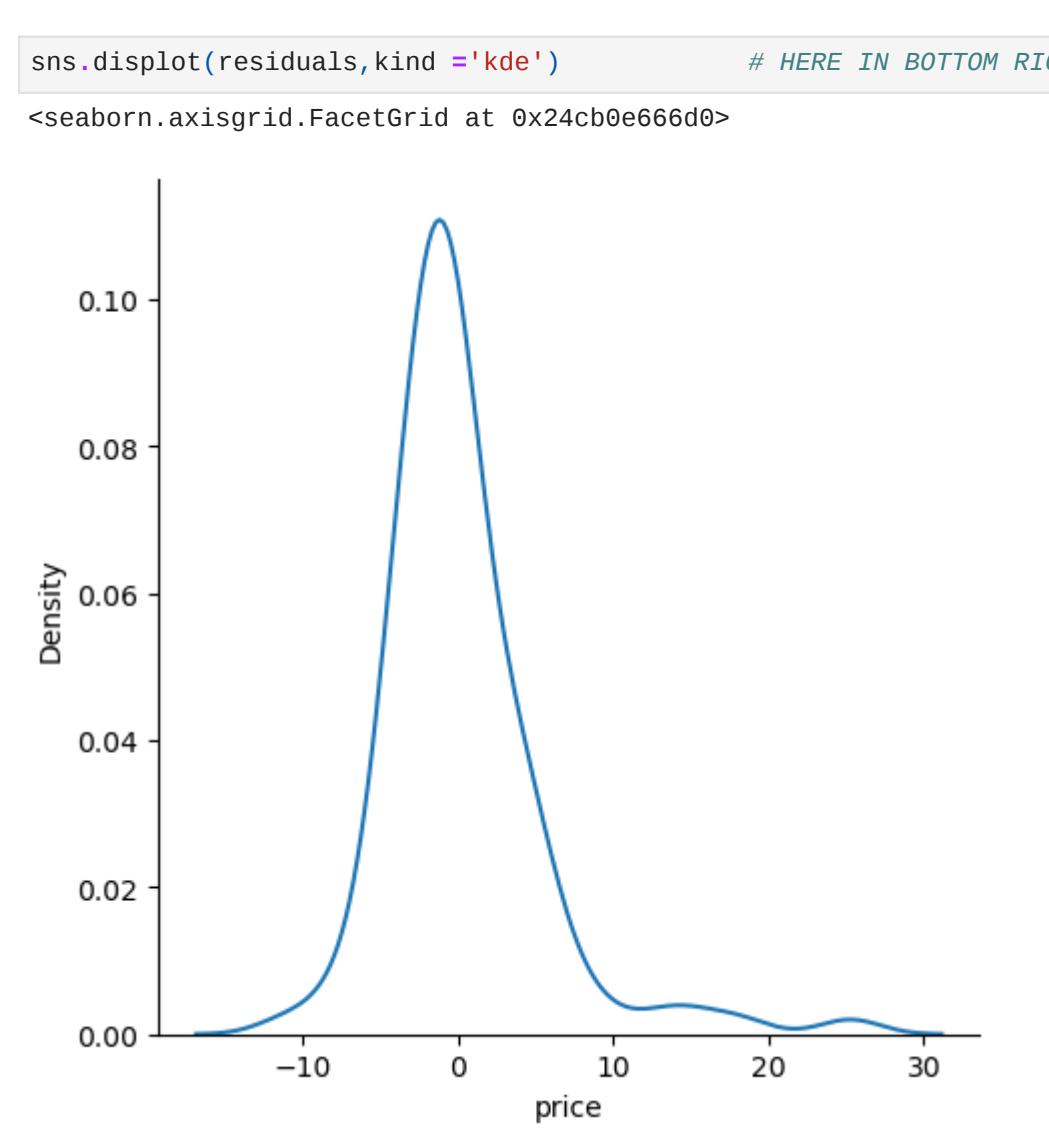
In [42]:
```
residuals
```

Out[42]:
```
173    -5.396724
274    -3.625565
491    -1.216944
72     -2.231979
452    -2.669880
         ...    
412    18.064237
436    -4.084867
411     1.016403
86      0.223780
75     -3.079024
Name: price, Length: 102, dtype: float64
```

plot residuals

In [43]:
```
sns.displot(residuals,kind ='kde')          # HERE IN BOTTOM RIGHT WE CAN SEE LITTLE DISTURBANCE IT IS ERROR OR RESIDUALS OR OUTLIERS
```

Out[43]:
```
<seaborn.axisgrid.FacetGrid at 0x24cb0e666d0>
```

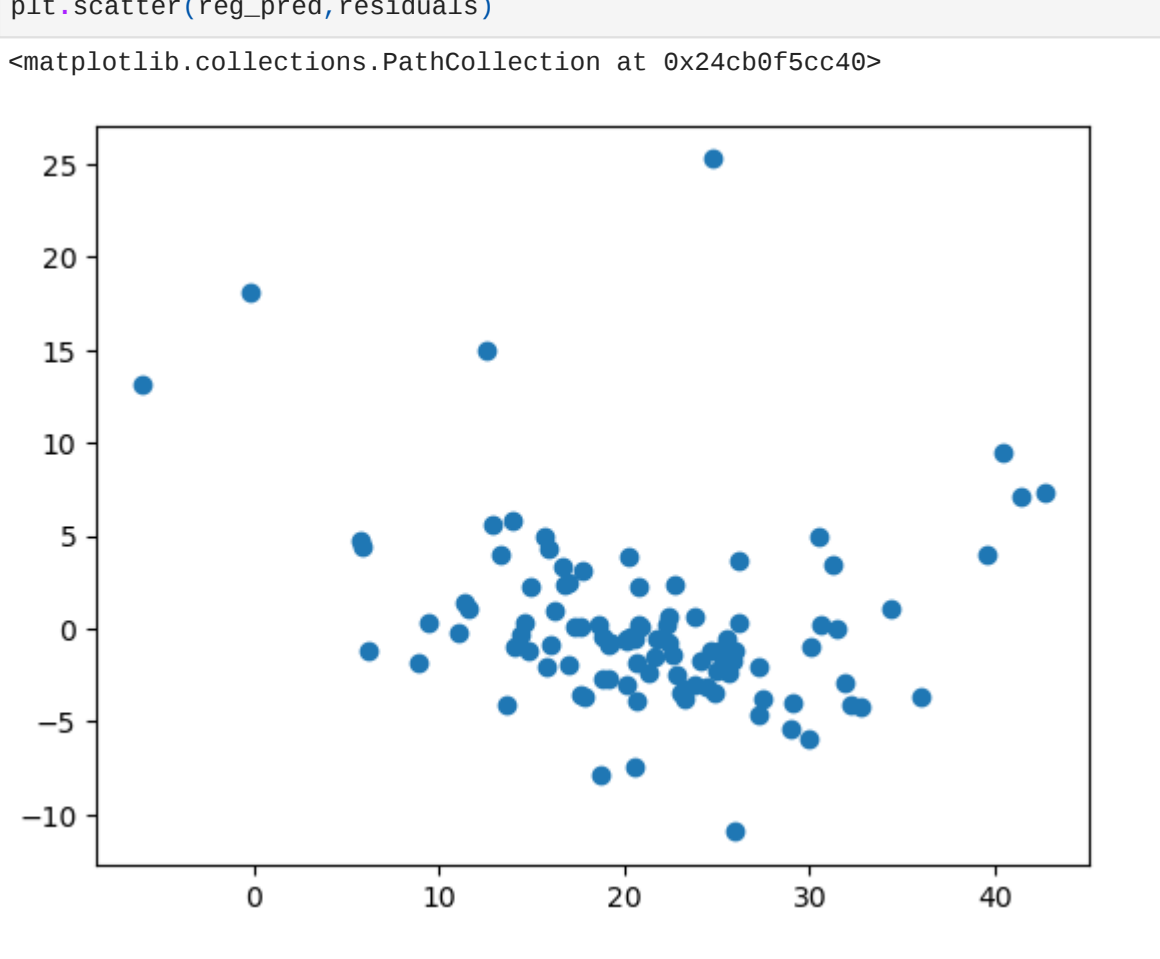


scatter plot with respect to residuals and prediction

uniform distribution

In [44]:
```
plt.scatter(reg_pred,residuals)
```

Out[44]:
```
<matplotlib.collections.PathCollection at 0x24cb0f5cc40>
```



performance matrix to check performance of model

In [45]:
```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
```

In [46]:
```
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)))
```

```
24.291119474973513
3.1890919658878474
4.928602182665336
```

check performance by R square and Adjusted R square

In [47]:
```
from sklearn.metrics import r2_score
score =r2_score(y_test,reg_pred)
print(score)
```

```
0.668759493535632
```

Now to check adj_r_score

In [48]:
```
1-(1-score)*(len(y_test)-1)/(len(y_test)-x_test.shape[1]-1)         # ADJUSTED R_SQ ALWAYS LESS THAN R_SQ
```

Out[48]:
```
0.6198262368988503
```

In [ ]: