```
In [29]:
          import pandas as pd
          import numpy as np
          import matplotlib.pyplot as plt
           import seaborn as sns
           import warnings
          warnings.filterwarnings('ignore')
 In [4]: df=pd.read_csv('wineQualityReds.csv')
          # df.head()
          df.tail()
 In [6]:
                Unnamed:
 Out[6]:
                          fixed.acidity
                                      volatile.acidity citric.acid residual.sugar chlorides free.sulfur.dioxide total.sulfur.dioxide density
                                                                                                                                pH sulph
          1594
                     1595
                                  62
                                              0.600
                                                         0.08
                                                                        20
                                                                               0.090
                                                                                                 32 0
                                                                                                                  44 0 0 99490 3 45
          1595
                     1596
                                  5.9
                                              0.550
                                                         0.10
                                                                        2.2
                                                                               0.062
                                                                                                 39.0
                                                                                                                  51.0 0.99512 3.52
          1596
                     1597
                                  6.3
                                              0.510
                                                         0.13
                                                                        2.3
                                                                               0.076
                                                                                                 29.0
                                                                                                                  40.0 0.99574 3.42
                                                                                                                  44.0 0.99547 3.57
          1597
                     1598
                                  5.9
                                              0.645
                                                                        20
                                                                               0.075
                                                                                                 32 0
                                                         0.12
          1598
                     1599
                                  6.0
                                              0.310
                                                         0.47
                                                                        3.6
                                                                               0.067
                                                                                                 18.0
                                                                                                                  42.0 0.99549 3.39
 In [7]:
          df.sample(5)
                Unnamed:
                          fixed.acidity
                                      volatile.acidity citric.acid residual.sugar chlorides free.sulfur.dioxide total.sulfur.dioxide density
                                                                                                                                pH sulph
          1158
                     1159
                                  6.7
                                              0.410
                                                         0.43
                                                                               0.076
                                                                                                 22.0
                                                                                                                  54.0 0.99572 3.42
                      648
                                              0.845
                                                         0.01
                                                                               0.070
                                                                                                                  14.0 0.99670 3.32
           647
                                  8.3
                                                                        2.2
                                                                                                  5.0
            17
                       18
                                  8.1
                                              0.560
                                                         0.28
                                                                        1.7
                                                                               0.368
                                                                                                 16.0
                                                                                                                  56.0 0.99680 3.11
          1472
                     1473
                                  7.6
                                              0.350
                                                         0.60
                                                                        2.6
                                                                               0.073
                                                                                                 23.0
                                                                                                                  44.0 0.99656 3.38
           997
                     998
                                  5.6
                                              0.660
                                                         0.00
                                                                        2.2
                                                                               0.087
                                                                                                  3.0
                                                                                                                  11.0 0.99378 3.71
 In [8]:
          df.shape
          (1599, 13)
 Out[8]:
 In [9]: df.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 1599 entries, 0 to 1598
          Data columns (total 13 columns):
           #
                Column
                                         Non-Null Count
                                                           Dtype
                Unnamed: 0
                                         1599 non-null
           0
                                                           int64
           1
                fixed.acidity
                                         1599 non-null
                                                           float64
           2
                                         1599 non-null
                                                           float64
                volatile.acidity
           3
                citric.acid
                                         1599 non-null
                                                           float64
                residual.sugar
                                                           float64
           4
                                         1599 non-null
           5
                chlorides
                                         1599 non-null
                                                           float64
                free.sulfur.dioxide
           6
                                         1599 non-null
                                                           float64
           7
                total.sulfur.dioxide
                                         1599 non-null
                                                           float64
           8
                density
                                         1599 non-null
                                                           float64
           9
                рΗ
                                         1599 non-null
                                                           float64
           10
                sulphates
                                         1599 non-null
                                                           float64
                alcohol
                                         1599 non-null
                                                           float64
           11
           12
                quality
                                         1599 non-null
                                                           int64
          dtypes: float64(11), int64(2)
          memory usage: 162.5 KB
In [12]: df.isnull().sum()
                                      0
          Unnamed: 0
Out[12]:
          fixed.acidity
                                      0
                                      0
          volatile.acidity
          citric.acid
                                      0
          residual.sugar
                                      0
                                      0
          chlorides
          free.sulfur.dioxide
                                      0
          total.sulfur.dioxide
                                      0
          density
                                      0
                                      0
          рН
          sulphates
                                      0
          alcohol
                                      0
          quality
                                      0
          dtype: int64
```

In [13]: df.shape

```
In [17]:
           duplicate=df.duplicated()
           print(duplicate.sum())
           df[duplicate]
            Unnamed: fixed.acidity volatile.acidity citric.acid residual.sugar chlorides free.sulfur.dioxide total.sulfur.dioxide density pH sulphates
Out[17]:
           df.dropna()
In [18]:
                 Unnamed:
Out[18]:
                            fixed.acidity volatile.acidity citric.acid residual.sugar chlorides free.sulfur.dioxide total.sulfur.dioxide density
                                                                                                                                        pH sulph
                         1
              0
                                    7.4
                                                 0.700
                                                            0.00
                                                                            1.9
                                                                                    0.076
                                                                                                       11.0
                                                                                                                         34.0 0.99780 3.51
                         2
                                                 0.880
                                                            0.00
                                                                                    0.098
                                                                                                                         67.0 0.99680 3.20
                                    7.8
                                                                            2.6
                                                                                                       25.0
              2
                         3
                                    7.8
                                                 0.760
                                                            0.04
                                                                            2.3
                                                                                    0.092
                                                                                                       15.0
                                                                                                                         54.0 0.99700 3.26
              3
                         4
                                    11.2
                                                 0.280
                                                            0.56
                                                                            1.9
                                                                                    0.075
                                                                                                       17.0
                                                                                                                         60.0 0.99800 3.16
                         5
                                                 0.700
                                                                                                                         34.0 0.99780 3.51
              4
                                    7.4
                                                            0.00
                                                                            1.9
                                                                                    0.076
                                                                                                       11.0
           1594
                      1595
                                    6.2
                                                 0.600
                                                            0.08
                                                                            2.0
                                                                                    0.090
                                                                                                       32.0
                                                                                                                         44.0 0.99490 3.45
                                                                                                                         51.0 0.99512 3.52
           1595
                      1596
                                    5.9
                                                 0.550
                                                            0.10
                                                                            2.2
                                                                                    0.062
                                                                                                       39.0
                      1597
                                    6.3
                                                 0.510
                                                            0.13
                                                                            2.3
                                                                                    0.076
                                                                                                       29.0
                                                                                                                         40.0 0.99574 3.42
           1596
           1597
                      1598
                                    5.9
                                                 0.645
                                                            0.12
                                                                            2.0
                                                                                    0.075
                                                                                                       32.0
                                                                                                                         44.0 0.99547 3.57
                                                 0.310
                                                                                                                         42.0 0.99549 3.39
           1598
                      1599
                                    6.0
                                                            0.47
                                                                            3.6
                                                                                    0.067
                                                                                                       18.0
           1599 rows × 13 columns
In [19]: print(df.quality.value_counts())
           5
                 681
                 638
           6
           7
                 199
           4
                  53
           8
                  18
           3
                  10
           Name: quality, dtype: int64
           sns.countplot(df['quality'])
In [31]:
           plt.grid()
           plt.show()
               1600
               1400
               1200
               1000
            count
                800
                600
                400
                200
                   0
                                                            0
In [24]: df.corr()
```

Out[13]: (1599, 13)

Out[24]:		Unnamed: 0	fixed.acidity	volatile.acidity	citric.acid	residual.sugar	chlorides	free.sulfur.dioxide	total.sulfur.dioxide	dens
	Unnamed: 0	1.000000	-0.268484	-0.008815	-0.153551	-0.031261	-0.119869	0.090480	-0.117850	-0.3683
	fixed.acidity	-0.268484	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.6680
	volatile.acidity	-0.008815	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.0220
	citric.acid	-0.153551	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.3649
	residual.sugar	-0.031261	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.3552
	chlorides	-0.119869	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.2006
	free.sulfur.dioxide	0.090480	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.0219
	total.sulfur.dioxide	-0.117850	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.0712
	density	-0.368372	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.0000
	рН	0.136005	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.3416
	sulphates	-0.125307	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.1485

0.109903

0.226373

0.042075 -0.221141

0.013732 -0.128907

-0.069408

-0.050656

-0.205654 -0.4961

-0.185100 -0.1749

In [30]: corr= df.corr()
 plt.figure(figsize=(30,20))
 sns.heatmap(corr,annot=True,cmap='coolwarm')

0.245123

0.066453

-0.061668

0.124052

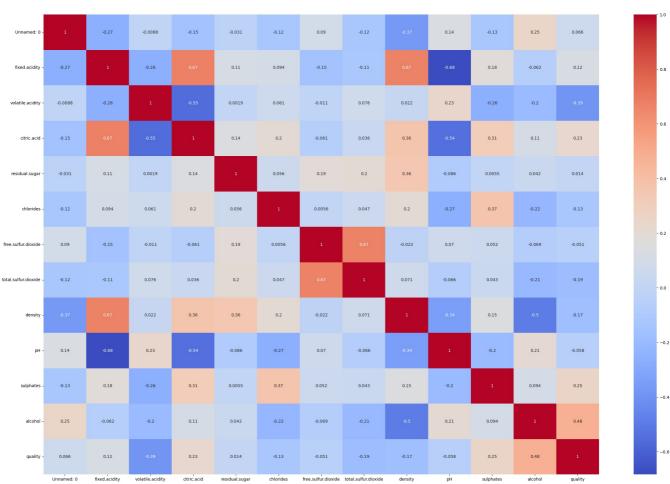
-0.202288

-0.390558

alcohol

quality

Out[30]: <Axes: >



In [32]: target_name='quality'
 y=df[target_name]
 x=df.drop(target_name,axis=1)

In [33]: x.head()

```
Unnamed:
Out[33]:
                         fixed.acidity volatile.acidity citric.acid residual.sugar chlorides free.sulfur.dioxide total.sulfur.dioxide density
                                                                                                                                    pH sulphates
           0
                      1
                                 7.4
                                               0.70
                                                         0.00
                                                                                0.076
                                                                                                   11.0
                                                                        1.9
                                                                                                                     34.0
                                                                                                                           0.9978 3.51
                                                                                                                                              0.56
           1
                      2
                                 7.8
                                               0.88
                                                         0.00
                                                                        2.6
                                                                                0.098
                                                                                                   25.0
                                                                                                                     67.0
                                                                                                                            0.9968 3.20
                                                                                                                                              0.68
           2
                      3
                                 7.8
                                               0.76
                                                         0.04
                                                                        2.3
                                                                                0.092
                                                                                                   15.0
                                                                                                                            0.9970 3.26
                                                                                                                                              0.65
                                                                                                                     54.0
           3
                      4
                                                                        1.9
                                11.2
                                               0.28
                                                         0.56
                                                                                0.075
                                                                                                   17.0
                                                                                                                     60.0
                                                                                                                            0.9980 3.16
                                                                                                                                              0.58
           4
                      5
                                 7.4
                                               0.70
                                                         0.00
                                                                        1.9
                                                                                0.076
                                                                                                   11.0
                                                                                                                     34.0
                                                                                                                            0.9978 3.51
                                                                                                                                              0.56
In [35]:
          x.shape
           (1599, 12)
Out[35]:
In [36]:
           y.head()
           0
                 5
Out[36]:
                 5
           1
           2
                 5
           3
                 6
           4
                 5
           Name: quality, dtype: int64
In [37]: y.shape
           (1599,)
Out[37]:
In [38]:
           from sklearn.preprocessing import StandardScaler
           sc = StandardScaler()
           x_res = sc.fit_transform(x)
In [39]: x.head()
Out[39]:
              Unnamed:
                         fixed.acidity volatile.acidity citric.acid residual.sugar chlorides free.sulfur.dioxide total.sulfur.dioxide density
                                                                                                                                    pH sulphates
           0
                      1
                                 7.4
                                               0.70
                                                         0.00
                                                                        1.9
                                                                                0.076
                                                                                                   11.0
                                                                                                                     34.0
                                                                                                                            0.9978 3.51
                                                                                                                                              0.56
           1
                      2
                                 7.8
                                               0.88
                                                         0.00
                                                                        2.6
                                                                                0.098
                                                                                                   25.0
                                                                                                                     67.0
                                                                                                                            0.9968 3.20
                                                                                                                                              0.68
           2
                      3
                                 7.8
                                               0.76
                                                         0.04
                                                                        2.3
                                                                                0.092
                                                                                                   15.0
                                                                                                                     54.0
                                                                                                                            0.9970 3.26
                                                                                                                                              0.65
           3
                                11.2
                                               0.28
                                                         0.56
                                                                        1.9
                                                                                0.075
                                                                                                   17.0
                                                                                                                     60.0
                                                                                                                            0.9980 3.16
                                                                                                                                              0.58
           4
                      5
                                 7.4
                                                                                                                           0.9978 3.51
                                               0.70
                                                         0.00
                                                                        1.9
                                                                                0.076
                                                                                                   11.0
                                                                                                                     34.0
                                                                                                                                              0.56
In [40]: x_res
Out[40]: array([[-1.73096794, -0.52835961,
                                                     0.96187667, ..., 1.28864292,
                     -0.57920652, -0.96024611],
                    [-1.72880152, -0.29854743,
                                                     1.96744245, ..., -0.7199333 ,
                      0.1289504 , -0.58477711],
                    [-1.7266351 , -0.29854743, -0.04808883, -0.58477711],
                                                     1.29706527, ..., -0.33117661,
                    [ 1.7266351 , -1.1603431 , 0.54204194, 0.54162988],
                                                  , -0.09955388, ..., 0.70550789,
                    [ 1.72880152, -1.39015528,
                                                     0.65462046, ...,
                                                                          1.6773996 .
                    0.30598963, -0.20930812],
[ 1.73096794, -1.33270223, -1.21684919, ..., 0.51112954,
                      0.01092425, 0.54162988]])
In [41]: from statsmodels.stats.outliers_influence import variance_inflation_factor
           vif_data = pd.DataFrame()
           vif data["vif"] =[variance inflation factor(x res,i) for i in range(x res.shape[1])]
           vif data["Features"]=x.columns
```

vif_data

```
0 1.270873
                           Unnamed: 0
           1 7.888640
                           fixed.acidity
           2 1.790625
                          volatile.acidity
           3 3.133061
                             citric.acid
           4 1.704435
                         residual.sugar
           5 1.485224
                             chlorides
           6 2.060964 free.sulfur.dioxide
           7 2.314581 total.sulfur.dioxide
           8 6.369056
                               density
           9 3.378271
                                  рΗ
          10 1.440547
                             sulphates
          11 3.058106
                               alcohol
In [42]: x_res.shape
          (1599, 12)
Out[42]:
          x1=x.drop(['residual.sugar','density'],axis=1)
In [43]:
          x1.shape
          (1599, 10)
Out[43]:
In [52]:
          from sklearn.preprocessing import StandardScaler
          scaler = StandardScaler()
          (scaler.fit(x1))
          rescaledx = scaler.transform(x1)
In [53]: rescaledx.shape
          (1599, 10)
Out[53]:
In [54]: y.value_counts()
                681
Out[54]:
               638
          7
                199
          4
                 53
                 18
                 10
          3
          Name: quality, dtype: int64
          sns.countplot(df['quality'])
In [56]:
          plt.grid()
          plt.show()
             1600
             1400
             1200
              1000
           count
               800
               600
               400
               200
                 0
In [57]: from sklearn.model_selection import train_test_split
          x_train,x_test,y_train,y_test=train_test_split(rescaledx,y,test_size=0.2,random_state=7)
```

Features

In [58]: x_train.shape,y_train.shape

Out[41]:

```
Out[58]: ((1279, 10), (1279,))
In [59]: x_test.shape,y_test.shape
          ((320, 10), (320,))
Out[59]:
In [60]: from sklearn.tree import DecisionTreeClassifier
           dt= DecisionTreeClassifier()
           dt.fit(x_train,y_train)
           dt.train pred=dt.predict(x train)
          dt_test_pred=dt.predict(x_test)
In [61]: from sklearn.metrics import confusion matrix, classification report, accuracy score
In [79]: print('Train Accuracy:',accuracy_score(y_train,dt.train_pred)*100)
          Train Accuracy: 100.0
In [81]: print('Accuracy Score:',accuracy score(y test,dt test pred)*100)
          Accuracy Score: 62.5
In [84]: print(confusion_matrix(y_test,dt_test_pred))
          [0 \ 0 \ 0 \ 0 \ 0]
             0
                 1
                    8
                        1
                            0
                               0]
            [ 1
                 5 82 30 3 2]
             3 3 29 94 17 0]
            0 1
                 1 4 9 21
                               21
                 0 0 2 0 2]]
            [ 0
In [85]: print(classification_report(y_test,dt_test_pred,digits=4))
                                         recall f1-score
                          precision
                                                               support
                       3
                              0.0000
                                         0.0000
                                                     0.0000
                       4
                              0.1000
                                         0.1000
                                                     0.1000
                                                                     10
                       5
                              0.6667
                                         0.6667
                                                     0.6667
                                                                    123
                       6
                              0.6912
                                         0.6438
                                                     0.6667
                                                                    146
                       7
                              0.5122
                                         0.5676
                                                     0.5385
                                                                     37
                       8
                                         0.5000
                                                     0.4000
                                                                      4
                              0.3333
                                                     0.6250
                                                                    320
               accuracy
                              0.3839
                                         0.4130
                                                     0.3953
                                                                    320
              macro avq
                              0.6381
                                         0.6250
                                                     0.6308
          weighted avg
                                                                    320
In [89]: (0.0000+0.1000+0.6667+0.6912+0.5122+0.3333)/6
          0.3838999999999996
Out[89]:
In [87]: from sklearn.metrics import precision_score,recall_score,fl_score,classification_report,confusion_matrix
          print("precision score of macro is:",round(precision_score(y_test,dt_test_pred,average='macro')*100,2))
print("precision score of micro is:",round(precision_score(y_test,dt_test_pred,average='micro')*100,2))
          print("precision score of weighted is:",round(precision_score(y_test,dt_test_pred,average='weighted')*100,2))
          precision score of macro is: 38.39
          precision score of micro is: 62.5
          precision score of weighted is: 63.81
In [88]: print("recall_score of macro is:",round(recall_score(y_test,dt_test_pred,average='macro')*100,2))
    print("recall_score of micro is:",round(recall_score(y_test,dt_test_pred,average='micro')*100,2))
          print("recall score of weighted is:",round(recall score(y test,dt test pred,average='weighted')*100,2))
          recall_score of macro is: 41.3
          recall score of micro is: 62.5
          recall score of weighted is: 62.5
In [90]: print('f1_score of macro:',round(f1_score(y_test,dt_test_pred,average='macro')*100,2))
    print('f1_score of micro:',round(f1_score(y_test,dt_test_pred,average='micro')*100,2))
          print('f1_score of weighted:',round(f1_score(y_test,dt_test_pred,average='weighted')*100,2))
          fl score of macro: 39.53
          fl_score of micro: 62.5
          fl_score of weighted: 63.08
In [91]: df.head()
```

```
Unnamed:
Out[91]:
                       fixed.acidity volatile.acidity citric.acid residual.sugar chlorides free.sulfur.dioxide total.sulfur.dioxide density
                                                                                                                            pH sulphates
          0
                     1
                               7.4
                                            0.70
                                                     0.00
                                                                    1.9
                                                                           0.076
                                                                                             11.0
                                                                                                              34.0
                                                                                                                    0.9978 3.51
                                                                                                                                     0.56
                     2
                                                     0.00
                                                                    2.6
                                                                           0.098
                                                                                             25.0
                                                                                                                    0.9968
                               7.8
                                            0.88
                                                                                                              67.0
                                                                                                                           3.20
                                                                                                                                     0.68
          2
                     3
                               7.8
                                            0.76
                                                     0.04
                                                                           0.092
                                                                                             15.0
                                                                                                                                     0.65
                                                                    2.3
                                                                                                                    0.9970 3.26
                                                                                                              54.0
          3
                     4
                              11.2
                                            0.28
                                                     0.56
                                                                    1.9
                                                                           0.075
                                                                                             17.0
                                                                                                              60.0
                                                                                                                    0.9980 3.16
                                                                                                                                     0.58
           4
                     5
                                                                    1.9
                               7.4
                                            0.70
                                                     0.00
                                                                           0.076
                                                                                             11.0
                                                                                                              34.0
                                                                                                                    0.9978 3.51
                                                                                                                                     0.56
          input_data = (1,7.4,0.70,0.00,1.9,0.07,11.0,34.0,0.9978,3.51)
In [103...
           input_data_as_numpy_array=np.asarray(input_data)
           input_data_reshaped=input_data_as_numpy_array.reshape(1,-1)
          prediction = dt.predict(input_data_reshaped)
          print(prediction)
          [6]
In [111...
          from sklearn.ensemble import RandomForestClassifier
           clf= RandomForestClassifier(random_state=1)
           clf.fit(x train,y train)
           clf_train_pred = clf.predict(x_train)
           clf_test_pred = clf.predict(x_test)
In [112... print('Train_accuracy:',accuracy_score(y_train,clf_train_pred)*100)
          Train accuracy: 100.0
In [114... print('Accuracy Score:',accuracy_score(y_test,clf_test_pred)*100)
          Accuracy Score: 69.375
In [115...
         print(confusion_matrix(y_test,clf_test_pred))
           Π
               1
                   8
                        0
                            1
                                 01
               0
                  98
                      23
                            2
                                 01
               1
                  26 100
                           19
                                 0]
               0
                   3
                     12
                           22
                                 0]
              0
                   0
                        1
                                 1]]
          print("recall_score of macro is:",round(recall_score(y_test,clf_test_pred,average='macro')*100,2))
print("recall_score of micro is:",round(recall_score(y_test,clf_test_pred,average='micro')*100,2))
In [117...
          print("recall_score of weighted is:",round(recall_score(y_test,clf_test_pred,average='weighted')*100,2))
          recall score of macro is: 48.53
          recall score of micro is: 69.38
          recall_score of weighted is: 69.38
          print('f1_score of macro:',round(f1_score(y_test,clf_test_pred,average='macro')*100,2))
In [118...
           print('f1_score of micro:',round(f1_score(y_test,clf_test_pred,average='micro')*100,2))
          print('f1 score of weighted:',round(f1 score(y test,clf test pred,average='weighted')*100,2))
          fl_score of macro: 51.31
          fl_score of micro: 69.38
          fl score of weighted: 68.71
In [127...
         from sklearn import svm
In [128...
          clf = svm.SVC(probability=True)
           clf.fit(x_train,y_train)
Out[128]:
                       SVC
           SVC(probability=True)
In [143...
          clf_train_pred=clf.predict(x_train)
           clf_train_pred=clf.predict(x_test)
In [149... print('Train Accuracy:',accuracy_score(y_test,clf_train_pred)*100)
          Train Accuracy: 61.875
In [153...
         print('Accuracy Score:',accuracy_score(y_test,clf_test_pred)*100)
          Accuracy Score: 69.375
```

In [154... print(confusion_matrix(y_test,clf_test_pred))

```
[[ 1 8 0
                                  01
              0 98 23
                            2
                                  0]
            ſ
               1 26 100 19
                                  0]
                   3 12 22
              0
                                  01
               0
                    0
                        1
                                  1]]
In [155= print("precision score of macro is:",round(precision_score(y_test,clf_test_pred,average='macro')*100,2))
           print("precision score of micro is:",round(precision_score(y_test,clf_test_pred,average='micro')*100,2))
           print("precision score of weighted is:",round(precision_score(y_test,clf_test_pred,average='weighted')*100,2))
           precision score of macro is: 68.79
           precision score of micro is: 69.38
           precision score of weighted is: 69.79
print("recall_score of macro is:",round(recall_score(y_test,clf_test_pred,average='macro')*100,2))
print("recall_score of micro is:",round(recall_score(y_test,clf_test_pred,average='micro')*100,2))
           print("recall_score of weighted is:",round(recall_score(y_test,clf_test_pred,average='weighted')*100,2))
           recall_score of macro is: 48.53
           recall_score of micro is: 69.38
           recall score of weighted is: 69.38
In [157_ print('f1_score of macro:',round(f1_score(y_test,clf_test_pred,average='macro')*100,2))
print('f1_score of micro:',round(f1_score(y_test,clf_test_pred,average='micro')*100,2))
           print('f1_score of weighted:',round(f1_score(y_test,clf_test_pred,average='weighted')*100,2))
           fl_score of macro: 51.31
           fl score of micro: 69.38
           fl_score of weighted: 68.71
 In [ ]:
```

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