Linear Regression (Boston House Pricing)

March 25, 2022

```
[ ]: from sklearn import linear_model
     from sklearn import datasets
     import pandas as pd
     data = datasets.load_boston() ## loads Boston dataset from datasets librar
     print(data['DESCR'])
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value
(attribute 14) is usually the target.

    :Attribute Information (in order):
        - 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      nitric 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 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
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of black people
by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's
```

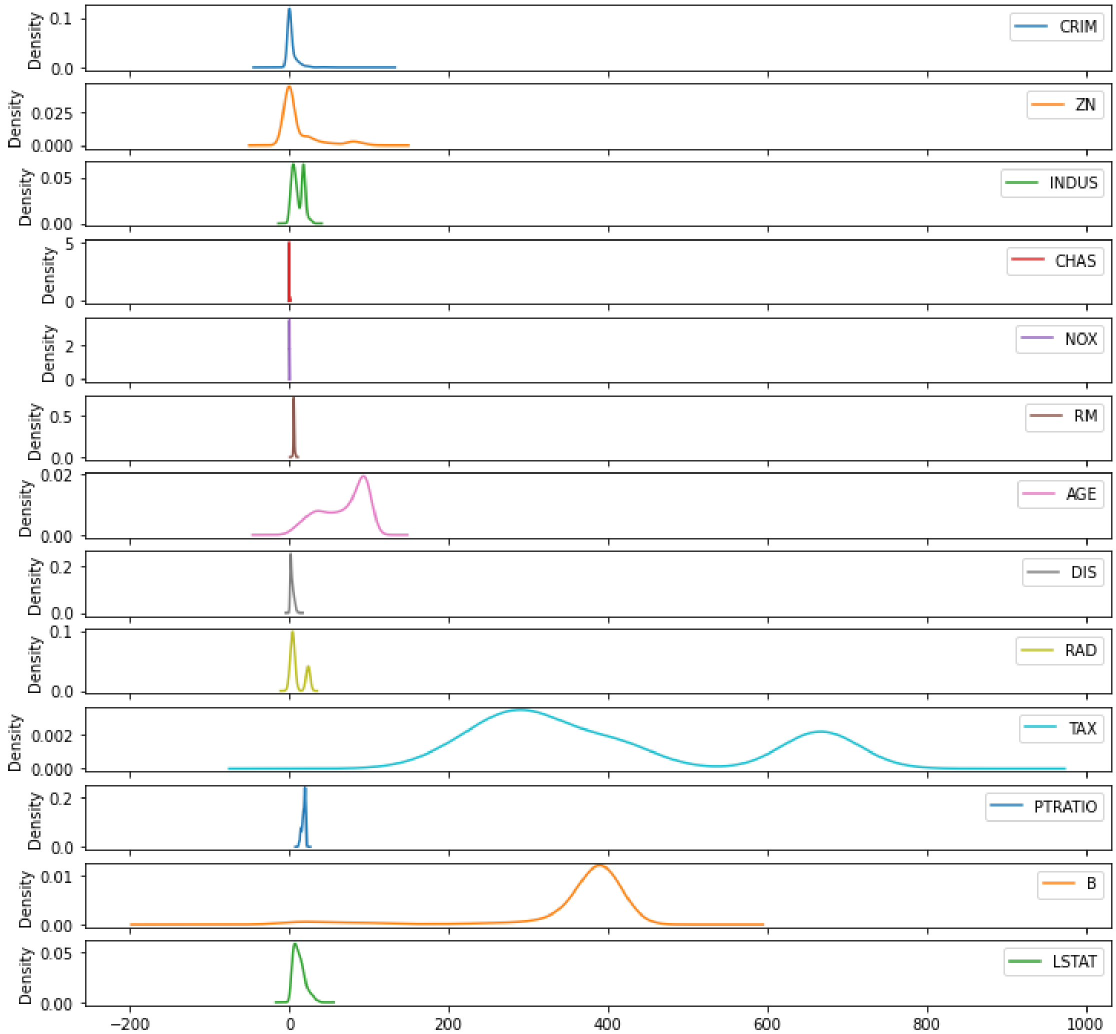
```
    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/


This dataset was taken from the StatLib library which is maintained at Carnegie
Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
…', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers that
address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential
Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - 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.


/home/niteesh/.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)
```

[ ]:
```
# define the data/predictors as the pre-set feature names
df = pd.DataFrame(data.data, columns=data.feature_names)

# Put the target (housing value -- MEDV) in another DataFrame
target = pd.DataFrame(data.target, columns=["MEDV"])
```

[ ]:
```
df.plot(kind='kde', subplots=True, figsize=(12,12))
```

[ ]:
```
array([<AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
       <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
       <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
       <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
       <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
       <AxesSubplot:ylabel='Density'>, <AxesSubplot:ylabel='Density'>,
       <AxesSubplot:ylabel='Density'>], dtype=object)
```




```
[ ]: df.corr()
```

[ ]:

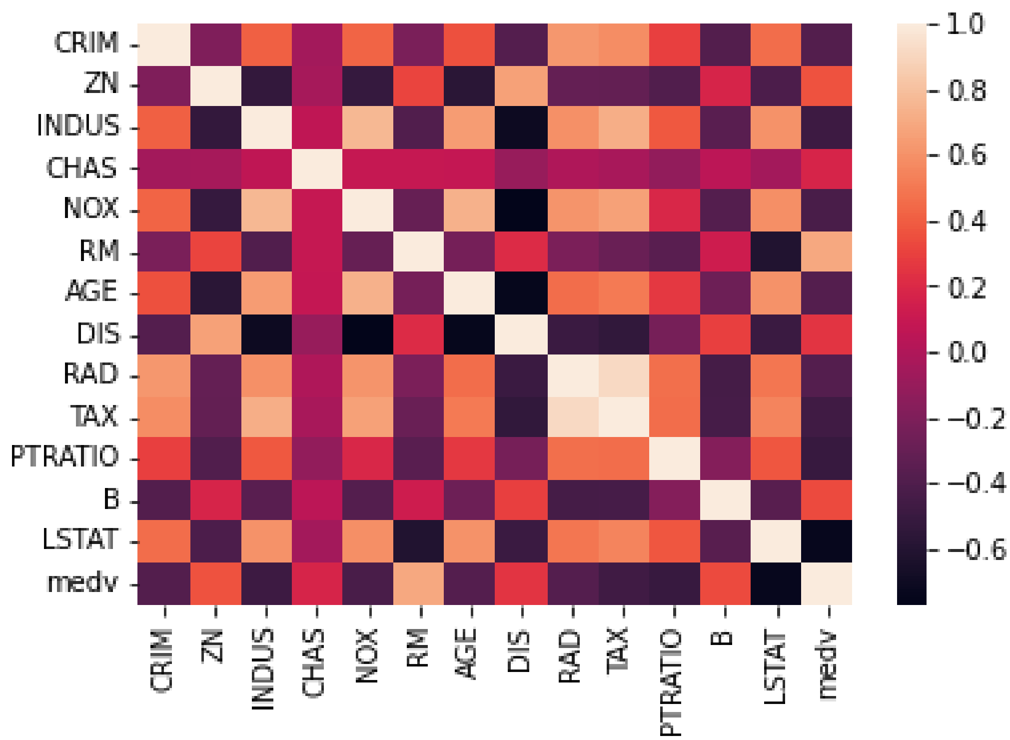
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	\
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	

```
LSTAT    0.455621 -0.412995  0.603800 -0.053929  0.590879 -0.613808  0.602339

              DIS       RAD       TAX   PTRATIO         B     LSTAT
CRIM    -0.379670  0.625505  0.582764  0.289946 -0.385064  0.455621
ZN       0.664408 -0.311948 -0.314563 -0.391679  0.175520 -0.412995
INDUS   -0.708027  0.595129  0.720760  0.383248 -0.356977  0.603800
CHAS    -0.099176 -0.007368 -0.035587 -0.121515  0.048788 -0.053929
NOX     -0.769230  0.611441  0.668023  0.188933 -0.380051  0.590879
RM       0.205246 -0.209847 -0.292048 -0.355501  0.128069 -0.613808
AGE     -0.747881  0.456022  0.506456  0.261515 -0.273534  0.602339
DIS      1.000000 -0.494588 -0.534432 -0.232471  0.291512 -0.496996
RAD     -0.494588  1.000000  0.910228  0.464741 -0.444413  0.488676
TAX     -0.534432  0.910228  1.000000  0.460853 -0.441808  0.543993
PTRATIO -0.232471  0.464741  0.460853  1.000000 -0.177383  0.374044
B        0.291512 -0.444413 -0.441808 -0.177383  1.000000 -0.366087
LSTAT   -0.496996  0.488676  0.543993  0.374044 -0.366087  1.000000
```

[ ]:
```python
df['medv'] = target
```

[ ]:
```python
import seaborn as sns

sns.heatmap(df.corr())
```

[ ]:
```
<AxesSubplot:>
```



[ ]:

```

```

[ ]:

```
target
```

[ ]:

```
     MEDV
0    24.0
1    21.6
2    34.7
3    33.4
4    36.2
..    …
501  22.4
502  20.6
503  23.9
504  22.0
505  11.9

[506 rows x 1 columns]
```

[ ]:

```

```

[ ]:

```
pandas.core.frame.DataFrame
```

[ ]:

```
d = pd.DataFrame(df,target['MEDV'])

d.to_csv("Boston House Prices dataset.csv", index = False)
```

[ ]:

```
X = df
y = target["MEDV"]
```

[ ]:

```
lm = linear_model.LinearRegression()
model = lm.fit(X,y)
```

[ ]:

```
predictions = lm.predict(X)
predictions
```

[ ]:

```
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])
```

[ ]:
```
lm.score(X,y)
```

[ ]:
```
1.0
```

[ ]:
```
lm.coef_
```

[ ]:
```
array([-8.54790267e-17, -2.49800181e-16, -5.85252333e-16, -1.44037004e-14,
       -5.88240665e-16,  1.13667078e-15, -1.84314369e-16, -4.45715513e-16,
       -2.58907479e-16, -1.04083409e-17,  7.64633582e-17, -2.98372438e-16,
       -4.51461785e-16,  1.00000000e+00])
```

```
[ ]:
```

```
[ ]:
```