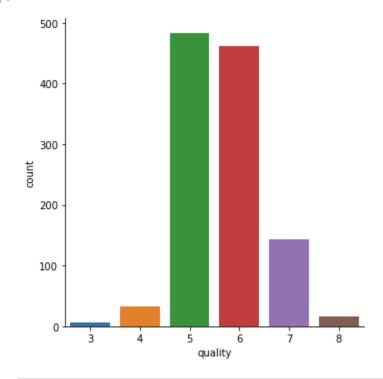
```
In [1]:
           import pandas as pd
          import numpy as np
           import seaborn as sns
           import matplotlib.pyplot as plt
           from sklearn.model_selection import train_test_split
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.metrics import accuracy_score
In [2]:
          wine_dataset = pd.read_csv('WineQT.csv')
          wine_dataset.head()
Out[2]:
                                                          free
                                                                  total
              fixed volatile
                             citric
                                   residual
                                            chlorides
                                                        sulfur
                                                                sulfur
                                                                        density
                                                                                 pH sulphates alcohol quality Id
             acidity
                     acidity
                              acid
                                     sugar
                                                      dioxide
                                                               dioxide
          0
                7.4
                       0.70
                              0.00
                                        1.9
                                                0.076
                                                         11.0
                                                                  34.0
                                                                        0.9978
                                                                                3.51
                                                                                           0.56
                                                                                                    9.4
                                                                                                             5
                                                                                                                 0
          1
                                                0.098
                7.8
                       0.88
                              0.00
                                        2.6
                                                         25.0
                                                                  67.0
                                                                        0.9968
                                                                                3.20
                                                                                           0.68
                                                                                                    9.8
                                                                                                             5
                                                                                                                 1
          2
                7.8
                       0.76
                              0.04
                                        2.3
                                                0.092
                                                         15.0
                                                                  54.0
                                                                        0.9970
                                                                                3.26
                                                                                           0.65
                                                                                                    9.8
                                                                                                             5
                                                                                                                 2
          3
               11.2
                       0.28
                              0.56
                                        1.9
                                                0.075
                                                         17.0
                                                                  60.0
                                                                        0.9980
                                                                                           0.58
                                                                                                    9.8
                                                                                                                 3
                                                                                3.16
                                                                                                             6
          4
                7.4
                       0.70
                              0.00
                                        1.9
                                                0.076
                                                         11.0
                                                                  34.0
                                                                        0.9978 3.51
                                                                                           0.56
                                                                                                    9.4
                                                                                                             5
                                                                                                                 4
In [3]:
          ### number of rows and columns
          wine_dataset.shape
          (1143, 13)
Out[3]:
In [4]:
          ##### checking for missing values
          wine_dataset.isnull().sum()
          fixed acidity
                                      0
Out[4]:
          volatile acidity
                                      0
          citric acid
                                      0
          residual sugar
                                      0
          chlorides
                                      0
          free sulfur dioxide
                                      0
          total sulfur dioxide
                                      0
          density
                                      0
                                      0
                                      0
          sulphates
          alcohol
                                      0
          quality
                                      0
          Id
                                      0
          dtype: int64
In [5]:
          ##### Data Analysis and Visualisation
          wine_dataset.describe()
                                                                                  free sulfur
Out[5]:
                                  volatile
                                                           residual
                                                                                               total sulfur
                                                                      chlorides
                 fixed acidity
                                             citric acid
                                                                                                              density
                                  acidity
                                                             sugar
                                                                                     dioxide
                                                                                                  dioxide
          count
                1143.000000
                              1143.000000
                                          1143.000000
                                                       1143.000000
                                                                    1143.000000
                                                                                 1143.000000
                                                                                             1143.000000 1143.000000
          mean
                    8.311111
                                 0.531339
                                              0.268364
                                                          2.532152
                                                                       0.086933
                                                                                   15.615486
                                                                                                45.914698
                                                                                                             0.996730
            std
                    1.747595
                                 0.179633
                                             0.196686
                                                          1.355917
                                                                       0.047267
                                                                                   10.250486
                                                                                               32.782130
                                                                                                             0.001925
```

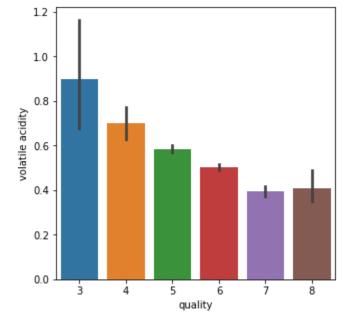
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070
25%	7.100000	0.392500	0.090000	1.900000	0.070000	7.000000	21.000000	0.995570
50%	7.900000	0.520000	0.250000	2.200000	0.079000	13.000000	37.000000	0.996680
75%	9.100000	0.640000	0.420000	2.600000	0.090000	21.000000	61.000000	0.997845
max	15.900000	1.580000	1.000000	15.500000	0.611000	68.000000	289.000000	1.003690

```
In [6]:
    #### number of values for each quality
    sns.catplot(x='quality', data = wine_dataset, kind = 'count')
```

Out[6]: <seaborn.axisgrid.FacetGrid at 0x1f5ff2d93a0>



```
In [7]:
         wine_dataset['quality'].value_counts()
             483
Out[7]:
             462
             143
        7
        4
              33
        8
               16
        3
        Name: quality, dtype: int64
In [8]:
         ##### volatile acidity vs Quality
         plot = plt.figure(figsize=(5,5))
         sns.barplot(x='quality',y='volatile acidity',data = wine_dataset)
        <AxesSubplot:xlabel='quality', ylabel='volatile acidity'>
Out[8]:
```

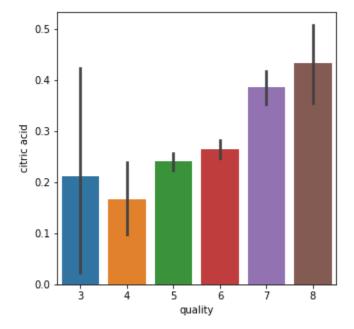


```
In [9]: ## Observsation #1. If the valatile acidity is high then wine quality is low viceversa.
```

```
In [10]: ##### citric acid vs Quality

plot = plt.figure(figsize=(5,5))
sns.barplot(x='quality',y='citric acid',data = wine_dataset)
```

Out[10]: <AxesSubplot:xlabel='quality', ylabel='citric acid'>



```
In [11]:

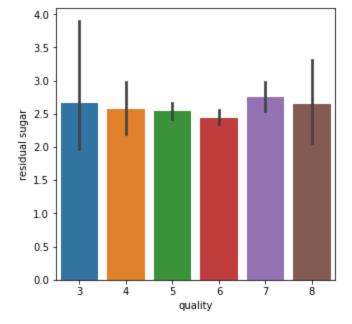
#### Observation

#1. If the citric acid quantitiy is high then the wine quality also high and viceversa.
```

```
In [12]: ##### residual sugar vs Quality

plot = plt.figure(figsize=(5,5))
    sns.barplot(x='quality',y='residual sugar',data = wine_dataset)
```

Loading [MathJax]/extensions/Safe.js | label='quality', ylabel='residual sugar'>



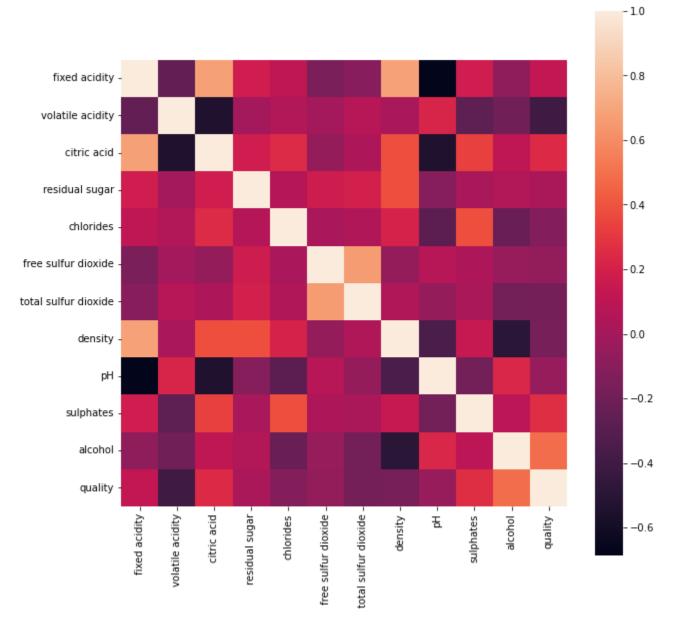
```
In [13]: wine_dataset = wine_dataset.drop('Id',axis = 1)
    wine_dataset.head()
```

Out[13]:		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality
	0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
	1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
	2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
	3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
	4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

```
In [14]:
    ##### Correlation
    correlation = wine_dataset.corr()
```

In [15]:
 ##### Constructing the heatmap to understand the correlation between the columns
 plt.figure(figsize=(10,10))
 sns.heatmap(correlation, cbar=True ,square=True)

Out[15]: <AxesSubplot:>



In []:

In [16]: wine_dataset.head()

Out[16]:

:	fixed acidity		citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality
(7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	L 7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

In [17]:

Observation

#1. By these we can see how these variables are correlated with each other.

In [18]: #### Data Preprocessing
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```
### separating data and labels
            X = wine_dataset.drop('quality',axis=1)
 In [19]:
            #### Label Binarisation
            Y = wine_dataset['quality'].apply(lambda y_value: 1 if y_value>=7 else 0)
 In [20]:
            print(Y)
           0
                   0
           1
                   0
           2
                   0
           3
                   0
                   0
           1138
                   0
           1139
                   0
           1140
                   0
           1141
                   0
           1142
                   0
           Name: quality, Length: 1143, dtype: int64
 In [21]:
            #### Train and Test Split
            X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size = 0.2, stratify = Y, re
 In [22]:
            print(X.shape, X_train.shape, X_test.shape)
           (1143, 11) (914, 11) (229, 11)
 In [23]:
            print(Y.shape, Y_train.shape, Y_test.shape)
           (1143,) (914,) (229,)
 In [24]:
            ##### Model Training
 In [25]:
            #### Random Forest Classifier
            model = RandomForestClassifier()
            model.fit(X_train,Y_train)
           RandomForestClassifier()
 Out[25]:
 In [26]:
            #### Model Evaluation
            #### Accuacy on training data
            X_train_prediction = model.predict(X_train)
            trainig_data_accu = accuracy_score(X_train_prediction, Y_train)
            trainig_data_accu
           1.0
 Out[26]:
 In [27]:
            #### Accuacy on test data
            X_test_prediction = model.predict(X_test)
            test_data_accu = accuracy_score(X_test_prediction, Y_test)
            test data accu
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```

```
0.8558951965065502
Out[27]:
In [28]:
          ###### Building a Predictive System
In [29]:
          input_data = (8.8, 0.41, 0.64, 2.2, 0.093000000000001, 9.0, 42.0, 0.9986, 3.54, 0.66, 10.5)
          #### Changing the input data to np array
          input_data_as_np_array = np.asarray(input_data)
          ### Reshaping the data as we are predicting the label for only one instance
          reshaped_input_data = input_data_as_np_array.reshape(1,-1)
          prediction = model.predict(reshaped_input_data)
          print(prediction)
          if (prediction[0]==1):
              print('Good Quality Wine')
          else:
              print('Bad Quality Wine')
         [0]
         Bad Quality Wine
 In [ ]:
```