Linear Regression(hp)

March 20, 2024

IMPORTING NECESSARY LIBRARIES

```
[10]: import pandas as pd
      import numpy as np
      df=pd.read_csv("C:\\Users\\KENNY\\Downloads\\archive (1)\\winequality-red.csv")
[10]:
            fixed acidity volatile acidity citric acid residual sugar
                                                                              chlorides \
                       7.4
                                        0.700
                                                      0.00
                                                                        1.9
                                                                                  0.076
      1
                       7.8
                                        0.880
                                                      0.00
                                                                        2.6
                                                                                  0.098
      2
                       7.8
                                        0.760
                                                      0.04
                                                                        2.3
                                                                                  0.092
      3
                      11.2
                                        0.280
                                                      0.56
                                                                        1.9
                                                                                  0.075
      4
                       7.4
                                        0.700
                                                      0.00
                                                                        1.9
                                                                                  0.076
                       6.2
      1594
                                        0.600
                                                      0.08
                                                                        2.0
                                                                                  0.090
      1595
                       5.9
                                        0.550
                                                      0.10
                                                                        2.2
                                                                                  0.062
                       6.3
                                                      0.13
                                                                        2.3
      1596
                                        0.510
                                                                                  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
                                                                     рΗ
                                                                         sulphates \
      0
                            11.0
                                                   34.0
                                                         0.99780
                                                                   3.51
                                                                               0.56
      1
                            25.0
                                                   67.0 0.99680
                                                                   3.20
                                                                               0.68
      2
                            15.0
                                                   54.0 0.99700
                                                                   3.26
                                                                               0.65
      3
                            17.0
                                                   60.0 0.99800
                                                                   3.16
                                                                               0.58
      4
                            11.0
                                                   34.0 0.99780
                                                                   3.51
                                                                               0.56
      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
                                                                               0.75
                                                   40.0 0.99574
                                                                   3.42
      1597
                            32.0
                                                   44.0 0.99547
                                                                   3.57
                                                                               0.71
      1598
                            18.0
                                                   42.0 0.99549
                                                                   3.39
                                                                               0.66
            alcohol
                     quality
                9.4
      0
                            5
                            5
      1
                9.8
      2
                9.8
                            5
      3
                9.8
                            6
```

```
4
           9.4
                       5
         10.5
1594
                       5
1595
         11.2
                       6
1596
         11.0
                       6
         10.2
1597
                       5
1598
         11.0
                       6
```

[1599 rows x 12 columns]

ASSINGING DATA TO DEPENDENT AND INDEPENDENT VARIABLES

```
[11]: x=df.drop(['quality'],axis=1)
y=df['quality']
```

SPLITTING DATA

STANDARDZING DATA

```
[13]: from sklearn.preprocessing import StandardScaler
    scaler=StandardScaler()
    scaler=scaler.fit_transform(x_train)
    # scaler=scaler.transform(x_test)
```

MODEL BUILDING

```
[14]: from sklearn.linear_model import LinearRegression
    model=LinearRegression()
    model.fit(x_train,y_train)
    y_pred=model.predict(x_test)
    y_pred
```

```
[14]: array([5.34666441, 5.05631345, 5.66446972, 5.46451484, 5.72518476, 5.27928659, 5.03421667, 5.12623347, 5.74534288, 5.68665032, 6.13959677, 5.23386892, 5.54991474, 5.25825299, 5.44810502, 6.46828999, 5.15018088, 5.59105157, 6.5560658, 5.32255751, 5.3918385, 5.19610791, 5.94475739, 6.36197631, 5.35484893, 5.41907575, 6.36483321, 5.35121573, 5.172392, 6.16987311, 5.25263058, 5.50657406, 5.75422105, 5.39101712, 5.45331031, 5.02757499, 6.16173243, 5.68661555, 5.6486077, 6.165471, 5.52872593, 5.24414488, 6.17724727, 5.16500868, 5.87598332, 5.81317121, 6.41982782, 5.6059474, 5.15232137, 5.55634632, 5.16044852, 5.10449459, 5.58371721, 6.33425313, 4.95134985, 4.98364804, 6.01041999, 5.40809804, 5.83802638, 5.2486897, 5.60717482, 5.96630957, 5.27619063, 5.30380113, 6.4949309,
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             5.68815279, 5.23225544, 5.2805354, 6.2724663, 5.19707213])
     MODEL ACCURACY
[15]: from sklearn.metrics import mean_absolute_error,mean_squared_error,r2_score
      MAE=mean_absolute_error(y_test,y_pred)
      MSE=mean_squared_error(y_test,y_pred)
      R2=r2_score(y_test,y_pred)
      print('MAE:', MAE)
      print('MSE:', MSE)
      print('R2:', R2)
     MAE: 0.5035304415524374
     MSE: 0.39002514396395427
     R2: 0.403180341279623
     OPTIMIZED MODEL
[16]: import pandas as pd
      import numpy as np
      df=pd.read csv("C:\\Users\\KENNY\\Downloads\\archive (1)\\winequality-red.csv")
[17]: x=df.drop(['quality'],axis=1)
      y=df['quality']
[18]: from sklearn.model_selection import train_test_split,GridSearchCV
      x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
       \hookrightarrow2, random state=42)
[19]: from sklearn.linear model import LinearRegression
      model=LinearRegression()
      # model.fit(x_train,y_train)
      # y pred=model.predict(x test)
[20]: param_grid={
          'fit_intercept':[True,False],
          'copy_X':[True,False],
          'n_jobs':[-1],
          'positive': [False, True]
      }
      # grid search=GridSearchCV()
[21]: grid search=GridSearchCV(model,param grid,cv=6)
      grid_search.fit(x_train,y_train)
      best param=grid search.best params
```

5.51985221, 5.16412612, 6.23283235, 5.32903476, 5.25839032,

```
print('Best Parameters:',best_param)
     Best Parameters: {'copy X': True, 'fit intercept': True, 'n jobs': -1,
     'positive': False}
[22]: best_model=LinearRegression(**best_param)
      best model.fit(x train,y train)
      pred=best_model.predict(x_test)
      pred
[22]: array([5.34666441, 5.05631345, 5.66446972, 5.46451484, 5.72518476,
             5.27928659, 5.03421667, 5.12623347, 5.74534288, 5.68665032,
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             5.68815279, 5.23225544, 5.2805354, 6.2724663, 5.19707213])
[24]: MAE=mean_absolute_error(y_test,pred)
      MSE=mean_squared_error(y_test,pred)
      R2=r2_score(y_test,y_pred)
      # results=model.score(x,y)
      print('MAE:', MAE)
      print('MSE:', MSE)
      print('R2:', R2)
     MAE: 0.5035304415524374
     MSE: 0.39002514396395427
     R2: 0.403180341279623
 []:
 []:
```