```
Pandas Library:
```

Useful for Data Processing & Analysis

Pandas Data Frame:

Pandas DataFrame is two-dimensional tabular data structure with labeled axes (rows and columns).

```
# importing the pandas library
import pandas as pd
import numpy as np
Creaating a Pandas DataFrame
# importing the boston house price data
from sklearn.datasets import load boston
boston_dataset = load_boston()
type(boston_dataset)
     sklearn.utils.Bunch
print(boston dataset)
     {'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+001.
             [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. , 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, 23.2, 21.8, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23.2, 23
```

pandas DataFrame

boston_df = pd.DataFrame(boston_dataset.data, columns = boston_dataset.feature_names)

boston_df.head()

	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

boston_df.shape

(506, 13)

type(boston_df)

pandas.core.frame.DataFrame

Importing the data from a CSV file to a pandas DataFrame

```
# csv file to pandas df
diabetes_df = pd.read_csv('/content/diabetes.csv')
```

type(diabetes_df)

pandas.core.frame.DataFrame

diabetes_df.head()

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

 ${\tt diabetes_df.shape}$

(768, 9)

Loading the data from a excel file to a Pandas DataFrame:

pd.read_excel('file path')

Exporting a DataFrame to a csv file

boston_df.to_csv('boston.csv')

Exporting the Pandas DataFrame to an excel File:

df.to_excel('filename')

creating a DatFrame with random values
random_df = pd.DataFrame(np.random.rand(20,10))

random_df.head()

	0	1	2	3	4	5	6	7	8	9
0	0.978586	0.798457	0.756065	0.574559	0.731437	0.976397	0.865563	0.887155	0.077107	0.370573
1	0.078777	0.295596	0.608408	0.310086	0.326199	0.086600	0.549180	0.753831	0.261745	0.916683
2	0.172873	0.971198	0.592191	0.482904	0.171601	0.981757	0.268020	0.415321	0.350072	0.943297
3	0.812212	0.612494	0.011446	0.817039	0.076837	0.712891	0.929890	0.560469	0.467133	0.629038
4	0.629319	0.046347	0.918180	0.317385	0.692454	0.793890	0.016952	0.352690	0.029239	0.436268

random_df.shape

(20, 10)

Inspecting a DataFrame

#finding the number of rows & columns
boston_df.shape

(506, 13)

first 5 rows in a DataFrame
boston_df.head()

	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

last 5 rows of the DataFrame
boston_df.tail()

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	LSTAT
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

informations about the DataFrame
boston_df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 13 columns):

Jucu	COTUMITS	(COCAT IS COTAINI	٥).
#	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
dtypes: float64(13)
memory usage: 51.5 KB
```

finding the number of missing values boston_df.isnull().sum()

> CRIM 0 ΖN 0 INDUS 0 CHAS 0 NOX 0 RM AGE 0 DIS 0 RAD 0 TAX 0 PTRATIO 0 В 0 LSTAT 0 dtype: int64

diabetes dataframe diabetes_df.head()

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFu
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	
3	1	89	66	23	94	28.1	
4	0	137	40	35	168	43.1	
- ◀)

counting the values based on the labels diabetes_df.value_counts('Outcome')

> Outcome 0 500 268 1 dtype: int64

group the values based on the mean diabetes_df.groupby('Outcome').mean()

		Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	вмі	Di
Out	tcome							
	0	3.298000	109.980000	68.184000	19.664000	68.792000	30.304200	
4	1	4.865672	141.257463	70.824627	22.164179	100.335821	35.142537	•

Statistical Measures

count or number of values boston_df.count()

> CRIM 506 506 ΖN INDUS 506 506 CHAS NOX 506 RM 506 AGE 506 DIS 506 RAD 506 TAX 506 PTRATIO 506 506 LSTAT 506 dtype: int64

```
# mean value - column wise
boston_df.mean()
     CRIM
                  3.613524
     ΖN
                 11.363636
     TNDUS
                 11.136779
                  0.069170
     CHAS
     NOX
                  0.554695
     RM
                  6.284634
     AGE
                 68.574901
     DIS
                  3.795043
     RAD
                  9.549407
     TAX
                408.237154
     PTRATIO
                 18.455534
                356.674032
     LSTAT
                 12.653063
     dtype: float64
# standard deviation - column wise
boston_df.std()
     CRIM
                  8.601545
     ΖN
                 23.322453
     INDUS
                  6.860353
     CHAS
                  0.253994
     NOX
                  0.115878
     RM
                  0.702617
     AGE
                 28.148861
     DIS
                  2.105710
     RAD
                  8.707259
     TAX
                168.537116
     PTRATIO
                  2.164946
     В
                 91.294864
     LSTAT
                  7.141062
     dtype: float64
# minimum value
boston_df.min()
     CRIM
                  0.00632
     ΖN
                  0.00000
     INDUS
                  0.46000
     CHAS
                  0.00000
     NOX
                  0.38500
     RM
                  3.56100
     AGE
                  2.90000
                  1.12960
     DIS
     RAD
                  1.00000
     TAX
                187.00000
     PTRATIO
                 12.60000
                  0.32000
     В
     LSTAT
                  1.73000
     dtype: float64
# maximum value
boston_df.max()
     CRIM
                 88.9762
     ΖN
                100.0000
                 27.7400
     INDUS
     CHAS
                  1.0000
     NOX
                  0.8710
                  8.7800
     RM
     AGE
                100.0000
     DIS
                 12.1265
                 24.0000
     RAD
     TAX
                711.0000
     PTRATIO
                 22.0000
                396.9000
     В
     LSTAT
                 37.9700
     dtype: float64
# all the statistical measures about the dataframe
```

boston_df.describe()

	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

Manipulating a DataFrame

adding a column to a dataframe
boston_df['Price'] = boston_dataset.target

boston_df.head()

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	LSTA
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	4.9
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	9.1
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	4.0
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	2.9
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	5.3 •

removing a row
boston_df.drop(index=0, axis=0)

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	В	LST
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.
5	0.02985	0.0	2.18	0.0	0.458	6.430	58.7	6.0622	3.0	222.0	18.7	394.12	5.
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.
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.
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.
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.
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.
505 rc	ows × 14 co	olumn	ıs										→

drop a column
boston_df.drop(columns='ZN', axis=1)

```
CRIM INDUS CHAS
                            NOX
                                    RM
                                        AGE
                                                DIS RAD
                                                           TAX PTRATIO
                                                                              B LSTAT F
     0.00632
               2.31
                      0.0 0.538 6.575 65.2 4.0900
                                                     1.0
                                                          296.0
                                                                    15.3 396.90
                                                                                   4.98
     0.02731
               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
               7.07
                      0.0 0.469 7.185 61.1
                                             4.9671
                                                     2.0
                                                          242.0
                                                                    17.8
                                                                         392.83
                                                                                   4.03
     0.03237
                                                          222.0
                                                                         394.63
 3
               2.18
                      0.0 0.458 6.998 45.8 6.0622
                                                     3.0
                                                                    18.7
                                                                                   2.94
     0.06905
               2.18
                      0.0 0.458 7.147 54.2 6.0622
                                                     3.0
                                                         222.0
                                                                    18.7
                                                                         396.90
                                                                                  5.33
    0.06263
501
              11.93
                      0.0 0.573 6.593 69.1 2.4786
                                                     1.0
                                                         273.0
                                                                    21.0
                                                                         391.99
                                                                                  9.67
                                                                    21.0
502 0.04527
               11.93
                      0.0 0.573 6.120 76.7 2.2875
                                                     1.0
                                                         273.0
                                                                         396.90
                                                                                   9.08
503 0.06076
              11 93
                      0.0 0.573 6.976 91.0 2.1675
                                                     1.0
                                                         273.0
                                                                         396.90
                                                                    21.0
                                                                                   5.64
504 0.10959
              11.93
                                                         273.0
                      0.0 0.573 6.794 89.3 2.3889
                                                     1.0
                                                                    21.0 393.45
                                                                                   6.48
505 0.04741
              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
```

locating a row using the index value boston_df.iloc[2]

```
CRIM
             0.02729
ΖN
             0.00000
INDUS
             7.07000
             0.00000
CHAS
NOX
             0.46900
RM
             7.18500
AGE
            61.10000
DIS
             4.96710
RAD
             2.00000
TAX
           242.00000
PTRATIO
            17.80000
           392,83000
В
LSTAT
             4.03000
            34.70000
Name: 2, dtype: float64
```

```
# locating a particular column
print(boston\_df.iloc[:,0]) \ \ \# \ first \ column
print(boston_df.iloc[:,1]) # second column
print(boston_df.iloc[:,2]) # third column
print(boston_df.iloc[:,-1]) # last column
```

```
0.00632
       0.02731
1
2
       0.02729
3
       0.03237
4
       0.06905
501
       0.06263
502
       0.04527
503
       0.06076
504
       0.10959
       0.04741
0
       18.0
1
        0.0
```

Name: CRIM, Length: 506, dtype: float64

2 0.0 3 0.0 4 0.0 501 0.0 502 0.0 503 0.0 504 0.0 505 0.0

Name: ZN, Length: 506, dtype: float64

2.31 1 7.07 2 7.07 3 2.18 4 2.18 11.93 501

```
503
      11.93
504
      11.93
     11.93
505
Name: INDUS, Length: 506, dtype: float64
0
      24.0
1
      21.6
2
      34.7
      33.4
3
4
      36.2
501
     22.4
502
      20.6
503
      23.9
     22.0
505
      11.9
Name: Price, Length: 506, dtype: float64
```

Correlation:

- 1. Positive Correlation
- 2. Negative Correlation

boston_df.corr()

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	D
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.3796
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.6644
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.7080
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.0991
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.7692
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.2052
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.7478
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.0000
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.4945
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.5344
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.2324
В	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.2915
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.4969
Price	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.2499