BOSTON HOUSE PRICE PREDICTION - Data Set

Steps Involved:

```
1. Loading the dataset
2. EDA - Cleaning the data, filling missing values, understanding data insights
3. ML - Linear Regression :
        Splitting data into train / test
        Score / Error
        Metrics
4. Predicting price for new input values
```

In [1]:

```
#Importing necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
#Importing libraries and modules of Machine Learning
import sklearn
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

In [3]:

```
#importing dataset
from sklearn.datasets import load_boston
```

In [4]:

```
#Assigning the file to a variable
boston=load_boston()
print(boston)
```

```
{'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.96
90e+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. ,
        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]),
 '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 Instances: 506 \n\n    :N
umber of Attributes: 13 numeric/categorical predictive. Median Value (attr
ibute 14) is usually the target.\n\n    :Attribute Information (in orde
r):\n        - CRIM     per capita crime rate by town\n        - ZN
proportion of residential land zoned for lots over 25,000 sq.ft.\n
- INDUS    proportion of non-retail business acres per town\n        - CHA
S     Charles River dummy variable (= 1 if tract bounds river; 0 otherwis
e)\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 to five Boston employment centres\n        - RAD      i
ndex of accessibility to radial highways\n        - TAX      full-value pr
operty-tax rate per $10,000\n        - PTRATIO  pupil-teacher ratio by tow
n\n        - B        1000(Bk - 0.63)^2 where Bk is the proportion of blac
ks by town\n        - LSTAT    % lower status of the population\n        -
MEDV     Median value of owner-occupied homes in $1000's\n\n    :Missing A
ttribute Values: None\n\n    :Creator: Harrison, D. and Rubinfeld, D.L.\n
\nThis is a copy of UCI ML housing dataset.\nhttps://archive.ics.uci.edu/m
l/machine-learning-databases/housing/\n\n\nThis dataset was taken from the
StatLib library which is maintained at Carnegie Mellon University.\n\nThe
Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic\npric
es and the demand for clean air', J. Environ. Economics & Management,\nvo
l.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostic
s\n...', Wiley, 1980.   N.B. Various transformations are used in the table
on\npages 244-261 of the latter.\n\nThe Boston house-price data has been u
sed in many machine learning papers that address regression\nproblems.
\n     \n.. topic:: References\n\n   - Belsley, Kuh & Welsch, 'Regression
diagnostics: Identifying Influential Data and Sources of Collinearity', Wi
ley, 1980. 244-261.\n   - 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.\n", 'filename': 'C:\\Users\\Lucky Girish\\anaconda3\\lib\\site-p
ackages\\sklearn\\datasets\\data\\boston_house_prices.csv'}
```

The loaded dataset is in the form of dictionary

In [5]:

```
#Getting the keys inside the dataset
boston.keys()
```

Out[5]:

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

In [6]:

```
#Getting the data inside it
boston.data
```

Out[6]:

```
array([[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]:

```
#Getting the target data
boston.target
```

Out[7]:

```
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. ,
       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]:

```
#Getting the column names- feature_names
boston.feature_names
```

Out[8]:

```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [9]:

```
#Making the dataset in form of dictionary into a dataframe
bos=pd.DataFrame(boston.data,columns=boston.feature_names)
```

In [10]:

```
bos
```

Out[10]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90

506 rows × 13 columns

In [11]:

```
bos.shape
```

Out[11]:

```
(506, 13)
```

In [12]:

```
#Adding the column target into the dataframe
bos['target']=boston.target
```

In [13]:

```
#To see the column names
bos.columns
```

Out[13]:

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'T
AX',
       'PTRATIO', 'B', 'LSTAT', 'target'],
      dtype='object')
```

In [14]:

```
bos.shape
```

Out[14]:

```
(506, 14)
```

In [15]:

```
bos.dtypes
```

Out[15]:

```
CRIM       float64
ZN         float64
INDUS      float64
CHAS       float64
NOX        float64
RM         float64
AGE        float64
DIS        float64
RAD        float64
TAX        float64
PTRATIO    float64
B          float64
LSTAT      float64
target     float64
dtype: object
```

In [16]:

```
#Checking for null values
bos.isnull().sum()
```

Out[16]:

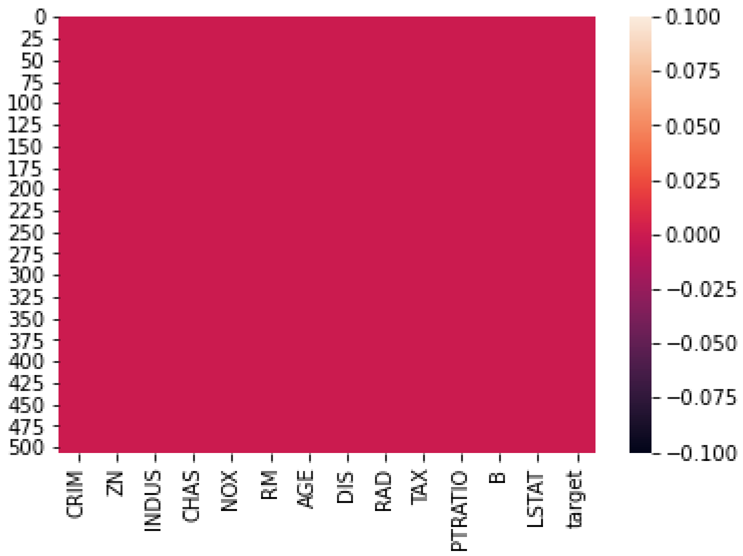
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
target     0
dtype: int64
```

In [17]:

```
#Visualization method to check null values
sns.heatmap(bos.isnull())
```

Out[17]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x154d80f1670>
```



In [18]:

```
#Statistical Summary
bos.describe()
```

Out[18]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
count	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
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

Observations: 1) std is high in few columns - indicates high spread of data and possibility of outliers 2) Large gap between 75% and Max. - Defiite presence of outliers 3) Mean > Median(50%) - Right Skew 4) Mean < Median(50%) - Left Skew

In [19]:

```
#To see the skewness present in each column
print(bos.skew())
```

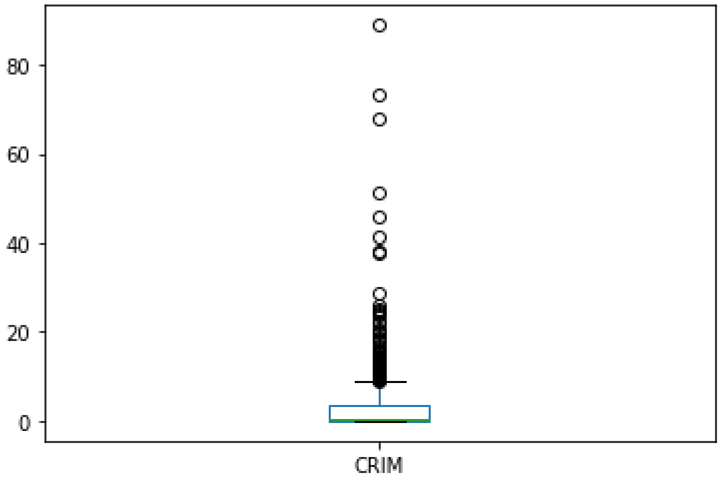
```
CRIM       5.223149
ZN         2.225666
INDUS      0.295022
CHAS       3.405904
NOX        0.729308
RM         0.403612
AGE       -0.598963
DIS        1.011781
RAD        1.004815
TAX        0.669956
PTRATIO   -0.802325
B         -2.890374
LSTAT      0.906460
target     1.108098
dtype: float64
```

In [20]:

```
#Visualization
bos['CRIM'].plot.box()
```

Out[20]:

<matplotlib.axes._subplots.AxesSubplot at 0x154d8955bb0>



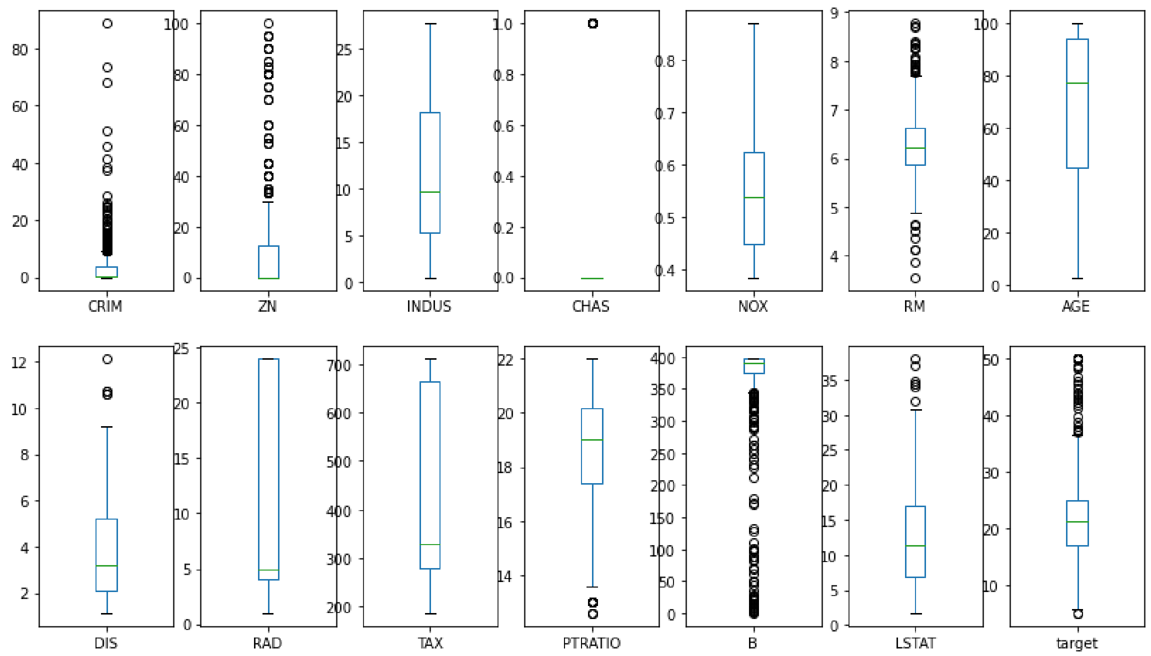
Above is the box plot for one column

In [21]:

```
#Plotting box for all columns
bos.plot(kind='box',subplots=True,layout=(2,7),figsize=(14,8))
```

Out[21]:

```
CRIM          AxesSubplot(0.125,0.536818;0.0945122x0.343182)
ZN         AxesSubplot(0.238415,0.536818;0.0945122x0.343182)
INDUS      AxesSubplot(0.351829,0.536818;0.0945122x0.343182)
CHAS       AxesSubplot(0.465244,0.536818;0.0945122x0.343182)
NOX        AxesSubplot(0.578659,0.536818;0.0945122x0.343182)
RM         AxesSubplot(0.692073,0.536818;0.0945122x0.343182)
AGE        AxesSubplot(0.805488,0.536818;0.0945122x0.343182)
DIS              AxesSubplot(0.125,0.125;0.0945122x0.343182)
RAD           AxesSubplot(0.238415,0.125;0.0945122x0.343182)
TAX           AxesSubplot(0.351829,0.125;0.0945122x0.343182)
PTRATIO       AxesSubplot(0.465244,0.125;0.0945122x0.343182)
B             AxesSubplot(0.578659,0.125;0.0945122x0.343182)
LSTAT         AxesSubplot(0.692073,0.125;0.0945122x0.343182)
target        AxesSubplot(0.805488,0.125;0.0945122x0.343182)
dtype: object
```



In [22]:

```
from scipy.stats import zscore
z=np.abs(zscore(bos))
z
```

Out[22]:

```
array([[0.41978194, 0.28482986, 1.2879095 , ..., 0.44105193, 1.0755623 ,
        0.15968566],
       [0.41733926, 0.48772236, 0.59338101, ..., 0.44105193, 0.49243937,
        0.10152429],
       [0.41734159, 0.48772236, 0.59338101, ..., 0.39642699, 1.2087274 ,
        1.32424667],
       ...,
       [0.41344658, 0.48772236, 0.11573841, ..., 0.44105193, 0.98304761,
        0.14880191],
       [0.40776407, 0.48772236, 0.11573841, ..., 0.4032249 , 0.86530163,
        0.0579893 ],
       [0.41500016, 0.48772236, 0.11573841, ..., 0.44105193, 0.66905833,
        1.15724782]])
```

In [23]:

```
threshold=3
print(np.where(z>3))
```

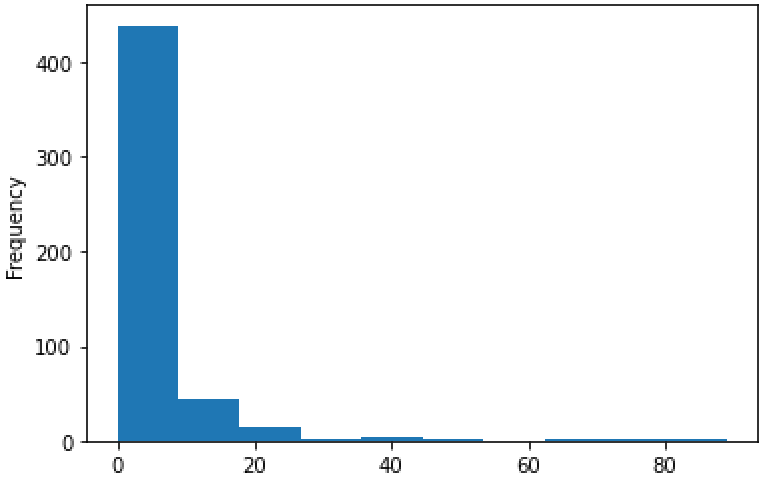
```
(array([ 55,  56,  57, 102, 141, 142, 152, 154, 155, 160, 162, 163, 199,
       200, 201, 202, 203, 204, 208, 209, 210, 211, 212, 216, 218, 219,
       220, 221, 222, 225, 234, 236, 256, 257, 262, 269, 273, 274, 276,
       277, 282, 283, 283, 284, 347, 351, 352, 353, 353, 354, 355, 356,
       357, 358, 363, 364, 364, 365, 367, 369, 370, 372, 373, 374, 374,
       380, 398, 404, 405, 406, 410, 410, 411, 412, 412, 414, 414, 415,
       416, 418, 418, 419, 423, 424, 425, 426, 427, 427, 429, 431, 436,
       437, 438, 445, 450, 454, 455, 456, 457, 466], dtype=int64), array([
1,  1,  1, 11, 12,  3,  3,  3,  3,  3,  3,  3,  1,  1,  1,  1,  1,
        1,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  3,  5,  3,  3,  1,  5,
        5,  3,  3,  3,  3,  3,  3,  1,  3,  1,  1,  7,  7,  1,  7,  7,  7,
        3,  3,  3,  3,  3,  5,  5,  5,  3,  3,  3, 12,  5, 12,  0,  0,  0,
        0,  5,  0, 11, 11, 11, 12,  0, 12, 11, 11,  0, 11, 11, 11, 11, 11,
       11,  0, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11, 11],
      dtype=int64))
```

In [24]:

```
#To check skewness visually
bos['CRIM'].plot.hist()
```

Out[24]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x154d88cb670>
```



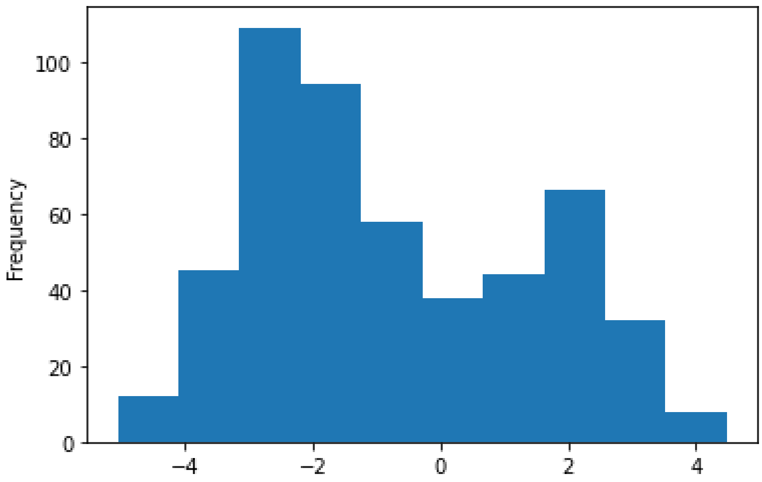
To remove the skewness: 1) Logtransformation - Method using Numpy 2) Squareroot transormation - Method in Numpy 3) Boxcox - Method in stats module of scipy library

In [25]:

```
#Removing skew using logtransformation
bos['CRIM']=np.log(bos['CRIM'])
bos['CRIM'].plot.hist()
```

Out[25]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x154d8aca730>
```



In [26]:

```
#Checking the skewness - earlier skewness is 5.22 , now it is reduced
bos['CRIM'].skew()
```

Out[26]:

```
0.4059344988496048
```

In [27]:

```
#Other method to remove skewness
from scipy.stats import boxcox
print(bos['ZN'].skew())
bos['ZN']=boxcox(bos['ZN'])[0]
bos['ZN'].plot.hist()
print(pd.Series(bos['ZN'].skew()))
```

```
2.2256663227354307

---------------------------------------------------------------------------
-
ValueError                                Traceback (most recent call las
t)
<ipython-input-27-7ee950276a4c> in <module>
      2 from scipy.stats import boxcox
      3 print(bos['ZN'].skew())
----> 4 bos['ZN']=boxcox(bos['ZN'])[0]
      5 bos['ZN'].plot.hist()
      6 print(pd.Series(bos['ZN'].skew()))

~\anaconda3\lib\site-packages\scipy\stats\morestats.py in boxcox(x, lmbda,
alpha)
   1041
   1042     if any(x <= 0):
-> 1043         raise ValueError("Data must be positive.")
   1044
   1045     if lmbda is not None:  # single transformation

ValueError: Data must be positive.
```

boxcox will not work for the data having 0 or -ve values inside it

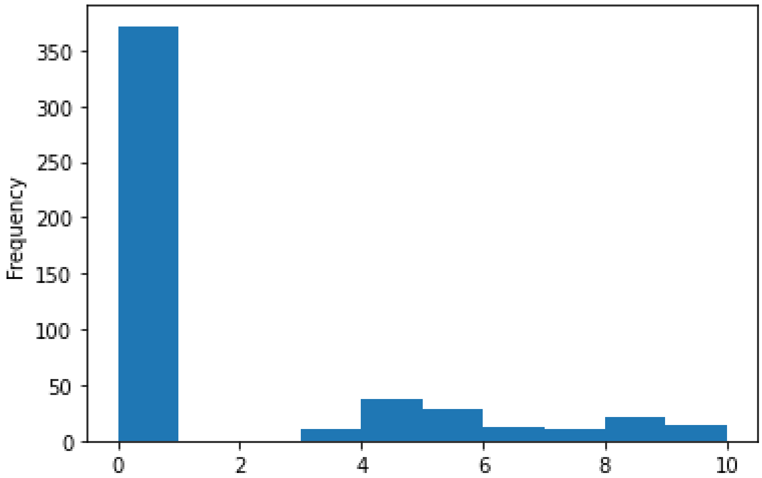
In [28]:

```
#Other method  squareroot
print('Beore:',bos['ZN'].skew())
bos['ZN']=np.sqrt(bos['ZN'])
print('After:',bos['ZN'].skew())
bos['ZN'].plot.hist()
```

```
Beore: 2.2256663227354307
After: 1.4762928299237978
```

Out[28]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x154d88b8100>
```



Bivariate Analysis

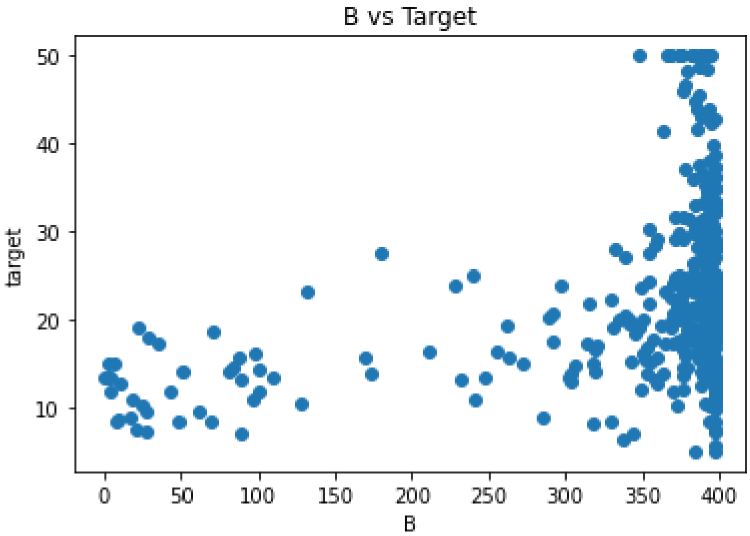
Checking the relationship between two variables

In [29]:

```
plt.scatter(bos['B'],bos['target'])
plt.title('B vs Target')
plt.xlabel('B')
plt.ylabel('target')
```

Out[29]:

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



From above we can say that after a certain increase in B numbers the price got increased and stabilized at a point

we can see for other columns also simillarly to understand relation between them

In [30]:

```
#Finding Collinearity
corr_hmap=bos.corr()
corr_hmap
```

Out[30]:

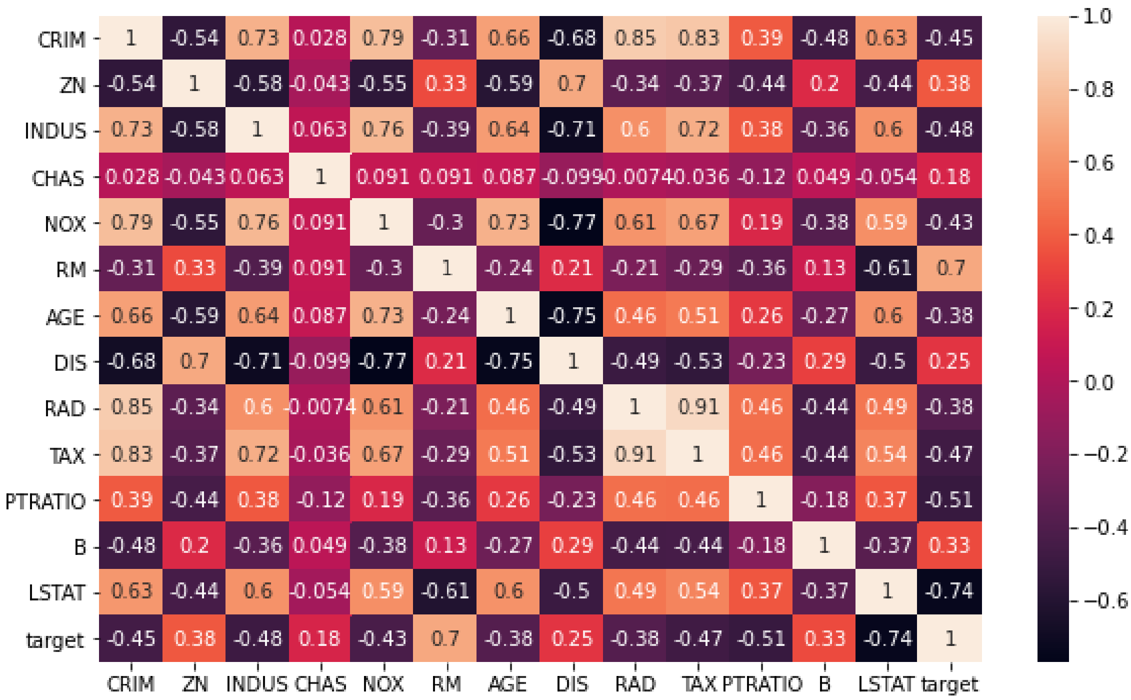
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	D
CRIM	1.000000	-0.544169	0.730821	0.028496	0.788616	-0.306943	0.658284	-0.6819
ZN	-0.544169	1.000000	-0.583917	-0.042605	-0.548889	0.333444	-0.588399	0.6971
INDUS	0.730821	-0.583917	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.7080
CHAS	0.028496	-0.042605	0.062938	1.000000	0.091203	0.091251	0.086518	-0.0991
NOX	0.788616	-0.548889	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.7692
RM	-0.306943	0.333444	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.2052
AGE	0.658284	-0.588399	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.7478
DIS	-0.681903	0.697175	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.0000
RAD	0.853407	-0.344420	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.4945
TAX	0.828234	-0.371003	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.5344
PTRATIO	0.389554	-0.440846	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.2324
B	-0.478755	0.203898	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.2915
LSTAT	0.626615	-0.439516	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.4969
target	-0.454302	0.382970	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.2499

In [31]:

```
# To better understand collinearity in easy way we use visualization
plt.figure(figsize=(10,6))
sns.heatmap(corr_hmap,annot=True)
```

Out[31]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x154d90606d0>
```



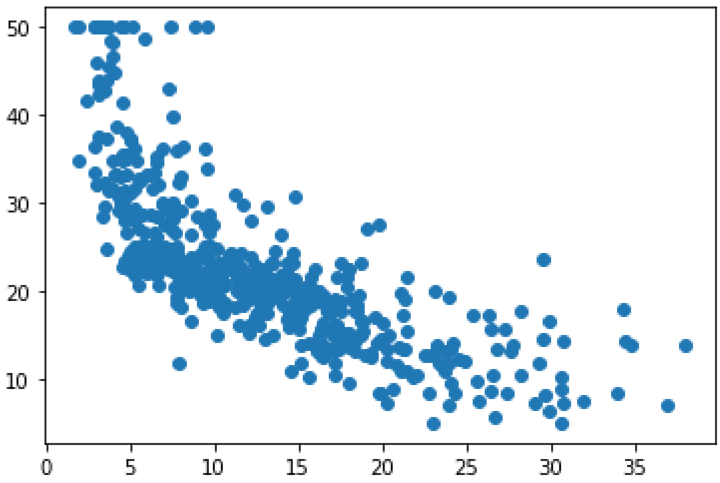
We can see that LSTAT is highly -ve correlated to target.Hence it is our choice to remove the column with high -ve correlation

In [33]:

```
#visualizing scatter plot b/w those variables
plt.scatter(bos['LSTAT'],bos['target'])
```

Out[33]:

```
<matplotlib.collections.PathCollection at 0x154d964f130>
```



In [34]:

```
#Remove the column LSTAT
bos.drop('LSTAT',axis=1,inplace=True)
```

In [35]:

```
#Verifying the shape of dataframe
bos.shape
```

Out[35]:

```
(506, 13)
```

In [36]:

```
#Checking the columns
bos.columns
```

Out[36]:

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'T
AX',
       'PTRATIO', 'B', 'target'],
      dtype='object')
```

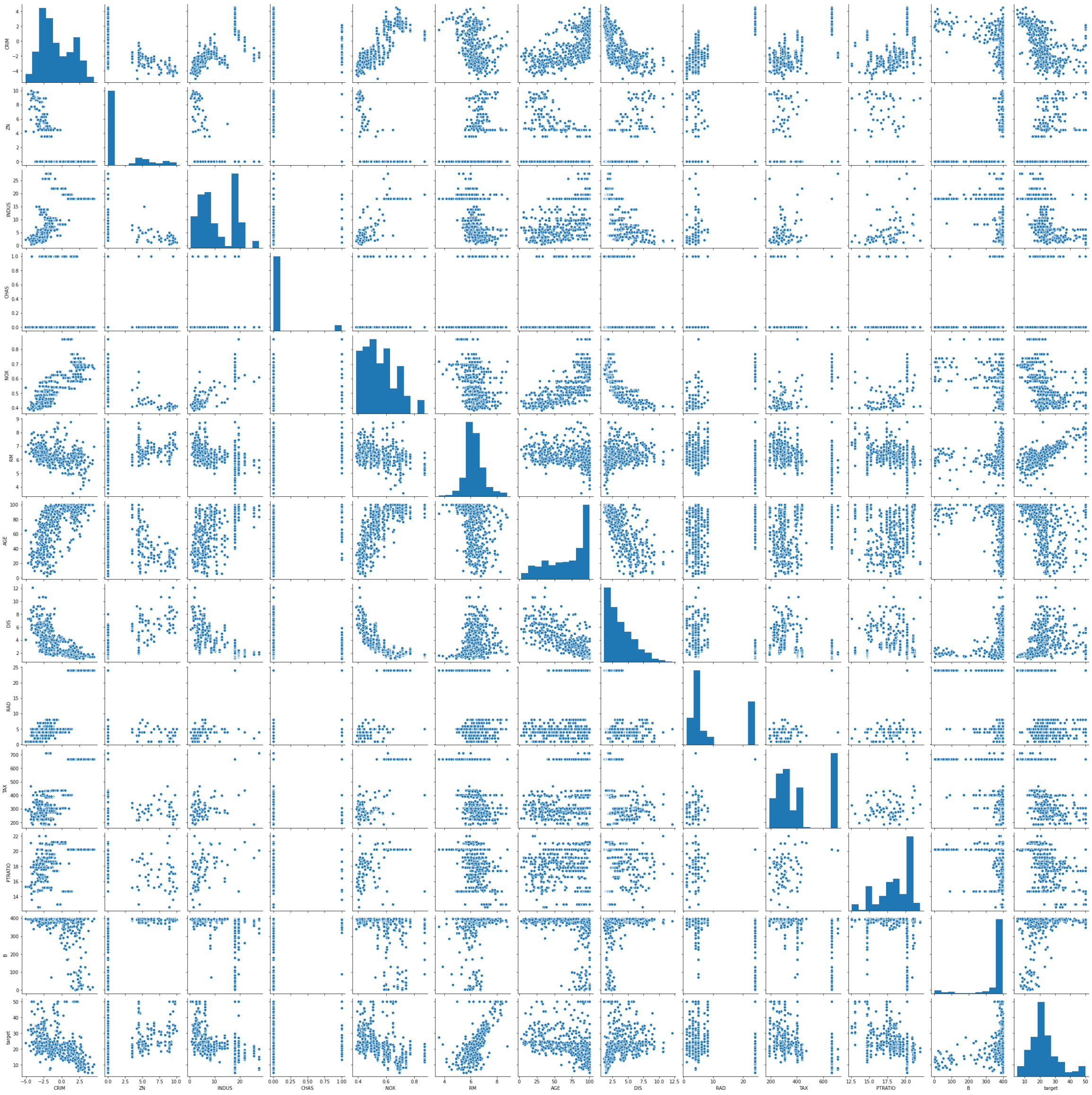
Hence verified the column is dropped from the dataframe

In [37]:

```
#Visualizing the plot b/w each and every column with respect to other
sns.pairplot(bos)
```

Out[37]:

```
<seaborn.axisgrid.PairGrid at 0x154d9657280>
```



Remove outliers

Step 1 : Find the ZSCORE Step 2 : Fix Threshold to 3 Step 3 : Copy all the data with Threshold < 3 to new dataset (To remove outliers)

In [38]:

```
bos_new=bos[(z<3).all(axis=1)]
```

In [39]:

```
bos_new.shape
```

Out[39]:

```
(415, 13)
```

In [40]:

```
bos_new
```

Out[40]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO
0	-5.064036	4.242641	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3
1	-3.600502	0.000000	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8
2	-3.601235	0.000000	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8
3	-3.430523	0.000000	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7
4	-2.672924	0.000000	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7
...	...	...	...	...	...	...	...	...	...	...	...
501	-2.770511	0.000000	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0
502	-3.095111	0.000000	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0
503	-2.800824	0.000000	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0
504	-2.211009	0.000000	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0
505	-3.048922	0.000000	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0

415 rows × 13 columns

EDA process completed: No null values No outliers Reduced skewness Data is clean and clear

Machine Learning :

Spliting data into x and y

In [44]:

```
#x - all columns except target
x=bos_new.iloc[:,0:-1]
x.head()
```

Out[44]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	
0	-5.064036	4.242641	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	39
1	-3.600502	0.000000	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	39
2	-3.601235	0.000000	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	39
3	-3.430523	0.000000	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	39
4	-2.672924	0.000000	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	39

In [45]:

```
#y - Target column
y=bos_new.iloc[:,-1]
y.head()
```

Out[45]:

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

In [46]:

```
print('x-shape:',x.shape)
print('y-shape:',y.shape)
```

```
x-shape: (415, 12)
y-shape: (415,)
```

Splitting the dataset into train & test

In [66]:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.33,random_state=42)
```

x, y are splitted into train & test, test_size: Indicates what percent of dataset to be given for test Best Practice: Train - 70 to 80% Test - 20 to 30%

In [48]:

```
x_train.shape
```

Out[48]:

```
(278, 12)
```

In [49]:

```
y_train.shape
```

Out[49]:

```
(278,)
```

In [50]:

```
x_test.shape
```

Out[50]:

```
(137, 12)
```

In [53]:

```
y_test.shape
```

Out[53]:

```
(137,)
```

In [54]:

```
#Performing Linear Regression
lm=LinearRegression()
```

In [61]:

```
#Training the machine
lm.fit(x_train,y_train)
```

Out[61]:

```
LinearRegression()
```

Equation: Linear Regression y=a+b1x1+b2x2+b3x3+............ y - Target a- intercept b1,b2,.... are - Coefficients

In [56]:

```
#Coefficients contributing the price
lm.coef_
```

Out[56]:

```
array([ 4.20107204e-01, -7.33616126e-02, -4.03862533e-02, -7.49469931e-14,
       -1.23908930e+01,  8.31024593e+00, -6.74958251e-02, -1.12488265e+00,
        5.34737983e-02, -1.16996703e-02, -7.92187861e-01,  9.30623364e-0
3])
```

In [57]:

```
#intercept
lm.intercept_
```

Out[57]:

```
1.983869035055985
```

In [60]:

```
bos_new.columns
```

Out[60]:

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'T
AX',
       'PTRATIO', 'B', 'target'],
      dtype='object')
```

In [70]:

```
#Checking accuracy of the model
lm.score(x_train,y_train)
```

Out[70]:

```
0.7450119286943324
```

From above we can say that model developed is 74% accurate

In [74]:

```
#Prediciting the value
pred=lm.predict(x_test)
print('Predicted prices:',pred)
print('Actual prices:',y_test)
```

```
Predicted prices: [20.45168573 14.52019351 31.42967261 18.3069961  13.1177
7161 20.77168031
 17.32313488 25.10347626 29.58033913 10.81655364 17.7284031  15.69675497
  8.99210376 24.29629885 27.93681697 10.67189387 25.61398791 27.38533415
 24.86303693 14.02481819 21.73039719 19.03733167 23.56195445 12.03370348
 21.9576397  21.59991725 31.67677043 27.62259851 22.14473797 25.01876689
 32.57545705 14.74189707 13.54832424 26.22086213 15.57559325 15.07756916
 26.87891623 22.3572384  13.77222749 19.1447321  17.10739289 18.06892298
 20.56075204 26.58750169 17.10981313 26.15912393 19.9527086  19.50701344
 17.76492844 24.44699271 20.77161761 19.06951418 39.77146615 13.45946854
 19.03536034 22.02308623 18.70268163 41.24085472 20.12757007 18.1515857
 26.53923876 16.79547193 24.44357011 28.07434513 14.52842251  5.36330712
 34.10754535 19.63309521 19.13504835 22.49835296 35.24732989 19.96569906
 24.24094327 24.57111093 15.2870426  22.51685956 16.45349721 17.94636363
 22.39303667 16.41852222 17.62230123 21.56509757 25.40539826 28.23329928
 17.82048597 26.79762217 21.34768799 23.81612908 21.56074927 21.73746465
  8.13902726 19.63243599 11.59085509 20.21490263 19.79343599 29.44583961
 16.17179833 39.10000921 24.39555908 24.79232602 11.14917742 20.71142065
 28.53545804  6.67392901 41.79060095 34.10572926 12.92674436 23.83085595
 26.86889281 20.73383993 12.58713547 28.69641386 18.98437047 16.95764746
 27.85524182 23.31633123 18.70904232 18.07511813 24.86068986 19.34047651
 31.00068642 21.76097999 14.62812269 18.74531797 20.88044364 19.81612673
 28.05596924 20.49332193 11.25421245 30.08299223 16.88378639 24.26832442
 23.54397374  9.19108138 24.74605263 20.34971798 19.38119143]
Actual prices: 58     23.3
146    15.6
187    32.0
59     19.6
407    27.9
       ...
287    23.2
488    15.2
318    23.1
113    18.7
184    26.4
Name: target, Length: 137, dtype: float64
```

In [78]:

```
#Checking the errors
print('Error:')
print("Mean_absolute_error:",mean_absolute_error(y_test,pred))
print("Mean_squared_error:",mean_squared_error(y_test,pred))
print("Root_Mean_squared_error:",np.sqrt(mean_squared_error(y_test,pred)))
```

```
Error:
Mean_absolute_error: 2.829957759398437
Mean_squared_error: 25.675871541206575
Root_Mean_squared_error: 5.067136424175549
```

METRICS

To check the performance of model

In [79]:

```
from sklearn.metrics import r2_score
print(r2_score(y_test,pred))
```

```
0.555949638355204
```

There is a change of 0.55 in y each and every time when x changes

In [80]:

```
#Predict price for new inputs
t=np.array([0.04741,0.0,11.93,0.0,0.573,6.030,80.8,2.5050,1.0,273.0,21.0,396.90])
t.shape
```

Out[80]:

```
(12,)
```

In [82]:

```
t=t.reshape(1,-1)
t.shape
```

Out[82]:

```
(1, 12)
```

In [83]:

```
lm.predict(t)
```

Out[83]:

```
array([20.17844867])
```