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ML FINAL EXAM ON 02 JUNE 2021

- to build a linear regression model and explain each components Implement using python*

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import datasets, linear_model, metrics
```

load the **boston dataset**

```
boston = datasets.load_boston(return_X_y=False)
```

```
boston
```

```
              [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,
               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]]),
       'feature_names': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS',
              'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'),
       'filename': '/usr/local/lib/python3.7/dist-packages/sklearn/datasets/data/boston_
       '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,
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19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
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16.8, 21.9, 27.5, 21.9, 23.1, 50. , 50. , 50. , 50. , 50. , 13.8,
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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])}
```

defining feature matrix(X) and response vector(y)

```
X = boston.data
y = boston.target
```

There are 506 rows and total 14 columns where, In x there are 13 columns for feature , In y there are one columns for target

There are 4 keys in the bunch [‘data’, ‘target’, ‘feature_names’, ‘DESCR’] as mentioned above. The data has 506 rows and 13 feature variable.

```
X.shape
```

```
(506, 13)
```

```
y.shape
```

```
(506,)
```

splitting X and y into training and testing sets

```
print(boston.DESCR)
```

```
.. _boston_dataset:

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

```
**Data Set Characteristics:**

    :Number of Instances: 506

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

    :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 otherwi
        - 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 blacks 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 Mell

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 addre
problems.

.. topic:: References

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

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.4,
                                                    random_state=1)
```

create linear regression object

```
reg = linear_model.LinearRegression()
```

train the model using the training sets

```
reg.fit(X_train, y_train)
```

regression coefficients

```
print('Coefficients: ', reg.coef_)
```

```
Coefficients:  [-8.95714048e-02  6.73132853e-02  5.04649248e-02  2.18579583e+00
 -1.72053975e+01  3.63606995e+00  2.05579939e-03 -1.36602886e+00
  2.89576718e-01 -1.22700072e-02 -8.34881849e-01  9.40360790e-03
 -5.04008320e-01]
```

variance score: 1 means perfect prediction

```
print('Variance score: {}'.format(reg.score(X_test, y_test)))
```

```
Variance score: 0.7209056672661777
```

setting plot style

```
plt.style.use('fivethirtyeight')
```

To create our model, we must “learn” or estimate the values of regression coefficients b_0 and b_1. And once we’ve estimated these coefficients, we can use the model to predict responses! In this article, we are going to use the principle of Least Squares . Now consider: y_i = \beta_0 + \beta_1x_i + \varepsilon_i = h(x_i) + \varepsilon_i \Rightarrow \varepsilon_i = y_i -h(x_i)
Here, e_i is residual error in ith observation. So, our aim is to minimize the total residual error

```
def estimate_coef(x, y):
    # number of observations/points
    n = np.size(x)

    # mean of x and y vector
    m_x = np.mean(x)
    m_y = np.mean(y)

    # calculating cross-deviation and deviation about x
    SS_xy = np.sum(y*x) - n*m_y*m_x
    SS_xx = np.sum(x*x) - n*m_x*m_x
```

```
    # calculating regression coefficients
    b_1 = SS_xy / SS_xx
    b_0 = m_y - b_1*m_x

    return (b_0, b_1)
```

```
def plot_regression_line(x, y, b):
    # plotting the actual points as scatter plot
    plt.scatter(x, y, color = "m",
               marker = "o", s = 30)

    # predicted response vector
    y_pred = b[0] + b[1]*x

    # plotting the regression line
    plt.plot(x, y_pred, color = "g")

    # putting labels
    plt.xlabel('x')
    plt.ylabel('y')

    # function to show plot
    plt.show()
```

Estimated coefficients:

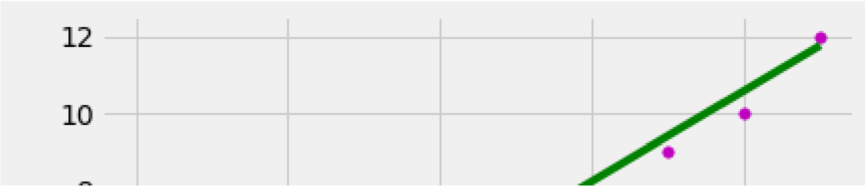
```
def main():
    # observations / data
    x = np.array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
    y = np.array([1, 3, 2, 5, 7, 8, 8, 9, 10, 12])

    # estimating coefficients
    b = estimate_coef(x, y)
    print("Estimated coefficients:\nb_0 = {}  \
          \nb_1 = {}".format(b[0], b[1]))

    # plotting regression line
    plot_regression_line(x, y, b)

if __name__ == "__main__":
    main()
```

```
Estimated coefficients:
b_0 = 1.2363636363636363
b_1 = 1.1696969696969697
```

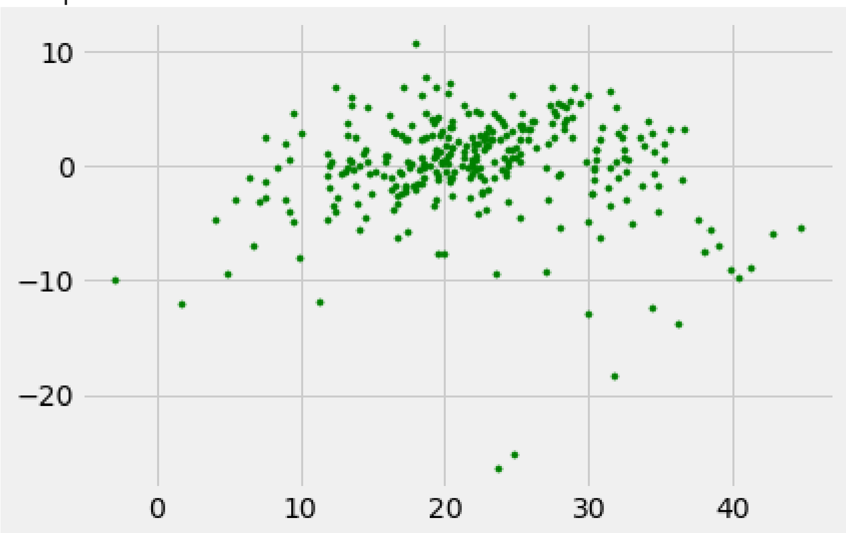


Multiple linear regression Multiple linear regression attempts to model the relationship between two or more features and a response by fitting a linear equation to the observed data

plotting residual errors in training data

```
plt.scatter(reg.predict(X_train), reg.predict(X_train) - y_train,
            color = "green", s = 10, label = 'Train data')
```

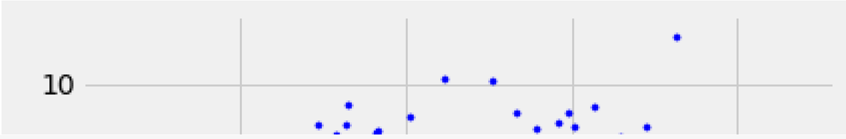
```
<matplotlib.collections.PathCollection at 0x7f2437923ed0>
```



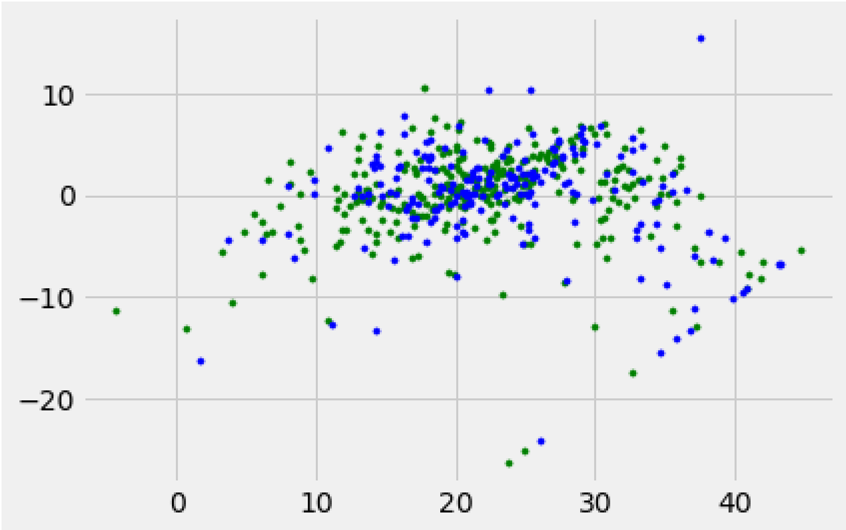
plotting residual errors in test data

```
plt.scatter(reg.predict(X_test), reg.predict(X_test) - y_test,
            color = "blue", s = 10, label = 'Test data')
```

```
<matplotlib.collections.PathCollection at 0x7f2437904dd0>
```



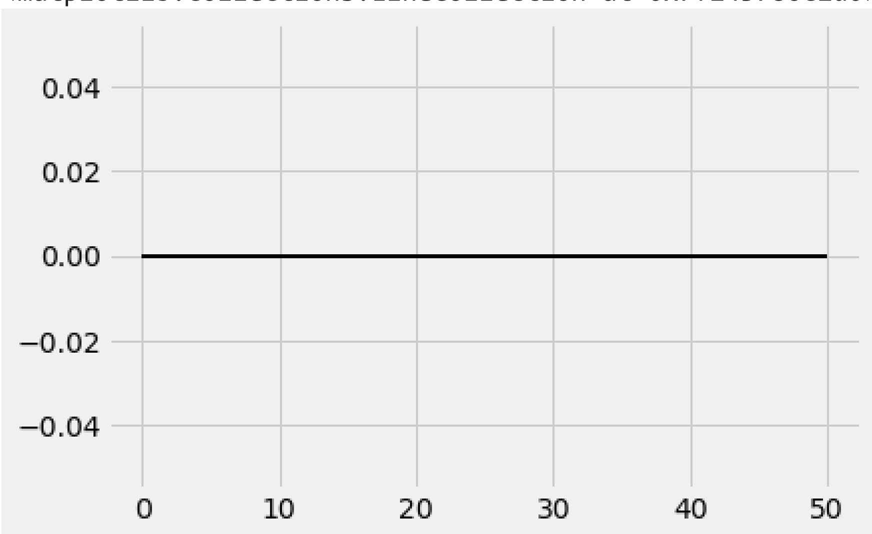

```
plt.scatter(reg.predict(X_train), reg.predict(X_train) - y_train,
            color = "green", s = 10, label = 'Train data')
plt.scatter(reg.predict(X_test), reg.predict(X_test) - y_test,
            color = "blue", s = 10, label = 'Test data')
plt.show()
```



plotting line for zero residual error

```
plt.hlines(y = 0, xmin = 0, xmax = 50, linewidth = 2)
```

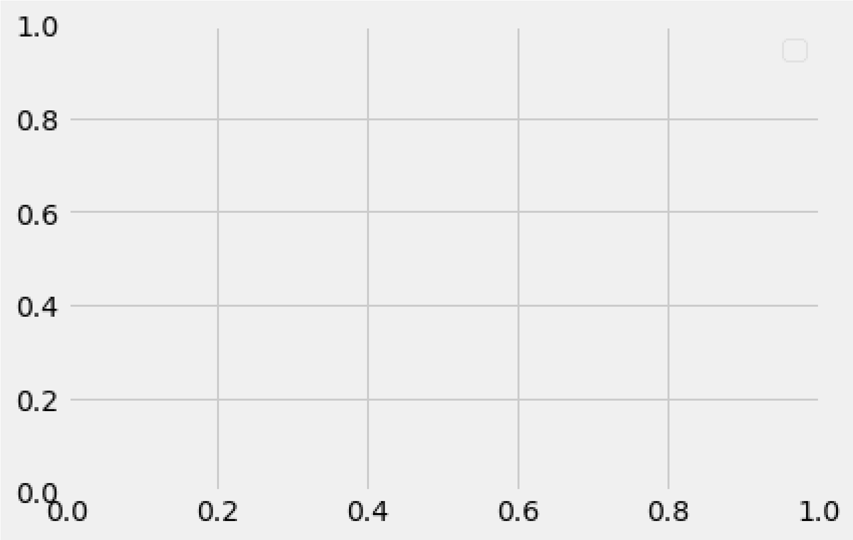
```
<matplotlib.collections.LineCollection at 0x7f243786c2d0>
```



plotting legend

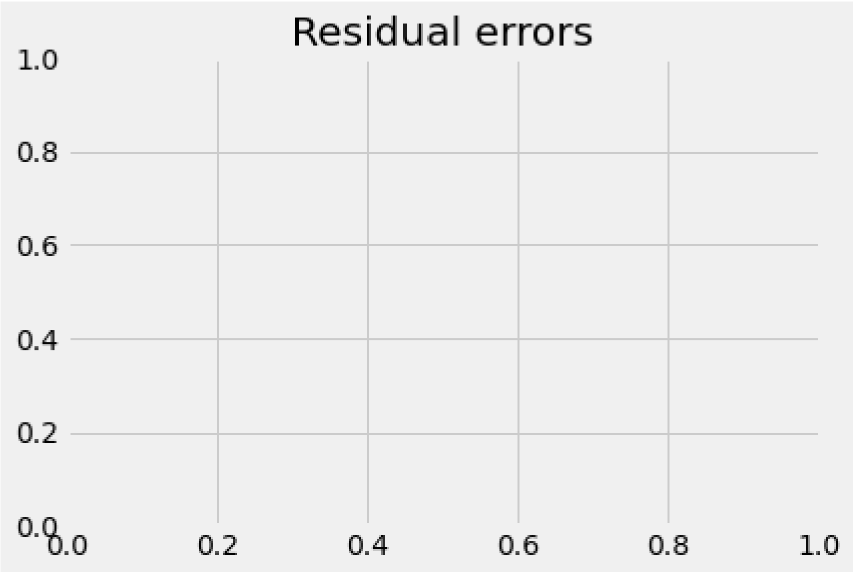
```
plt.legend(loc = 'upper right')
```

```
No handles with labels found to put in legend.
<matplotlib.legend.Legend at 0x7f243787ac50>
```

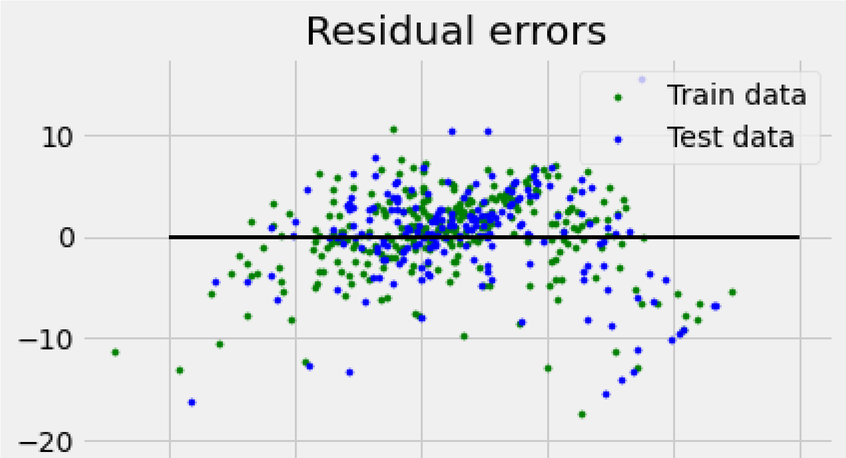


plot title

```
plt.title("Residual errors")
plt.show()
```




```
plt.scatter(reg.predict(X_train), reg.predict(X_train) - y_train,
            color = "green", s = 10, label = 'Train data')
plt.scatter(reg.predict(X_test), reg.predict(X_test) - y_test,
            color = "blue", s = 10, label = 'Test data')
plt.hlines(y = 0, xmin = 0, xmax = 50, linewidth = 2)
plt.legend(loc = 'upper right')
plt.title("Residual errors")
plt.show()
```




```
# Mean X and Y
mean_x = np.mean(X)
mean_y = np.mean(y)

# Total number of values
n = len(X)

# Using the formula to calculate m and c
numer = 0
denom = 0
for i in range(n):
    numer += (X[i] - mean_x) * (y[i] - mean_y)
    denom += (X[i] - mean_x) ** 2
    m = numer / denom
    c = mean_y - (m * mean_x)

# Print coefficients
print(m, c)
```

```
[-6.82675435e-03  1.93400822e-02 -8.65216721e-03  8.33753038e-05
 -9.40446529e-05  1.10197483e-03 -1.22813721e-01  1.09854680e-03
 -8.15772581e-03 -5.07922474e-03 -3.78049638e-03  3.08913388e-03
 -1.44417592e-02] [23.01118408 21.17757004 23.139098   22.52696389 22.53939641 22.45!
 31.13885096 22.45582679 23.10445053 22.88872775 22.7977207  22.31633846
 23.54479768]
```

Calculating R2 Score

+ Code + Text

```
from sklearn.metrics import mean_squared_error
Y_pred = reg.predict(X)

# Calculating R2 Score
r2_score = reg.score(X, y)

print(r2_score)
```

```
0.7406426641094095
```

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