2-day32-multiple-linear-regression

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Multiple Linear Regression By:Loga Aswin

[26]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn import metrics
```

[2]:
```
data = pd.read_csv('/content/winequality-red.csv')

print(data.head())
```

```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol  quality
0      9.4        5
1      9.8        5
2      9.8        5
3      9.8        6
4      9.4        5
```

[31]:
```
data.tail()
```

[31]:
```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
1594            6.2             0.600         0.08             2.0      0.090
1595            5.9             0.550         0.10             2.2      0.062
```

```
1596            6.3             0.510         0.13             2.3      0.076
1597            5.9             0.645         0.12             2.0      0.075
1598            6.0             0.310         0.47             3.6      0.067

      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
1594                 32.0                  44.0  0.99490  3.45       0.58
1595                 39.0                  51.0  0.99512  3.52       0.76
1596                 29.0                  40.0  0.99574  3.42       0.75
1597                 32.0                  44.0  0.99547  3.57       0.71
1598                 18.0                  42.0  0.99549  3.39       0.66

      alcohol  quality
1594     10.5        5
1595     11.2        6
1596     11.0        6
1597     10.2        5
1598     11.0        6
```

[4]:
```
data.describe()
```

[4]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    1599.000000       1599.000000  1599.000000     1599.000000
mean        8.319637          0.527821     0.270976        2.538806
std         1.741096          0.179060     0.194801        1.409928
min         4.600000          0.120000     0.000000        0.900000
25%         7.100000          0.390000     0.090000        1.900000
50%         7.900000          0.520000     0.260000        2.200000
75%         9.200000          0.640000     0.420000        2.600000
max        15.900000          1.580000     1.000000       15.500000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  1599.000000          1599.000000           1599.000000  1599.000000
mean      0.087467            15.874922             46.467792     0.996747
std       0.047065            10.460157             32.895324     0.001887
min       0.012000             1.000000              6.000000     0.990070
25%       0.070000             7.000000             22.000000     0.995600
50%       0.079000            14.000000             38.000000     0.996750
75%       0.090000            21.000000             62.000000     0.997835
max       0.611000            72.000000            289.000000     1.003690

                pH    sulphates      alcohol      quality
count  1599.000000  1599.000000  1599.000000  1599.000000
mean      3.311113     0.658149    10.422983     5.636023
std       0.154386     0.169507     1.065668     0.807569
min       2.740000     0.330000     8.400000     3.000000
25%       3.210000     0.550000     9.500000     5.000000
50%       3.310000     0.620000    10.200000     6.000000
```

```
75%        3.400000      0.730000     11.100000      6.000000
max        4.010000      2.000000     14.900000      8.000000
```

[5]:
```
data.isnull().sum()
```

[5]:
```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

Prepare Data:

[10]:
```
X = data[['fixed acidity', 'volatile acidity', 'alcohol']].values

y = data['quality'].values
```

Split Data into Training and Testing Sets:

[18]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=0)
```

Build and Train the Multiple Linear Regression Model:

[19]:
```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

[19]:
```
LinearRegression()
```

Make Predictions:

[20]:
```
y_pred = regressor.predict(X_test)
```

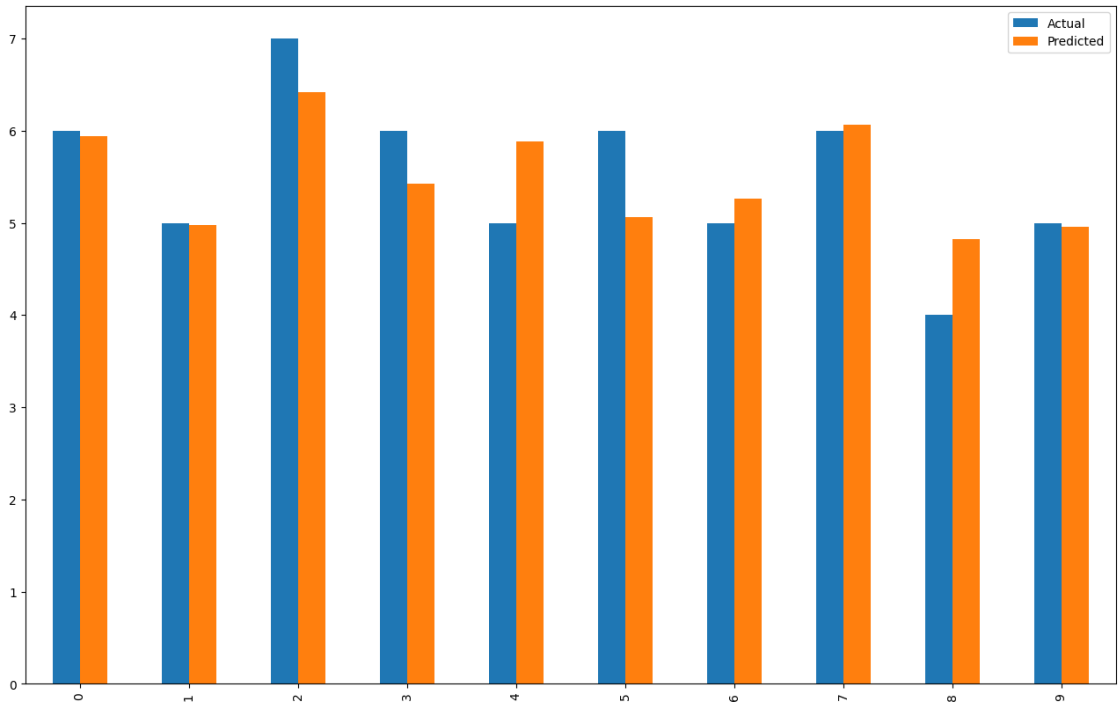
[22]:
```
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df1 = df.head(10)
df1
```

[22]:

	Actual	Predicted
0	6	5.940980
1	5	4.981045

```
2        7   6.417707
3        6   5.422189
4        5   5.886753
5        6   5.063754
6        5   5.263226
7        6   6.068822
8        4   4.823850
9        5   4.962100
```

[28]:
```
df1.plot(kind='bar',figsize=(16,10))
plt.show()
```



Evaluate the Model:

[27]:
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
```

```
Mean Absolute Error: 0.4879795661109293
Mean Squared Error: 0.4096570425100601
```

Interpret the Results:

[30]:
```
coefficients = regressor.coef_
intercept = regressor.intercept_
```

```
print("Coefficients:", coefficients)
print("Intercept:", intercept)
```

```
Coefficients: [ 0.03543676 -1.34814989  0.32700295]
Intercept: 2.6602616401275987
```