

```
import numpy as np
import pandas as pd
import sklearn
```

```
from sklearn.datasets import load_boston
df=load_boston()
```

```
df.keys()
```

```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

```
print(df.DESCR)
```

```
.. _boston_dataset:
```

```
Boston house prices dataset
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```

```
**Data Set Characteristics:**
```

```
:Number of Instances: 506
```

```
:Number of Attributes: 13 numeric/categorical predictive. Median Value (att
```

```
:Attribute Information (in order):
```

- CRIM per capita crime rate by town
- ZN proportion of residential land zoned for lots over 25,000 sq
- INDUS proportion of non-retail business acres per town
- CHAS Charles River dummy variable (= 1 if tract bounds river; 0 o
- 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  $1000(B_k - 0.63)^2$  where  $B_k$  is the proportion of blacks by to
- 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

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 problems.

.. topic:: References

- Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Da
- Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In P

```
boston=pd.DataFrame(df.data, columns=df.feature_names)
boston.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
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
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
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
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
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

```
boston['MEDV']=df.target
boston.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
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
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
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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
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

```
boston.isnull()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	L
0	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	False	False	False	False	False	False	False	False	False	False	False	False	False
502	False	False	False	False	False	False	False	False	False	False	False	False	False

```
boston.isnull().sum()
```

```
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
MEDV     0
dtype: int64
```

```
from sklearn.model_selection import train_test_split
X=boston.drop('MEDV', axis=1)
Y=boston['MEDV']
X_train, X_test, Y_train, Y_test=train_test_split(X, Y, test_size=0.15,random_state=5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test. shape)

(430, 13)
(76, 13)
(430,)
(76,)
```

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

```
lin_model=LinearRegression()
lin_model.fit(X_train,Y_train)
```

```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

```
y_train_predict=lin_model.predict(X_train)
rmse=(np.sqrt(mean_squared_error(Y_train, y_train_predict)))
```

```
print("The model performance for training set")
print('RMSE in {}'.format(rmse))
print("\n")
```

```
y_test_predict=lin_model.predict(X_test)
rmse=(np.sqrt(mean_squared_error(Y_test, y_test_predict)))
```

```
print("The model performance for testing set")
print('RMSE is {}'.format(rmse))
```

```
The model performance for training set
RMSE in 4.710901797319796
```

```
The model performance for testing set
RMSE is 4.687543527902972
```