```
In [56]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         %matplotlib inline
In [80]: from sklearn.datasets import load boston
In [84]: df = load boston()
In [82]: df.keys()
Out[82]: dict keys(['data', 'target', 'feature names', 'DESCR', 'filename', 'data module'])
In [83]: df.data
Out[83]: 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+001,
                 [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+001,
                 [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
                 7.8800e+00]])
```

In [61]: df.target

```
Out[61]: 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 [63]: boston = pd.DataFrame(df.data, columns=df.feature_names)
boston.head()

Out[63]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	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 [64]: boston.columns

In [65]: boston.head()

Out[65]:

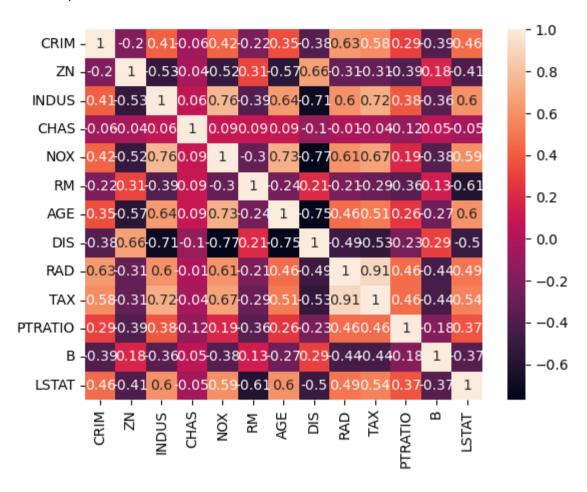
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	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 [66]: boston.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):
             Non-Null Count Dtype
     Column
     ----
     CRIM
              506 non-null
                              float64
 0
     ΖN
              506 non-null
                              float64
 1
     INDUS
              506 non-null
                              float64
     CHAS
              506 non-null
                              float64
 3
     NOX
              506 non-null
                              float64
 4
     RM
              506 non-null
                              float64
 5
              506 non-null
                              float64
 6
     AGE
              506 non-null
                              float64
     DIS
 8
     RAD
              506 non-null
                              float64
              506 non-null
                              float64
 9
     TAX
    PTRATIO 506 non-null
                              float64
 11 B
              506 non-null
                              float64
 12 LSTAT
              506 non-null
                              float64
dtypes: float64(13)
memory usage: 51.5 KB
```

```
In [67]: import seaborn as sns
sns.heatmap(boston.corr().round(2),annot = True)
```

Out[67]: <AxesSubplot:>



```
In [69]: X = boston[['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
                 'PTRATIO', 'B', 'LSTAT']]
          y = boston['TAX']
 In [70]: from sklearn.model selection import train test split
 In [94]: X train, X test, y train, y test = train test split(X, y, test size=0.33, random state=42)
 In [95]: from sklearn.linear model import LinearRegression
 In [96]: lr = LinearRegression()
 In [97]: lr.fit(X train,y train)
 Out[97]: LinearRegression()
 In [98]: print(lr.intercept )
          149.5080471422711
 In [99]: lr.coef
Out[99]: array([-8.61013588e-02, 1.08204397e+00, 6.40734555e+00, -2.54068403e+01,
                  8.89176241e+01, -7.54174543e+00, 5.85521999e-02, -1.76527488e+00,
                  1.39854219e+01, 3.08875087e+00, -2.26712449e-02, -2.50944616e-01])
In [100]: X train.columns
Out[100]: Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
                 'PTRATIO', 'B', 'LSTAT'],
                dtype='object')
```

```
In [101]: cdf = pd.DataFrame(lr.coef_,X.columns,columns = ['Coeff'])
In [102]: cdf
Out[102]:
                         Coeff
              CRIM
                     -0.086101
                ΖN
                      1.082044
              INDUS
                      6.407346
              CHAS -25.406840
                     88.917624
               NOX
                RM
                     -7.541745
               AGE
                      0.058552
                DIS
                     -1.765275
               RAD
                     13.985422
            PTRATIO
                      3.088751
                  В
                     -0.022671
             LSTAT -0.250945
  In [ ]:
```