

Red Wine Quality Prediction Project:

```
In [2]: # importing data sets library
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
```

```
In [3]: import warnings
warnings.filterwarnings('ignore')
```

```
In [4]: df = pd.read_csv('https://raw.githubusercontent.com/dsrs scientist/DSData/master/winequality-red.csv')
df
```

```
Out[4]:
```

| | fixed acidity | volatile acidity | citric acid | residual sugar | chlorides | free sulfur dioxide | total sulfur dioxide | density | pH | sulphates | alcohol |
|------|------------------|---------------------|----------------|-------------------|-----------|---------------------------|----------------------------|---------|------|-----------|---------|
| 0 | 7.4 | 0.700 | 0.00 | 1.9 | 0.076 | 11.0 | 34.0 | 0.99780 | 3.51 | 0.56 | 9.4 |
| 1 | 7.8 | 0.880 | 0.00 | 2.6 | 0.098 | 25.0 | 67.0 | 0.99680 | 3.20 | 0.68 | 10.1 |
| 2 | 7.8 | 0.760 | 0.04 | 2.3 | 0.092 | 15.0 | 54.0 | 0.99700 | 3.26 | 0.65 | 9.8 |
| 3 | 11.2 | 0.280 | 0.56 | 1.9 | 0.075 | 17.0 | 60.0 | 0.99800 | 3.16 | 0.58 | 9.8 |
| 4 | 7.4 | 0.700 | 0.00 | 1.9 | 0.076 | 11.0 | 34.0 | 0.99780 | 3.51 | 0.56 | 9.4 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 1594 | 6.2 | 0.600 | 0.08 | 2.0 | 0.090 | 32.0 | 44.0 | 0.99490 | 3.45 | 0.58 | 10.0 |
| 1595 | 5.9 | 0.550 | 0.10 | 2.2 | 0.062 | 39.0 | 51.0 | 0.99512 | 3.52 | 0.76 | 10.4 |
| 1596 | 6.3 | 0.510 | 0.13 | 2.3 | 0.076 | 29.0 | 40.0 | 0.99574 | 3.42 | 0.75 | 10.1 |
| 1597 | 5.9 | 0.645 | 0.12 | 2.0 | 0.075 | 32.0 | 44.0 | 0.99547 | 3.57 | 0.71 | 10.0 |
| 1598 | 6.0 | 0.310 | 0.47 | 3.6 | 0.067 | 18.0 | 42.0 | 0.99549 | 3.39 | 0.66 | 10.4 |

1599 rows × 12 columns

```
In [5]: df.head(15)
```

Out[5]:

| | fixed acidity | volatile acidity | citric acid | residual sugar | chlorides | free sulfur dioxide | total sulfur dioxide | density | pH | sulphates | alcohol |
|----|------------------|---------------------|----------------|-------------------|-----------|---------------------------|----------------------------|---------|------|-----------|---------|
| 0 | 7.4 | 0.700 | 0.00 | 1.9 | 0.076 | 11.0 | 34.0 | 0.9978 | 3.51 | 0.56 | 9.4 |
| 1 | 7.8 | 0.880 | 0.00 | 2.6 | 0.098 | 25.0 | 67.0 | 0.9968 | 3.20 | 0.68 | 9.8 |
| 2 | 7.8 | 0.760 | 0.04 | 2.3 | 0.092 | 15.0 | 54.0 | 0.9970 | 3.26 | 0.65 | 9.8 |
| 3 | 11.2 | 0.280 | 0.56 | 1.9 | 0.075 | 17.0 | 60.0 | 0.9980 | 3.16 | 0.58 | 9.8 |
| 4 | 7.4 | 0.700 | 0.00 | 1.9 | 0.076 | 11.0 | 34.0 | 0.9978 | 3.51 | 0.56 | 9.4 |
| 5 | 7.4 | 0.660 | 0.00 | 1.8 | 0.075 | 13.0 | 40.0 | 0.9978 | 3.51 | 0.56 | 9.4 |
| 6 | 7.9 | 0.600 | 0.06 | 1.6 | 0.069 | 15.0 | 59.0 | 0.9964 | 3.30 | 0.46 | 9.4 |
| 7 | 7.3 | 0.650 | 0.00 | 1.2 | 0.065 | 15.0 | 21.0 | 0.9946 | 3.39 | 0.47 | 10.0 |
| 8 | 7.8 | 0.580 | 0.02 | 2.0 | 0.073 | 9.0 | 18.0 | 0.9968 | 3.36 | 0.57 | 9.5 |
| 9 | 7.5 | 0.500 | 0.36 | 6.1 | 0.071 | 17.0 | 102.0 | 0.9978 | 3.35 | 0.80 | 10.5 |
| 10 | 6.7 | 0.580 | 0.08 | 1.8 | 0.097 | 15.0 | 65.0 | 0.9959 | 3.28 | 0.54 | 9.2 |
| 11 | 7.5 | 0.500 | 0.36 | 6.1 | 0.071 | 17.0 | 102.0 | 0.9978 | 3.35 | 0.80 | 10.5 |
| 12 | 5.6 | 0.615 | 0.00 | 1.6 | 0.089 | 16.0 | 59.0 | 0.9943 | 3.58 | 0.52 | 9.9 |
| 13 | 7.8 | 0.610 | 0.29 | 1.6 | 0.114 | 9.0 | 29.0 | 0.9974 | 3.26 | 1.56 | 9.1 |
| 14 | 8.9 | 0.620 | 0.18 | 3.8 | 0.176 | 52.0 | 145.0 | 0.9986 | 3.16 | 0.88 | 9.2 |

```
In [6]: # Checking missing value in data set
df.isnull().sum()
```

```
Out[6]: fixed acidity          0
volatile acidity          0
citric acid              0
residual sugar           0
chlorides                0
free sulfur dioxide      0
total sulfur dioxide     0
density                 0
pH                     0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

```
In [7]: df.shape
```

```
Out[7]: (1599, 12)
```

```
In [8]: df.columns
```

```
Out[8]: Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
              'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
              'pH', 'sulphates', 'alcohol', 'quality'],
              dtype='object')
```

```
In [9]: df.columns.tolist()
```

```
Out[9]: ['fixed acidity',
        'volatile acidity',
        'citric acid',
        'residual sugar',
        'chlorides',
        'free sulfur dioxide',
        'total sulfur dioxide',
        'density',
        'pH',
        'sulphates',
        'alcohol',
        'quality']
```

```
In [10]: df.dtypes
```

```
Out[10]: fixed acidity      float64
volatile acidity    float64
citric acid         float64
residual sugar      float64
chlorides           float64
free sulfur dioxide float64
total sulfur dioxide float64
density             float64
pH                  float64
sulphates           float64
alcohol             float64
quality             int64
dtype: object
```

```
In [11]: df.isnull().sum()
```

```
Out[11]: fixed acidity      0
volatile acidity    0
citric acid         0
residual sugar      0
chlorides           0
free sulfur dioxide 0
total sulfur dioxide 0
density             0
pH                  0
sulphates           0
alcohol             0
quality             0
dtype: int64
```

```
In [12]: df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  -
 0   fixed acidity          1599 non-null   float64
 1   volatile acidity       1599 non-null   float64
 2   citric acid            1599 non-null   float64
 3   residual sugar         1599 non-null   float64
 4   chlorides              1599 non-null   float64
 5   free sulfur dioxide    1599 non-null   float64
 6   total sulfur dioxide   1599 non-null   float64
 7   density                1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates              1599 non-null   float64
10   alcohol                1599 non-null   float64
11   quality                1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB

```

```

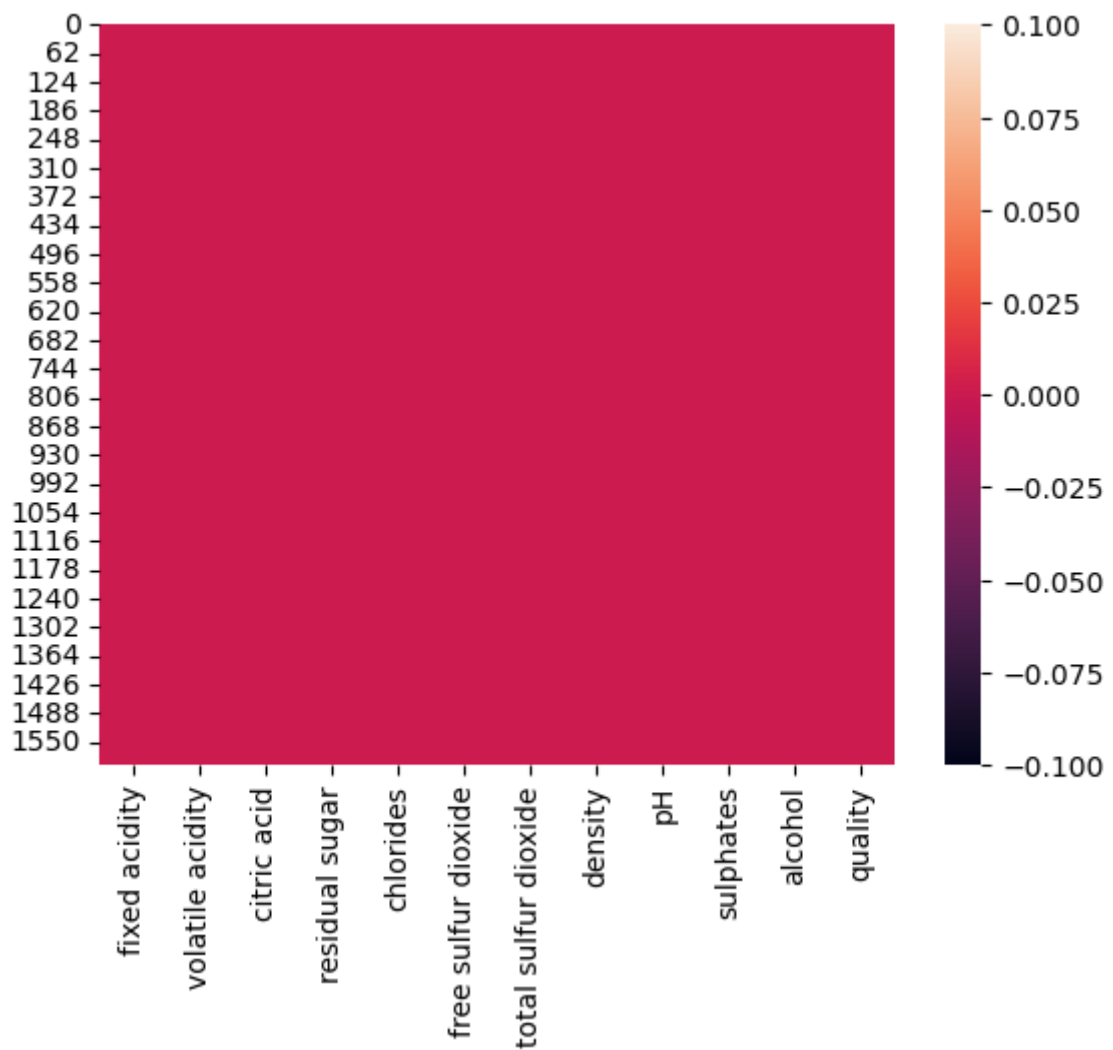
In [13]: # Visualisation by using heatmap
sns.heatmap(df.isnull())

```

```

Out[13]: <Axes: >

```



```

In [14]: df['fixed acidity'].unique()

```

```
Out[14]: array([ 7.4,  7.8, 11.2,  7.9,  7.3,  7.5,  6.7,  5.6,  8.9,  8.5,  8.1,
          7.6,  6.9,  6.3,  7.1,  8.3,  5.2,  5.7,  8.8,  6.8,  4.6,  7.7,
          8.7,  6.4,  6.6,  8.6, 10.2,  7. ,  7.2,  9.3,  8. ,  9.7,  6.2,
          5. ,  4.7,  8.4, 10.1,  9.4,  9. ,  8.2,  6.1,  5.8,  9.2, 11.5,
          5.4,  9.6, 12.8, 11. , 11.6, 12. , 15. , 10.8, 11.1, 10. , 12.5,
          11.8, 10.9, 10.3, 11.4,  9.9, 10.4, 13.3, 10.6,  9.8, 13.4, 10.7,
          11.9, 12.4, 12.2, 13.8,  9.1, 13.5, 10.5, 12.6, 14. , 13.7,  9.5,
          12.7, 12.3, 15.6,  5.3, 11.3, 13. ,  6.5, 12.9, 14.3, 15.5, 11.7,
          13.2, 15.9, 12.1,  5.1,  4.9,  5.9,  6. ,  5.5])
```

```
In [15]: df['fixed acidity'].nunique()
```

```
Out[15]: 96
```

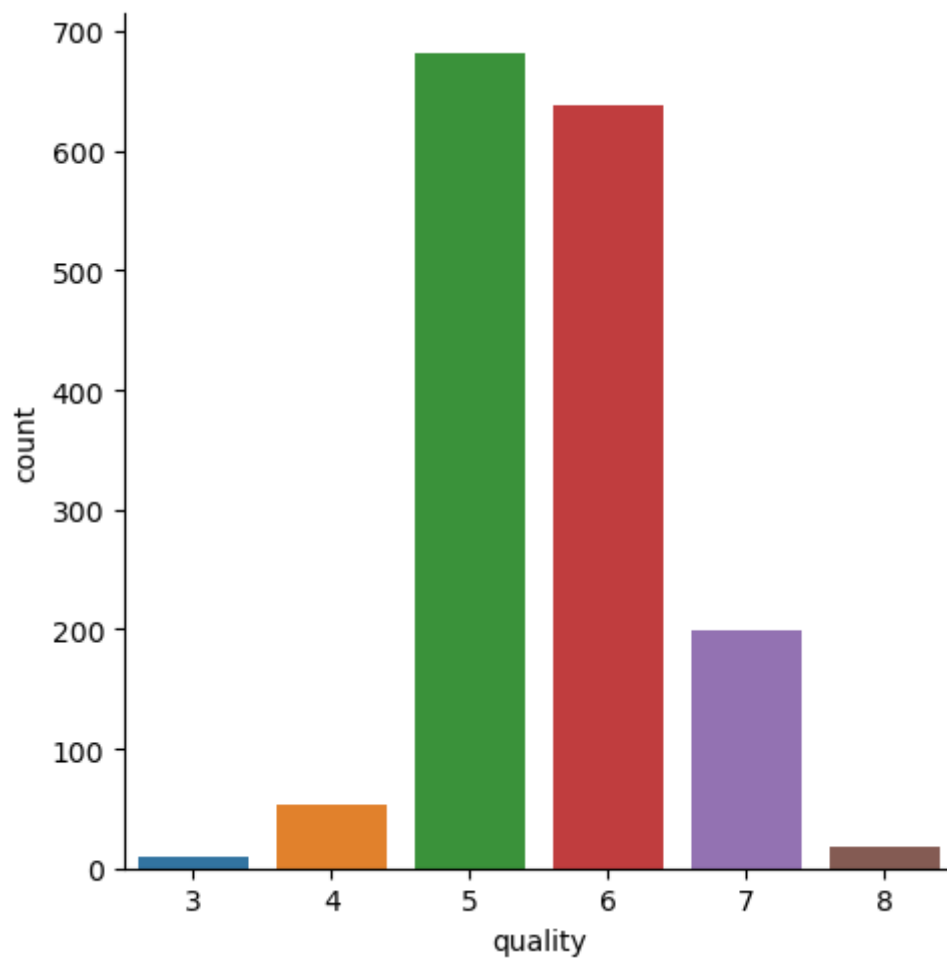
```
In [16]: # data analysis and visualization
df.describe()
```

```
Out[16]:
```

| | fixed acidity | volatile acidity | citric acid | residual sugar | chlorides | free sulfur dioxide | total sulfur dioxide |
|--------------|------------------|---------------------|-------------|-------------------|-------------|------------------------|-------------------------|
| 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% | 7.900000 | 0.520000 | 0.260000 | 2.200000 | 0.079000 | 14.000000 | 38.000000 |
| 75% | 9.200000 | 0.640000 | 0.420000 | 2.600000 | 0.090000 | 21.000000 | 62.000000 |
| max | 15.900000 | 1.580000 | 1.000000 | 15.500000 | 0.611000 | 72.000000 | 289.000000 |

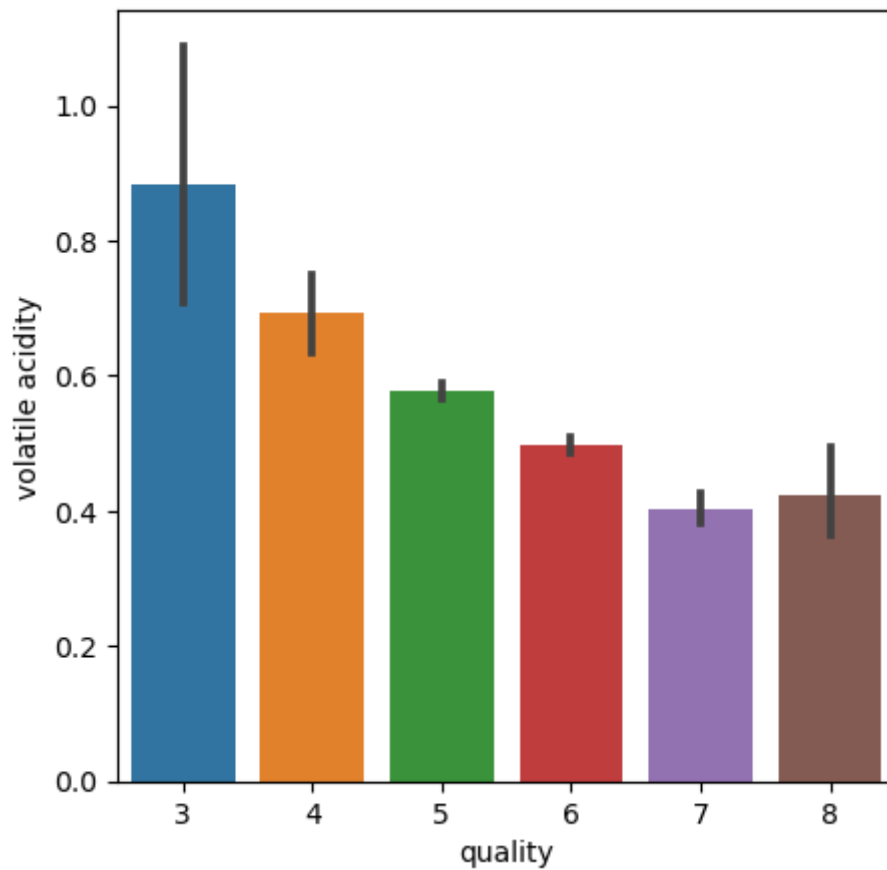
```
In [17]: # Number of values of each quality
sns.catplot(x='quality', data = df, kind = "count")
```

```
Out[17]: <seaborn.axisgrid.FacetGrid at 0x1e5f2df6dd0>
```



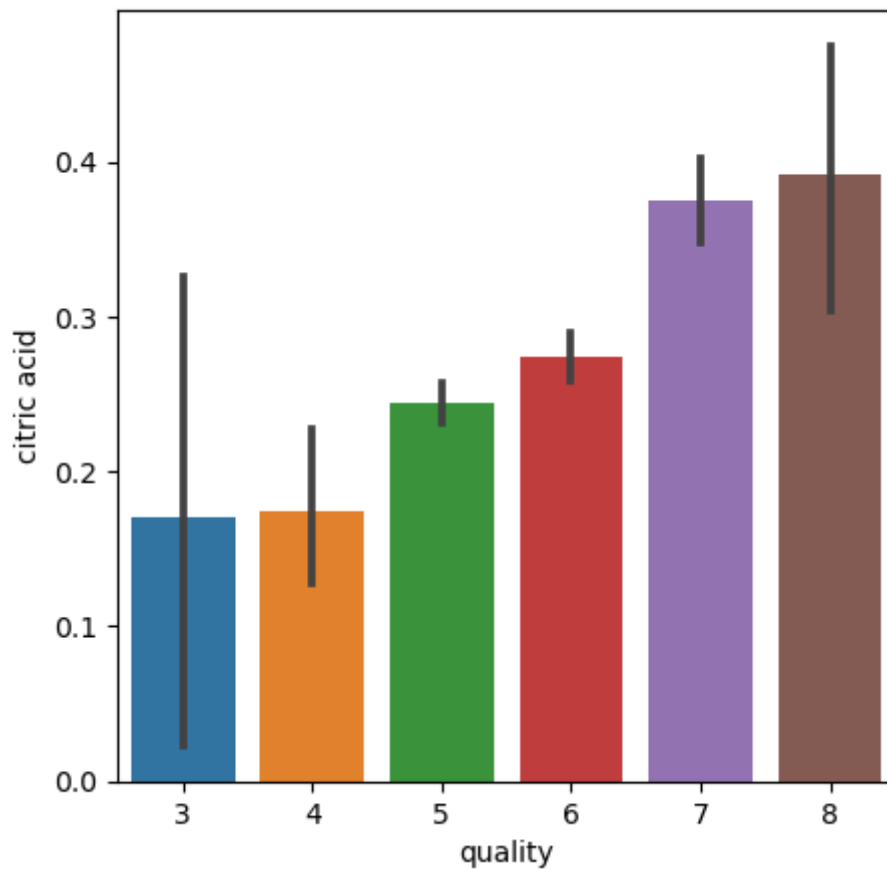
```
In [18]: # volatile Acidity v/s Quality
plot = plt.figure(figsize=(5,5))
sns.barplot(x= 'quality', y = 'volatile acidity', data = df)
print('volatile acidity is inversely proptional to quality')
```

volatile acidity is inversely proptional to quality



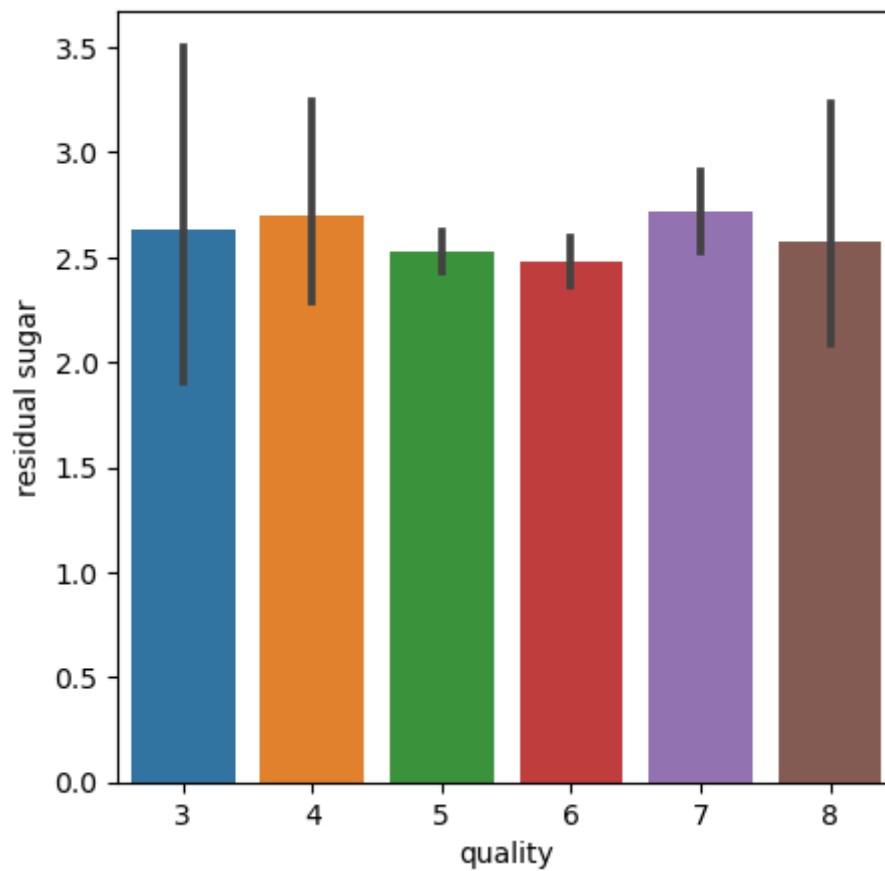
```
In [19]: # citric acid v/s Quality
plot = plt.figure(figsize=(5,5))
sns.barplot(x= 'quality', y = 'citric acid', data = df)
print('volatile acidity is directly proptional to quality')
```

volatile acidity is directly proptional to quality



```
In [20]: # residual sugar v/s Quality
plot = plt.figure(figsize=(5,5))
sns.barplot(x= 'quality', y = 'residual sugar', data = df)
```

```
Out[20]: <Axes: xlabel='quality', ylabel='residual sugar'>
```



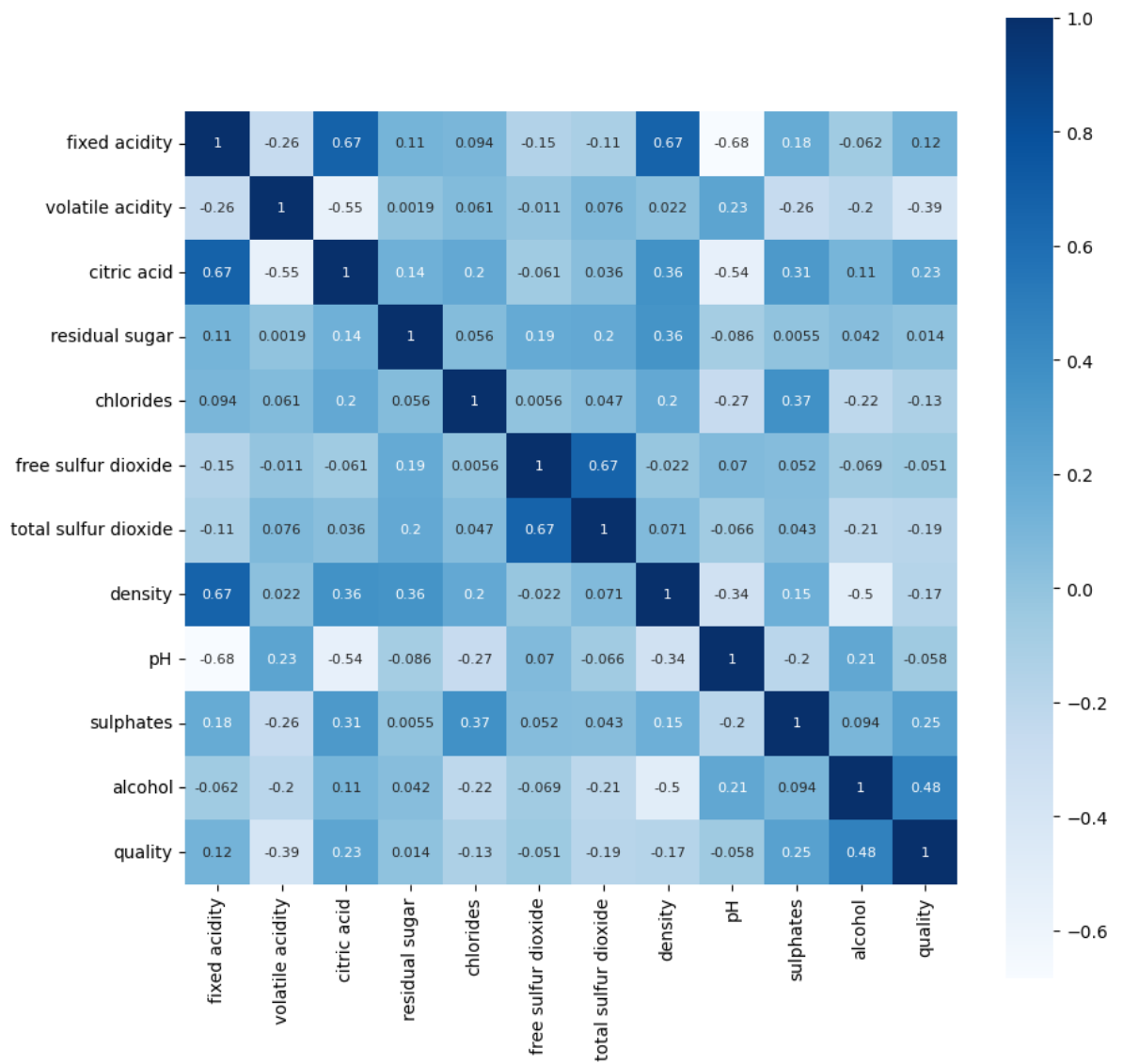
```
In [21]: correlation = df.corr()
correlation
```


Out[21]:

| | fixed acidity | volatile acidity | citric acid | residual sugar | chlorides | free sulfur dioxide | total sulfur dioxide | density | |
|----------------------|---------------|------------------|-------------|----------------|-----------|---------------------|----------------------|-----------|-----------|
| fixed acidity | 1.000000 | -0.256131 | 0.671703 | 0.114777 | 0.093705 | -0.153794 | -0.113181 | 0.668047 | -0.682978 |
| volatile acidity | -0.256131 | 1.000000 | -0.552496 | 0.001918 | 0.061298 | -0.010504 | 0.076470 | 0.022026 | 0.234937 |
| citric acid | 0.671703 | -0.552496 | 1.000000 | 0.143577 | 0.203823 | -0.060978 | 0.035533 | 0.364947 | -0.541904 |
| residual sugar | 0.114777 | 0.001918 | 0.143577 | 1.000000 | 0.055610 | 0.187049 | 0.203028 | 0.355283 | -0.085652 |
| chlorides | 0.093705 | 0.061298 | 0.203823 | 0.055610 | 1.000000 | 0.005562 | 0.047400 | 0.200632 | -0.265026 |
| free sulfur dioxide | -0.153794 | -0.010504 | -0.060978 | 0.187049 | 0.005562 | 1.000000 | 0.667666 | -0.021946 | 0.070377 |
| total sulfur dioxide | -0.113181 | 0.076470 | 0.035533 | 0.203028 | 0.047400 | 0.667666 | 1.000000 | 0.071269 | -0.066495 |
| density | 0.668047 | 0.022026 | 0.364947 | 0.355283 | 0.200632 | -0.021946 | 0.071269 | 1.000000 | -0.341699 |
| pH | -0.682978 | 0.234937 | -0.541904 | -0.085652 | -0.265026 | 0.070377 | -0.066495 | -0.341699 | 1.000000 |
| sulphates | 0.183006 | -0.260987 | 0.312770 | 0.005527 | 0.371260 | 0.051658 | 0.042947 | 0.148506 | -0.000000 |
| alcohol | -0.061668 | -0.202288 | 0.109903 | 0.042075 | -0.221141 | -0.069408 | -0.205654 | -0.496180 | -0.000000 |
| quality | 0.124052 | -0.390558 | 0.226373 | 0.013732 | -0.128907 | -0.050656 | -0.185100 | -0.174919 | -0.000000 |

```
In [22]: plt.figure(figsize=(10,10))
sns.heatmap(correlation, cbar = True, square = True, annot = True, annot_kws={'size': 10})
```

Out[22]: <Axes: >



```
In [23]: #data preprocessing
x = df.drop('quality',axis=1)
```

```
In [24]: print(x)
```

| | fixed acidity | volatile acidity | citric acid | residual sugar | chlorides \ |
|------|---------------|------------------|-------------|----------------|-------------|
| 0 | 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 |
| ... | ... | ... | ... | ... | ... |
| 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 |
| 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 | 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 |
|------|---------|
| 0 | 9.4 |
| 1 | 9.8 |
| 2 | 9.8 |
| 3 | 9.8 |
| 4 | 9.4 |
| ... | ... |
| 1594 | 10.5 |
| 1595 | 11.2 |
| 1596 | 11.0 |
| 1597 | 10.2 |
| 1598 | 11.0 |

[1599 rows x 11 columns]

```
In [26]: #label binarization
Y = df['quality'].apply(lambda y_value: 1 if y_value>= 7 else 0)

print(Y)
```

```
0      0
1      0
2      0
3      0
4      0
..
1594   0
1595   0
1596   0
1597   0
1598   0
Name: quality, Length: 1599, dtype: int64
```

```
In [27]: #train & Test Split

X_train, X_test, Y_train, Y_test = train_test_split(x, Y, test_size=0.2, random_st
```

```
In [28]: print(Y.shape, Y_train.shape, Y_test.shape)
(1599,) (1279,) (320,)
```

```
In [29]: #Model Training: Random Forest Classifier
model = RandomForestClassifier()
```

```
In [30]: model.fit(X_train, Y_train)
```

```
Out[30]: ▾ RandomForestClassifier
RandomForestClassifier()
```

```
In [31]: #Accuracy Score
# accuracy on test data
X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
```

```
In [32]: print('Accuracy : ', test_data_accuracy)
Accuracy : 0.925
```

```
In [33]: #Building a Predictive System
```

```
In [34]: input_data = ('7.3,0.65,0.0,1.2,0.065,15.0,21.0,0.9946,3.39,0.47,10.0,')
```

```
In [35]: input_data = (7.5,0.5,0.36,6.1,0.071,17.0,102.0,0.9978,3.35,0.8,10.5)
```

```
In [36]: input_data_as_numpy_array = np.asarray(input_data)
```

```
In [37]: input_data_resaped = input_data_as_numpy_array.reshape(1,-1)
```

```
In [38]: prediction = model.predict(input_data_resaped)
print(prediction)

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

[0]
Bad Quality Wine
```

```
In [ ]:
```