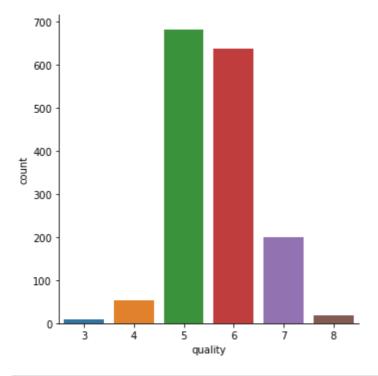
```
In [1]:
          import numpy as np
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
          import warnings
          warnings.filterwarnings("ignore")
          wine_dataset = pd.read_csv(r"C:\Users\s323\Desktop\Gatherings\Data Science\Datasets
In [2]:
In [3]:
          wine_dataset.head()
Out[3]:
                                                            free
                                                                    total
               fixed volatile citric
                                     residual
                                              chlorides
                                                          sulfur
                                                                   sulfur
                                                                                    рΗ
                                                                          density
                                                                                        sulphates alcohol
             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
          1
                 7.8
                        0.88
                               0.00
                                          2.6
                                                  0.098
                                                            25.0
                                                                     67.0
                                                                           0.9968
                                                                                   3.20
                                                                                              0.68
                                                                                                        9.8
          2
                7.8
                        0.76
                               0.04
                                          2.3
                                                  0.092
                                                            15.0
                                                                     54.0
                                                                           0.9970
                                                                                  3.26
                                                                                              0.65
                                                                                                        9.8
          3
                11.2
                        0.28
                               0.56
                                          1.9
                                                  0.075
                                                            17.0
                                                                     60.0
                                                                            0.9980 3.16
                                                                                              0.58
                                                                                                        9.8
          4
                7.4
                        0.70
                               0.00
                                          1.9
                                                  0.076
                                                            11.0
                                                                     34.0
                                                                           0.9978 3.51
                                                                                              0.56
                                                                                                        9.4
          wine_dataset.shape
          (1599, 12)
Out[4]:
          wine_dataset.columns
In [6]:
          Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
Out[6]:
                  'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
                  'pH', 'sulphates', 'alcohol', 'quality'],
                 dtype='object')
          wine dataset.describe()
In [8]:
Out[8]:
                        fixed
                                   volatile
                                                             residual
                                                                                     free sulfur
                                                                                                 total sulfur
                                              citric acid
                                                                         chlorides
                                   acidity
                                                                                        dioxide
                                                                                                    dioxide
                      acidity
                                                               sugar
          count 1599.000000
                              1599.000000
                                            1599.000000
                                                         1599.000000
                                                                      1599.000000
                                                                                   1599.000000
                                                                                                1599.000000
          mean
                    8.319637
                                  0.527821
                                               0.270976
                                                            2.538806
                                                                         0.087467
                                                                                     15.874922
                                                                                                  46.467792
            std
                    1.741096
                                  0.179060
                                               0.194801
                                                            1.409928
                                                                         0.047065
                                                                                     10.460157
                                                                                                  32.895324
           min
                    4.600000
                                  0.120000
                                               0.000000
                                                            0.900000
                                                                         0.012000
                                                                                      1.000000
                                                                                                   6.000000
           25%
                    7.100000
                                  0.390000
                                               0.090000
                                                            1.900000
                                                                         0.070000
                                                                                      7.000000
                                                                                                  22.000000
           50%
                                  0.520000
                                                                         0.079000
                                                                                     14.000000
                    7.900000
                                               0.260000
                                                            2.200000
                                                                                                  38.000000
           75%
                    9.200000
                                  0.640000
                                               0.420000
                                                                         0.090000
                                                                                     21.000000
                                                            2.600000
                                                                                                  62.000000
                   15.900000
                                  1.580000
                                               1.000000
                                                           15.500000
                                                                         0.611000
                                                                                     72.000000
                                                                                                 289.000000
           max
```

## **Data Analysis and Visualization**

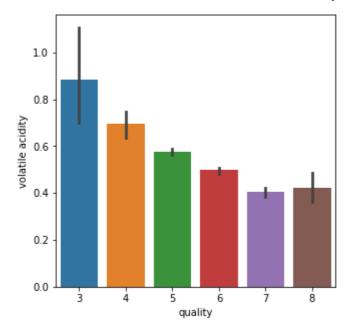
```
wine_dataset.isnull().sum()
In [14]:
         fixed acidity
Out[14]:
         volatile acidity
                                  0
                                  0
         citric acid
         residual sugar
                                  0
         chlorides
                                  0
         free sulfur dioxide
                                  0
         total sulfur dioxide
                                  0
         density
                                  0
                                  0
         рΗ
         sulphates
                                  0
         alcohol
                                  0
         quality
         dtype: int64
In [17]: # No of values for each quality
          sns.catplot(x='quality', data = wine_dataset, kind = 'count')
```

<seaborn.axisgrid.FacetGrid at 0x20817ccf0d0> Out[17]:



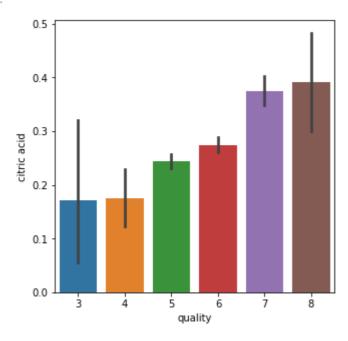
```
# volatile acidity vs quality
In [18]:
         plot = plt.figure(figsize=(5,5))
         sns.barplot(x="quality",y="volatile acidity",data=wine_dataset)
```

<AxesSubplot:xlabel='quality', ylabel='volatile acidity'> Out[18]:



```
In [19]: # citric acid vs quality
    plot = plt.figure(figsize=(5,5))
    sns.barplot(x="quality",y="citric acid",data=wine_dataset)
```

Out[19]: <AxesSubplot:xlabel='quality', ylabel='citric acid'>

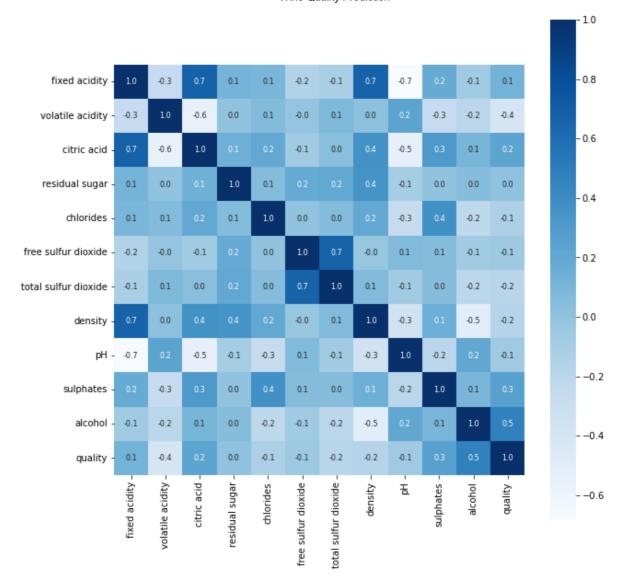


#### Co-relation

- Two types:
- 1. Positive- When they are directly prpotional
- 2. Negative- When they are inversely propotional

```
In [20]: correlation = wine_dataset.corr()

In [22]: plt.figure(figsize=(10,10))
    sns.heatmap(correlation, cbar=True, square =True, fmt =".1f", annot=True, annot_kw:
Out[22]: <AxesSubplot:>
```



• 12 columns vertical as well as horizontal- more dark means postively and highly corelated and less dark vice versa

# **Data Preprocessing**

```
In [23]: X = wine_dataset.drop("quality",axis =1)
In [24]: print(X)
```

```
fixed acidity volatile acidity citric acid residual sugar chlorides \
0
                                 0.700
                                               0.00
                                                                 1.9
                7.4
                                                                          0.076
1
                7.8
                                 0.880
                                               0.00
                                                                          0.098
                                                                 2.6
2
                7.8
                                 0.760
                                               0.04
                                                                 2.3
                                                                          0.092
3
               11.2
                                 0.280
                                               0.56
                                                                 1.9
                                                                          0.075
4
                                 0.700
                7.4
                                               0.00
                                                                 1.9
                                                                          0.076
                . . .
                                  . . .
                                                                 . . .
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 \
0
                     11.0
                                            34.0 0.99780 3.51
                                                                       0.56
                     25.0
                                            67.0 0.99680 3.20
1
                                                                       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
                      . . .
                                                            . . .
                                                                        . . .
                                             . . .
                                                      . . .
                     32.0
                                            44.0 0.99490 3.45
1594
                                                                       0.58
                                            51.0 0.99512 3.52
1595
                     39.0
                                                                       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
          9.4
0
          9.8
1
2
          9.8
3
          9.8
4
          9.4
1594
         10.5
1595
         11.2
1596
         11.0
1597
         10.2
         11.0
1598
```

[1599 rows x 11 columns]

# **Label Binarization or Label Encoding**

```
• Quality = 7 and 8 - Good - 1
```

• Quality = 6 or less than 6- Bad- 0

```
Y = wine_dataset["quality"].apply(lambda y_value:1 if y_value>=7 else 0)
In [27]:
          print (Y)
In [28]:
          0
                  0
          1
                  0
          2
                  0
          3
                  0
                  0
          1594
          1595
                  0
          1596
                  0
          1597
          1598
         Name: quality, Length: 1599, dtype: int64
```

#### Train and Test split

```
In [47]: from sklearn.model_selection import train_test_split
    x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size=0.2, random_state=3)
In [48]: print(X.shape,x_train.shape,x_test.shape)
    (1599, 11) (1279, 11) (320, 11)
```

### **Model Training**

```
In [49]: from sklearn.ensemble import RandomForestClassifier
In [50]: model= RandomForestClassifier()
In [51]: model.fit(x_train,y_train)
Out[51]: RandomForestClassifier()
```

#### **Predictions**

```
In [52]:
         from sklearn.metrics import accuracy_score
In [53]:
         train_model_predictions = model.predict(x_train)
         train_data_accuracy = accuracy_score(train_model_predictions,y_train)
In [54]:
         train_data_accuracy
         1.0
Out[54]:
         test_model_predictions = model.predict(x_test)
In [55]:
         test_data_accuracy = accuracy_score(test_model_predictions,y_test)
         test_data_accuracy
In [56]:
         0.921875
Out[56]:
```

# Building a new predictive system

```
In [58]: input_data = (7.5,0.5,0.36,6.1,0.071,17.0,102.0,0.9978,3.35,0.8,10.5)
# changing input data into a numpy array
# since original is tuple
input_data_as_numpy_array = np.asarray(input_data)

In [59]: # now we need to reshape the array as we only want value for one instance not whole
input_data_as_numpy_array_reshpe = input_data_as_numpy_array.reshape(1,-1)

In [60]: prediction = model.predict(input_data_as_numpy_array_reshpe)

In [63]: print(prediction)
[0]
```

```
In [64]: if (prediction[0]==1):
    print('Good Quality Wine')
else:
    print('Bad Quality Wine')
```

Bad Quality Wine