## Linear Regression (boston dataset)

## December 18, 2022

```
[1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn as sl
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn.datasets import load_boston
```

## [2]: df=load\_boston()

C:\Users\Deepak\ana-conda-3\lib\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

```
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)
[3]: df
[3]: {'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,
             [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,
```

housing = fetch\_california\_housing()

```
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,
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 '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
                                 :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
          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 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
                                                  index of accessibility to
                                   full-value property-tax rate per $10,000\n
radial highways\n
                        - TAX
- 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\
                       :Missing Attribute Values: None\n\n
```

Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing dataset.\nhttps://archive.ics.uci.edu/ml/machine-learningdatabases/housing/\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\nprices and the demand for clean air', J. Environ. Economics & Management,\nvol.5, 81-102, 1978. Used in Belsley, Kuh & Welsch, 'Regression diagnostics\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 used in many machine learning papers that address regression\nproblems. \n.. topic:: References\n\n \n Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of Collinearity', Wiley, 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': 'boston\_house\_prices.csv',
'data\_module': 'sklearn.datasets.data'}

```
[4]: dataset=pd.DataFrame(df.data)
```

## [5]: dataset

[5]:		0	1	2	3	4	5	6	7	8	9	10	\
	0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	
	1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	
	2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	
	3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	
	4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	
		•••		•••	•••			•••	•••				
	501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	
	502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	
	503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	
	504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	
	505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	

11 12 0 396.90 4.98 1 396.90 9.14 2 392.83 4.03 3 394.63 2.94 4 396.90 5.33 501 391.99 9.67 502 396.90 9.08 503 396.90 5.64 504 393.45 6.48 505 396.90 7.88

```
[6]: X=dataset
    y=df.target
[7]: y
[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,
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           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.,

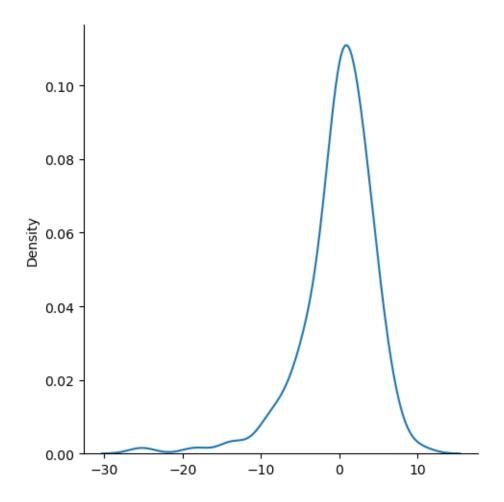
```
9.5, 14.5, 14.1, 16.1, 14.3, 11.7, 13.4, 9.6, 8.7, 8.4, 12.8,
             10.5, 17.1, 18.4, 15.4, 10.8, 11.8, 14.9, 12.6, 14.1, 13., 13.4,
             15.2, 16.1, 17.8, 14.9, 14.1, 12.7, 13.5, 14.9, 20., 16.4, 17.7,
             19.5, 20.2, 21.4, 19.9, 19. , 19.1, 19.1, 20.1, 19.9, 19.6, 23.2,
             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])
[8]: from sklearn.model_selection import train_test_split
      X_train, X_test, y_train, y_test = train_test_split(
          X, y, test_size=0.30, random_state=42)
      X_{train}
[8]:
                 0
                        1
                               2
                                    3
                                           4
                                                   5
                                                         6
                                                                 7
                                                                        8
                                                                               9
                                                                                   \
                                                                            222.0
            0.02985
                      0.0
                             2.18
                                   0.0
                                        0.458
                                                6.430
                                                       58.7
                                                             6.0622
                                                                       3.0
      5
      116
            0.13158
                      0.0
                            10.01
                                   0.0
                                        0.547
                                                6.176
                                                       72.5
                                                             2.7301
                                                                       6.0
                                                                            432.0
      45
            0.17142
                      0.0
                             6.91
                                   0.0
                                        0.448
                                                5.682
                                                       33.8
                                                             5.1004
                                                                       3.0
                                                                            233.0
                      0.0
                                   0.0
      16
            1.05393
                             8.14
                                        0.538
                                                5.935
                                                       29.3
                                                             4.4986
                                                                       4.0
                                                                            307.0
      468
           15.57570
                      0.0
                            18.10
                                   0.0
                                        0.580
                                               5.926
                                                       71.0
                                                             2.9084
                                                                      24.0
                                                                            666.0
                                        0.520
      106
            0.17120
                      0.0
                             8.56
                                  0.0
                                                5.836
                                                       91.9
                                                             2.2110
                                                                       5.0
                                                                            384.0
            0.29916
                             6.96
                                                       42.1
                                                             4.4290
      270
                     20.0
                                   0.0
                                        0.464
                                               5.856
                                                                       3.0
                                                                            223.0
      348
            0.01501
                             2.01
                                   0.0
                                        0.435
                                                       29.7
                                                             8.3440
                                                                            280.0
                     80.0
                                                6.635
                                                                       4.0
      435
           11.16040
                      0.0
                            18.10
                                   0.0
                                        0.740
                                                6.629
                                                       94.6
                                                             2.1247
                                                                      24.0
                                                                            666.0
      102
            0.22876
                      0.0
                             8.56
                                   0.0 0.520
                                               6.405
                                                       85.4
                                                             2.7147
                                                                       5.0
                                                                           384.0
                             12
             10
                     11
           18.7
                 394.12
      5
                           5.21
      116
           17.8
                 393.30
                         12.04
      45
           17.9
                 396.90
                         10.21
                           6.58
      16
           21.0
                 386.85
      468
           20.2
                 368.74 18.13
      . .
      106
          20.9
                 395.67
                         18.66
      270
          18.6
                 388.65
                         13.00
      348
           17.0
                 390.94
                           5.99
           20.2
      435
                 109.85
                         23.27
      102
          20.9
                  70.80
                         10.63
      [354 rows x 13 columns]
[9]: from sklearn.preprocessing import StandardScaler
      scaler = StandardScaler()
[10]: X_train=scaler.fit_transform(X_train)
```

```
[11]: X_test=scaler.transform(X_test)
[12]: from sklearn.linear_model import LinearRegression
      from sklearn.model_selection import cross_val_score
[13]: regression=LinearRegression()
      regression.fit(X_train,y_train)
[13]: LinearRegression()
[14]: | mse=cross_val_score(regression, X_train, y_train, scoring='neg_mean_squared_error', cv=10)
[15]: np.mean(mse)
[15]: -25.55066079166079
[16]: reg_pred=regression.predict(X_test)
[17]: reg_pred
[17]: array([28.64896005, 36.49501384, 15.4111932, 25.40321303, 18.85527988,
             23.14668944, 17.3921241, 14.07859899, 23.03692679, 20.59943345,
             24.82286159, 18.53057049, -6.86543527, 21.80172334, 19.22571177,
             26.19191985, 20.27733882, 5.61596432, 40.44887974, 17.57695918,
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```

```
[18]: import seaborn as sns
sns.displot(reg_pred-y_test,kind='kde')
```

[18]: <seaborn.axisgrid.FacetGrid at 0x244e5ed5790>



```
[19]: from sklearn.metrics import r2_score

[20]: score=r2_score(reg_pred,y_test)

[21]: score

[21]: 0.6693702691495591

[]:
```