In [3]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn import datasets
```

In [14]:
```
df = datasets.load_boston()
```

```
/home/ubuntu/.local/lib/python3.10/site-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function
load_boston is deprecated; `load_boston` is deprecated in 1.0 and will be removed in 1.2.

    The Boston housing prices dataset has an ethical problem. You can refer to
    the documentation of this function for further details.

    The scikit-learn maintainers therefore strongly discourage the use of this
    dataset unless the purpose of the code is to study and educate about
    ethical issues in data science and machine learning.

    In this special case, you can fetch the dataset from the original
    source::

        import pandas as pd
        import numpy as np

        data_url = "http://lib.stat.cmu.edu/datasets/boston"
        raw_df = pd.read_csv(data_url, sep="\s+", skiprows=22, header=None)
        data = np.hstack([raw_df.values[::2, :], raw_df.values[1::2, :2]])
        target = raw_df.values[1::2, 2]

    Alternative datasets include the California housing dataset (i.e.
    :func:`~sklearn.datasets.fetch_california_housing`) and the Ames housing
    dataset. You can load the datasets as follows::

        from sklearn.datasets import fetch_california_housing
        housing = fetch_california_housing()

    for the California housing dataset and::

        from sklearn.datasets import fetch_openml
        housing = fetch_openml(name="house_prices", as_frame=True)

    for the Ames housing dataset.
  warnings.warn(msg, category=FutureWarning)
```

In [15]:
```
df
```

Out[15]:
```
{'data': 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]]),
 '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 C
haracteristics:**  \n\n    :Number of Instances: 506 \n\n    :Number of Attributes: 13 numeric/categorical
predictive. Median Value (attribute 14) is usually the target.\n\n    :Attribute Information (in order):\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        - CHAS
Charles River dummy variable (= 1 if tract bounds river; 0 otherwise)\n        - NOX      nitric oxides co
ncentration (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 Bost
on employment centres\n        - RAD      index of accessibility to radial highways\n        - TAX      fu
ll-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 of owner-occupied homes in $1000's\n\n    :Missing Attribu
te Values: None\n\n    :Creator: Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing data
set.\nhttps://archive.ics.uci.edu/ml/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 H
arrison, D. and Rubinfeld, D.L. 'Hedonic\nprices and the demand for clean air', J. Environ. Economics & Ma
nagement,\nvol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics\n...', Wiley, 198
0.   N.B. Various transformations are used in the table on\npages 244-261 of the latter.\n\nThe Boston hou
```

```
se-price data has been used in many machine learning papers that address regression\nproblems.   \n     \
n.. topic:: References\n\n   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Dat
a and Sources of Collinearity', Wiley, 1980. 244-261.\n   - Quinlan,R. (1993). Combining Instance-Based an
d Model-Based Learning. In Proceedings on the Tenth International Conference of Machine Learning, 236-243,
University of Massachusetts, Amherst. Morgan Kaufmann.\n",
 'filename': 'boston_house_prices.csv',
 'data_module': 'sklearn.datasets.data'}
```

In [8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1012 entries, 0 to 1011
Data columns (total 11 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       1012 non-null   float64
 1   1       1012 non-null   float64
 2   2       1012 non-null   float64
 3   3       506 non-null    float64
 4   4       506 non-null    float64
 5   5       506 non-null    float64
 6   6       506 non-null    float64
 7   7       506 non-null    float64
 8   8       506 non-null    float64
 9   9       506 non-null    float64
 10  10      506 non-null    float64
dtypes: float64(11)
memory usage: 87.1 KB
```

In [16]:
```
df.DESCR
```

Out[16]:
```
".. _boston_dataset:\n\nBoston house prices dataset\n---------------------------\n\n**Data Set Characteris
tics:**  \n\n    :Number of Instances: 506 \n\n    :Number of Attributes: 13 numeric/categorical predictiv
e. Median Value (attribute 14) is usually the target.\n\n    :Attribute Information (in order):\n        -
CRIM     per capita crime rate by town\n        - ZN       proportion of residential land zoned for lots o
ver 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 co
ncentration (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 Bost
on employment centres\n        - RAD      index of accessibility to radial highways\n        - TAX      fu
ll-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 of owner-occupied homes in $1000's\n\n    :Missing Attribu
te Values: None\n\n    :Creator: Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing data
set.\nhttps://archive.ics.uci.edu/ml/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 H
arrison, D. and Rubinfeld, D.L. 'Hedonic\nprices and the demand for clean air', J. Environ. Economics & Ma
nagement,\nvol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics\n...', Wiley, 198
0.   N.B. Various transformations are used in the table on\npages 244-261 of the latter.\n\nThe Boston hou
se-price data has been used in many machine learning papers that address regression\nproblems.   \n     \
n.. topic:: References\n\n   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Dat
a and Sources of Collinearity', Wiley, 1980. 244-261.\n   - Quinlan,R. (1993). Combining Instance-Based an
d Model-Based Learning. In Proceedings on the Tenth International Conference of Machine Learning, 236-243,
University of Massachusetts, Amherst. Morgan Kaufmann.\n"
```

In [18]:
```
df.keys()
```

Out[18]:
```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename', 'data_module'])
```

In [ ]:
```
'''
The data contains the following columns:

'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': nitrogen 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 mean of 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
'black': 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town.
'lstat': lower status of the population (percent).
'medv': median value of owner-occupied homes in $$1000s
'''
```

In [19]:
```
df.feature_names
```

Out[19]:
```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [21]:
```
len(df.feature_names)
```

Out[21]:
```
13
```

In [26]:
```
df1 = pd.DataFrame(df.data,columns=df.feature_names)
```

In [27]:
```
df1
```

Out[27]:

	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
...	...	...	...	...	...	...	...	...	...	...	...	...	...
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	9.67
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	9.08
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	5.64
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	6.48
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	7.88

506 rows × 13 columns

In [28]:
```
df1.isnull().sum()
```

Out[28]:
```
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
dtype: int64
```

In [29]:
```
df1['MEDV'] = df.target
```

In [30]:
```
df1
```

Out[30]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
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
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
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	9.67	22.4
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	9.08	20.6
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	5.64	23.9
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	6.48	22.0
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	7.88	11.9

506 rows × 14 columns

In [51]:
```
corr_matrix=df1.corr().round(2)
```

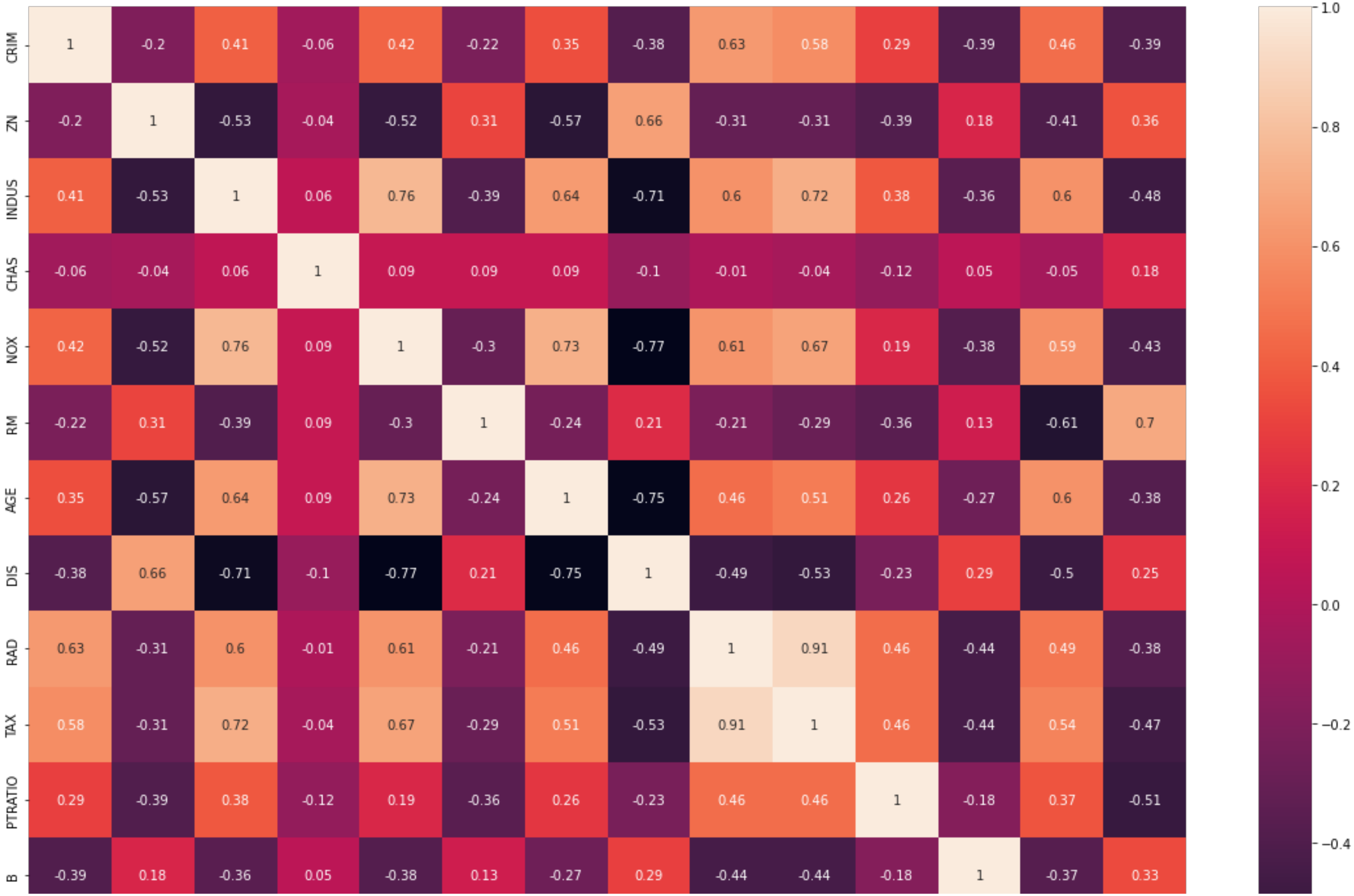
In [52]:
```
corr_matrix
```

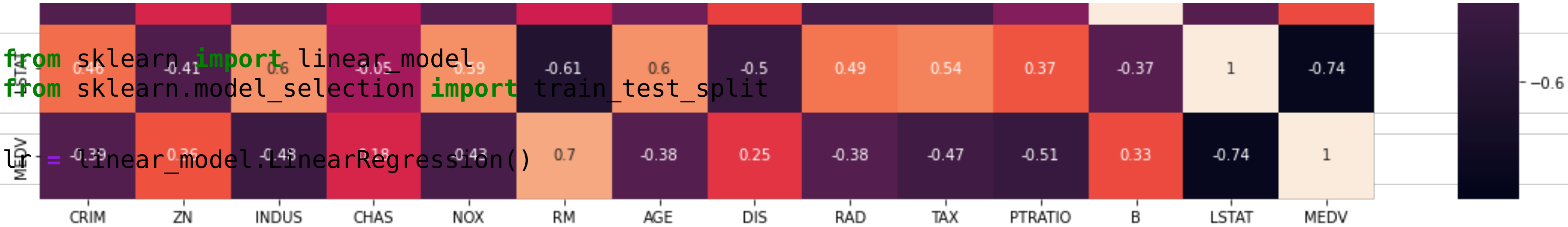
Out[52]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
CRIM	1.00	-0.20	0.41	-0.06	0.42	-0.22	0.35	-0.38	0.63	0.58	0.29	-0.39	0.46	-0.39
ZN	-0.20	1.00	-0.53	-0.04	-0.52	0.31	-0.57	0.66	-0.31	-0.31	-0.39	0.18	-0.41	0.36
INDUS	0.41	-0.53	1.00	0.06	0.76	-0.39	0.64	-0.71	0.60	0.72	0.38	-0.36	0.60	-0.48
CHAS	-0.06	-0.04	0.06	1.00	0.09	0.09	0.09	-0.10	-0.01	-0.04	-0.12	0.05	-0.05	0.18
NOX	0.42	-0.52	0.76	0.09	1.00	-0.30	0.73	-0.77	0.61	0.67	0.19	-0.38	0.59	-0.43
RM	-0.22	0.31	-0.39	0.09	-0.30	1.00	-0.24	0.21	-0.21	-0.29	-0.36	0.13	-0.61	0.70
AGE	0.35	-0.57	0.64	0.09	0.73	-0.24	1.00	-0.75	0.46	0.51	0.26	-0.27	0.60	-0.38
DIS	-0.38	0.66	-0.71	-0.10	-0.77	0.21	-0.75	1.00	-0.49	-0.53	-0.23	0.29	-0.50	0.25
RAD	0.63	-0.31	0.60	-0.01	0.61	-0.21	0.46	-0.49	1.00	0.91	0.46	-0.44	0.49	-0.38
TAX	0.58	-0.31	0.72	-0.04	0.67	-0.29	0.51	-0.53	0.91	1.00	0.46	-0.44	0.54	-0.47
PTRATIO	0.29	-0.39	0.38	-0.12	0.19	-0.36	0.26	-0.23	0.46	0.46	1.00	-0.18	0.37	-0.51
B	-0.39	0.18	-0.36	0.05	-0.38	0.13	-0.27	0.29	-0.44	-0.44	-0.18	1.00	-0.37	0.33
LSTAT	0.46	-0.41	0.60	-0.05	0.59	-0.61	0.60	-0.50	0.49	0.54	0.37	-0.37	1.00	-0.74
MEDV	-0.39	0.36	-0.48	0.18	-0.43	0.70	-0.38	0.25	-0.38	-0.47	-0.51	0.33	-0.74	1.00

In [58]:
```
plt.figure(figsize=(20,15))
ax=plt.subplot(111)
sns.heatmap(corr_matrix,ax=ax, annot=True)
```

Out[58]: <AxesSubplot: >





In [36]:
```
from sklearn import linear_model
from sklearn.model_selection import train_test_split
```

In [37]:
```
lr = linear_model.LinearRegression()
```

80-20 Train-Test Ratio:

In [68]:
```
x_train, x_test, y_train, y_test = train_test_split(data, target, test_size=0.2, random_state=42)
```

In [69]:
```
lr.fit(x_train, y_train)
```

Out[69]:
```
▾ LinearRegression
LinearRegression()
```

In [70]:
```
y_pred = lr.predict(x_test)
```

In [71]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, y_pred)
mse
```

Out[71]: 24.291119474973485

In [72]:
```
root_mse = mse**(1/2)
root_mse
```

Out[72]: 4.928602182665333

70-30 Train-Test Ratio:

In [59]:
```
x_train, x_test, y_train, y_test = train_test_split(data, target, test_size=0.3, random_state=42)
```

In [60]:
```
lr.fit(x_train, y_train)
```
Out[60]:
```
▾ LinearRegression
LinearRegression()
```

In [61]:
```
y_pred = lr.predict(x_test)
```

In [63]:
```
from sklearn.metrics import mean_squared_error
mse = mean_squared_error(y_test, y_pred)
```

In [64]:
```
mse
```
Out[64]:
```
21.51744423117753
```

In [66]:
```
root_mse = mse**(1/2)
root_mse
```
Out[66]:
```
4.638689926172855
```

In [ ]: