# In [1]:

import numpy as np
import pandas as pd

# In [2]:

from sklearn.datasets import load\_boston
from sklearn.tree import DecisionTreeRegressor

## In [3]:

```
data=load_boston()
data
```

# Out[3]:

```
{'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.96
90e+02,
         4.9800e+00],
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         9.1400e+00],
        [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
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         5.6400e+00],
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        6.4800e+00],
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        21. , 23.8, 23.1, 20.4, 18.5, 25. , 24.6, 23. , 22.2, 19.3, 22.6,
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9]),
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E', 'DIS', 'RAD',
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-----\n\n**Data Set Characteristics:** \n\n
                                                          :Number of Inst
ances: 506 \n\n
                  :Number of Attributes: 13 numeric/categorical predictiv
e. Median Value (attribute 14) is usually the target.\n\n
formation (in order):\n
                               - CRIM
                                         per capita crime rate by town\n
- ZN
           proportion of residential land zoned for lots over 25,000 sq.f
t.\n
           - INDUS
                      proportion of non-retail business acres per town\n
          Charles River dummy variable (= 1 if tract bounds river; 0 othe
- CHAS
                           nitric oxides concentration (parts per 10 milli
rwise)\n
on)\n
                        average number of rooms per dwelling\n
       proportion of owner-occupied units built prior to 1940\n
                                                                       - D
Ε
IS
       weighted distances to five Boston employment centres\n
                                                                      - RA
       index of accessibility to radial highways\n
                                                          - TAX
                                                                     full-
value property-tax rate per $10,000\n
                                             - PTRATIO pupil-teacher rati
o by town\n
                  - B
                              1000(Bk - 0.63)^2 where Bk is the proportion
of blacks by town\n

    LSTAT

                                     % lower status of the population\n
- MEDV
          Median value of owner-occupied homes in $1000's\n\n
                             :Creator: Harrison, D. and Rubinfeld, D.L.\n
Attribute Values: None\n\n
\nThis is a copy of UCI ML housing dataset.\nhttps://archive.ics.uci.edu/m
l/machine-learning-databases/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\npric
es and the demand for clean air', J. Environ. Economics & Management,\nvo
                   Used in Belsley, Kuh & Welsch, 'Regression diagnostic
1.5, 81-102, 1978.
s\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 u
sed in many machine learning papers that address regression\nproblems.
       \n.. topic:: References\n\n
                                    - Belsley, Kuh & Welsch, 'Regression
diagnostics: Identifying Influential Data and Sources of Collinearity', Wi
ley, 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': 'G:\\anaconda\\lib\\site-packages\\sklearn\\datasets\\data\\b
oston house prices.csv'}
```

# In [4]:

```
features=data['data']
labels=data['target']
```

#### In [5]:

```
from sklearn.model_selection import train_test_split
```

#### In [6]:

```
x_train, x_test, y_train, y_test = train_test_split(features,labels)
```

```
In [7]:
```

### In [8]:

```
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):
                  per capita crime rate by town
                  proportion of residential land zoned for lots over 25,000
        - ZN
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
                  proportion of owner-occupied units built prior to 1940
        - AGE
        - 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
                   1000(Bk - 0.63)^2 where Bk is the proportion of blacks by
town
                   % lower status of the population
        - LSTAT
        - 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/ (https://
archive.ics.uci.edu/ml/machine-learning-databases/housing/)
This dataset was taken from the StatLib library which is maintained at Carne
gie 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 diagnostic
...', 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 th
```

- Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential

localhost:8889/notebooks/r2. score.ipynb

at address regression

.. topic:: References

problems.

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.

```
In [9]:
data.keys()
Out[9]:
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
In [14]:
y_pred = dtr.predict(x_test)
In [11]:
dtr = DecisionTreeRegressor()
dtr.fit(x_train, y_train)
Out[11]:
DecisionTreeRegressor()
In [15]:
from sklearn.metrics import mean_squared_error,r2_score
mean_squared_error(y_pred, y_test)
r2_score(y_pred, y_test)
Out[15]:
0.8637379166892709
In [ ]:
In [ ]:
```