WINE QUALITY PREDICTION

The data was downloaded from UCI Machine Learning Repository. This dataset consists of red and white variants of the Portuguese "Vinho Verde" wine.The dataset describes the amount of various chemicals present in wine and their effect on it's quality. The datasets can be viewed as classification or regression tasks. The classes are ordered and not balanced (e.g. there are much more normal wines than excellent or poor ones).Our task is to predict the quality of wine using the given data.

What are the factors that affect the quality of wine?

Wine quality depends on a lot of factors like alcohol content,presence of sulphates,its pH values etc. The taste,smell and potency of the wine is defined by its chemical ingredients and its percentages in wines.

We will perform following tasks in our notebook:

1. Data Exploration (Understanding the dataset)
2. Data Wrangling (Data cleaning and Data Manipulation)
3. Data visualization
4. Data Exploratory Analysis
5. Analysis of quality with other factors (correlation)
6. Data Modeling (Machine Learning Models)
7. Building a classification
8. Predict the outcome
9. Calculating the accuracy score
10. Findings and Results

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```python
# This Python 3 environment comes with many helpful analytics libraries installed

# importing libraries for data analysis and data manipulation

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# loading the libraries for creating the plot

import matplotlib.pyplot as plt
import seaborn as sb
import math

# import the dataset from our local machine
Winedata = pd.read_csv("C:\\Users\\nidhi\\Downloads\\winequalityN.csv")
Winedata
```

```
       type  fixed acidity  volatile acidity  citric acid  residual sugar  \
0     white            7.0             0.270         0.36            20.7
1     white            6.3             0.300         0.34             1.6
2     white            8.1             0.280         0.40             6.9
3     white            7.2             0.230         0.32             8.5
4     white            7.2             0.230         0.32             8.5
...     ...            ...               ...          ...             ...
6492    red            6.2             0.600         0.08             2.0
6493    red            5.9             0.550         0.10             2.2
6494    red            6.3             0.510         0.13             2.3
6495    red            5.9             0.645         0.12             2.0
6496    red            6.0             0.310         0.47             3.6

      chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
0         0.045                 45.0                 170.0  1.00100  3.00
1         0.049                 14.0                 132.0  0.99400  3.30
2         0.050                 30.0                  97.0  0.99510  3.26
3         0.058                 47.0                 186.0  0.99560  3.19
4         0.058                 47.0                 186.0  0.99560  3.19
...         ...                  ...                   ...      ...   ...
6492      0.090                 32.0                  44.0  0.99490  3.45
6493      0.062                 39.0                  51.0  0.99512  3.52
6494      0.076                 29.0                  40.0  0.99574  3.42
6495      0.075                 32.0                  44.0  0.99547  3.57
6496      0.067                 18.0                  42.0  0.99549  3.39

      sulphates  alcohol  quality
0          0.45      8.8        6
1          0.49      9.5        6
2          0.44     10.1        6
```

```
3           0.40      9.9        6
4           0.40      9.9        6
...          ...      ...      ...
6492        0.58     10.5        5
6493         NaN     11.2        6
6494        0.75     11.0        6
6495        0.71     10.2        5
6496        0.66     11.0        6

[6497 rows x 13 columns]
```

```
# to see the number of rows and columns in our dataset
Winedata.shape
```

```
(6497, 13)
```

```
Winedata.columns
```

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

Understanding the wine data columns

1. fixed acidity most acids involved with wine or fixed or nonvolatile (do not evaporate readily)

2. volatile acidity the amount of acetic acid in wine, which at too high of levels can lead to an unpleasant, vinegar taste

3. citric acid found in small quantities, citric acid can add 'freshness' and flavor to wines

4. residual sugar the amount of sugar remaining after fermentation stops, it's rare to find wines with less than 1 gram/liter and wines with greater than 45 grams/liter are considered sweet

5. chlorides the amount of salt in the wine

6. free sulfur dioxide the free form of SO2 exists in equilibrium between molecular SO2 (as a dissolved gas) and bisul-fite ion; it prevents microbial growth and the oxidation of wine

7. total sulfur dioxide amount of free and bound forms of S02; in low concentrations, SO2 is mostly undetectable in wine, but at free SO2 concentrations over 50 ppm, SO2 becomes evident in the nose and taste of wine

8. density the density of water is close to that of water depending on the percent alcohol and sugar con-tent

9. pH describes how acidic or basic a wine is on a scale from 0 (very acidic) to 14 (very basic); most wines are between 3–4 on the pH scale

10. sulphates a wine additive which can contribute to sulfur dioxide gas (S02) levels, which acts as an antimicrobial and antioxidant

11. alcohol the percent alcohol content of the wine

12. quality output variable (based on sensory data, score between 0 and 10)

13. type This column will show the type of the wine whether it's a red wine or white wine

```
# to view any random sample of 8 rows
Winedata.sample(8)
```

```
       type  fixed acidity  volatile acidity  citric acid  residual sugar  \
1960  white            8.5              0.17         0.31             1.0
1590  white            7.9              0.14         0.74             1.2
4728  white            7.2              0.21         0.31            10.5
5998    red            8.4              0.34         0.42             2.1
742   white            7.0              0.20         0.37             2.0
2458  white            7.8              0.32         0.33            10.4
3439  white            6.7              0.40         0.22             8.8
6027    red           10.5              0.43         0.35             3.3

      chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
1960      0.024                 13.0                  91.0  0.99300  2.79
1590      0.028                 30.0                 165.0  0.99100  3.08
4728      0.035                 36.0                 122.0  0.99478  3.12
5998      0.072                 23.0                  36.0  0.99392  3.11
742       0.030                 26.0                 136.0  0.99320  3.28
2458      0.031                 47.0                 194.0  0.99692  3.07
3439      0.052                 24.0                 113.0  0.99576  3.22
6027      0.092                 24.0                  70.0  0.99798  3.21

      sulphates  alcohol  quality
1960       0.37     10.1        5
1590       0.82     12.3        6
4728       0.40     10.6        6
5998       0.78     12.4        6
742        0.61     10.2        6
2458       0.58      9.6        6
3439       0.45      9.4        5
6027       0.69     10.5        6
```

```
# let us try to see the first 5 lines of our data
Winedata.head()
```

```
    type  fixed acidity  volatile acidity  citric acid  residual sugar  \
0  white            7.0              0.27         0.36            20.7
1  white            6.3              0.30         0.34             1.6
```

```
2  white            8.1              0.28         0.40              6.9
3  white            7.2              0.23         0.32              8.5
4  white            7.2              0.23         0.32              8.5

   chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
0      0.045                 45.0                 170.0   1.0010  3.00
1      0.049                 14.0                 132.0   0.9940  3.30
2      0.050                 30.0                  97.0   0.9951  3.26
3      0.058                 47.0                 186.0   0.9956  3.19
4      0.058                 47.0                 186.0   0.9956  3.19

   sulphates  alcohol  quality
0       0.45      8.8        6
1       0.49      9.5        6
2       0.44     10.1        6
3       0.40      9.9        6
4       0.40      9.9        6
```

```
# to see the descriptive statistics
Winedata.describe()
```

```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    6487.000000       6489.000000  6494.000000     6495.000000
mean        7.216579          0.339691     0.318722        5.444326
std         1.296750          0.164649     0.145265        4.758125
min         3.800000          0.080000     0.000000        0.600000
25%         6.400000          0.230000     0.250000        1.800000
50%         7.000000          0.290000     0.310000        3.000000
75%         7.700000          0.400000     0.390000        8.100000
max        15.900000          1.580000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  6495.000000          6497.000000           6497.000000  6497.000000
mean      0.056042            30.525319            115.744574     0.994697
std       0.035036            17.749400             56.521855     0.002999
min       0.009000             1.000000              6.000000     0.987110
25%       0.038000            17.000000             77.000000     0.992340
50%       0.047000            29.000000            118.000000     0.994890
75%       0.065000            41.000000            156.000000     0.996990
max       0.611000           289.000000            440.000000     1.038980

                pH    sulphates      alcohol      quality
count  6488.000000  6493.000000  6497.000000  6497.000000
mean      3.218395     0.531215    10.491801     5.818378
std       0.160748     0.148814     1.192712     0.873255
min       2.720000     0.220000     8.000000     3.000000
25%       3.110000     0.430000     9.500000     5.000000
50%       3.210000     0.510000    10.300000     6.000000
75%       3.320000     0.600000    11.300000     6.000000
max       4.010000     2.000000    14.900000     9.000000
```

```python
# let us check the data types of all the variables to get a better understanding of our data
Winedata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6497 entries, 0 to 6496
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   type                  6497 non-null   object 
 1   fixed acidity         6487 non-null   float64
 2   volatile acidity      6489 non-null   float64
 3   citric acid           6494 non-null   float64
 4   residual sugar        6495 non-null   float64
 5   chlorides             6495 non-null   float64
 6   free sulfur dioxide   6497 non-null   float64
 7   total sulfur dioxide  6497 non-null   float64
 8   density               6497 non-null   float64
 9   pH                    6488 non-null   float64
 10  sulphates             6493 non-null   float64
 11  alcohol               6497 non-null   float64
 12  quality               6497 non-null   int64  
dtypes: float64(11), int64(1), object(1)
memory usage: 660.0+ KB
```

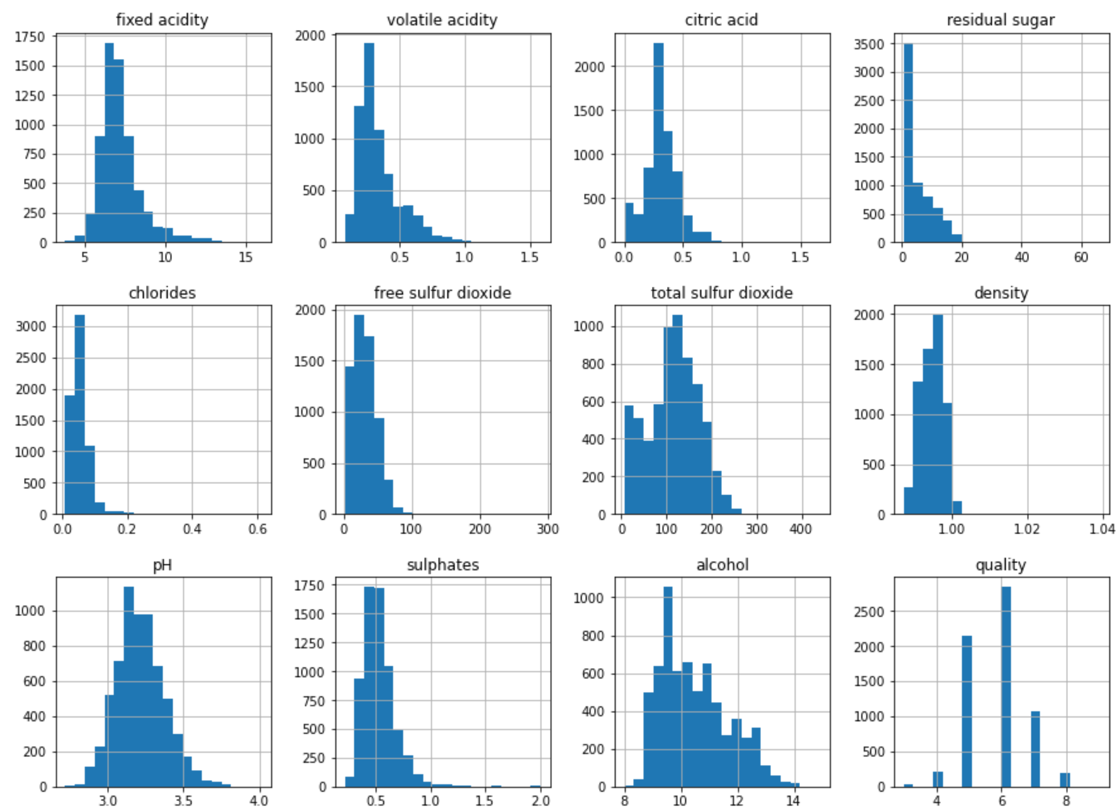
```python
# to check skewness
Winedata.skew()
```

```
fixed acidity           1.722805
volatile acidity        1.495512
citric acid             0.473032
residual sugar          1.435000
chlorides               5.399849
free sulfur dioxide     1.220066
total sulfur dioxide   -0.001177
density                 0.503602
pH                      0.386966
sulphates               1.798467
alcohol                 0.565718
quality                 0.189623
dtype: float64
```

```python
Winedata.hist(figsize=(15,15), layout=(4,4), bins=20)
```

```
array([[<AxesSubplot:title={'center':'fixed acidity'}>,
        <AxesSubplot:title={'center':'volatile acidity'}>,
        <AxesSubplot:title={'center':'citric acid'}>,
        <AxesSubplot:title={'center':'residual sugar'}>],
       [<AxesSubplot:title={'center':'chlorides'}>,
        <AxesSubplot:title={'center':'free sulfur dioxide'}>,
        <AxesSubplot:title={'center':'total sulfur dioxide'}>,
```

```
 <AxesSubplot:title={'center':'density'}>],
[<AxesSubplot:title={'center':'pH'}>,
 <AxesSubplot:title={'center':'sulphates'}>,
 <AxesSubplot:title={'center':'alcohol'}>,
 <AxesSubplot:title={'center':'quality'}>],
[<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>]],
dtype=object)
```



Observation from histogram:

1. "fixed.acidity" is a measure of inside liquid concentration. The histogram a right-skewed distributed with some outliers located at right side. The most frequent values are between 7-8.
2. "volatile.acidity" is measure of acidity above-surface of liquid. The histogram is right-skewed distributed with some outliers located at right side. The most frequent values are between 0.4-0.6.
3. "citric.acid" is right-skewed distributed with some outliers located at very right side. The most frequent values 0. It's also interesting a lot of wine have citric.acid = 0
4. "residual.sugar" is right-skewed distributed
5. "chlorides" is right-skewed distributed The most frequent values are between 0.05-0.1
6. "free.sulfur.dioxide" is right-skewed distributed
7. "sulphates" is a right-skewed distributed

Data Pre-processing

```
# to check for duplicates in the data
Winedata.duplicated()
```

```
0       False
1       False
2       False
3       False
4        True
        ...
6492    False
6493    False
6494     True
6495    False
6496    False
Length: 6497, dtype: bool
```

```
#to check for the duplicate records in the dataset
Winedata.duplicated().sum()
```

```
1168
```

```
Winedata.shape
```

```
(6497, 13)
```

```
# to remove the duplicate records
Winedata.drop_duplicates(inplace=True)
```

```
Winedata.shape
```

```
(5329, 13)
```

```
Winedata.duplicated().sum()
```

```
0
```

```
# to find missing values
Winedata.isnull()
```

```
       type  fixed acidity  volatile acidity  citric acid  residual sugar  \
0     False          False             False        False           False
1     False          False             False        False           False
2     False          False             False        False           False
3     False          False             False        False           False
4     False          False             False        False           False
...     ...            ...               ...          ...             ...
6492  False          False             False        False           False
6493  False          False             False        False           False
```

```
6494  False         False             False        False            False
6495  False         False             False        False            False
6496  False         False             False        False            False

      chlorides  free sulfur dioxide  total sulfur dioxide  density     pH  \
0         False                False                 False    False  False
1         False                False                 False    False  False
2         False                False                 False    False  False
3         False                False                 False    False  False
4         False                False                 False    False  False
...         ...                  ...                   ...      ...    ...
6492      False                False                 False    False  False
6493      False                False                 False    False  False
6494      False                False                 False    False  False
6495      False                False                 False    False  False
6496      False                False                 False    False  False

      sulphates  alcohol  quality
0         False    False    False
1         False    False    False
2         False    False    False
3         False    False    False
4         False    False    False
...         ...      ...      ...
6492      False    False    False
6493       True    False    False
6494      False    False    False
6495      False    False    False
6496      False    False    False

[6497 rows x 13 columns]
```

```python
# to check for missing values
Winedata.isnull().sum()
```

```
type                     0
fixed acidity           10
volatile acidity         8
citric acid              3
residual sugar           2
chlorides                2
free sulfur dioxide      0
total sulfur dioxide     0
density                  0
pH                       9
sulphates                4
alcohol                  0
quality                  0
dtype: int64
```

```
Winedata=Winedata.dropna()
#After removing let's check whether all the missing values are removed
Winedata.isnull().sum()
```

```
type                    0
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
```

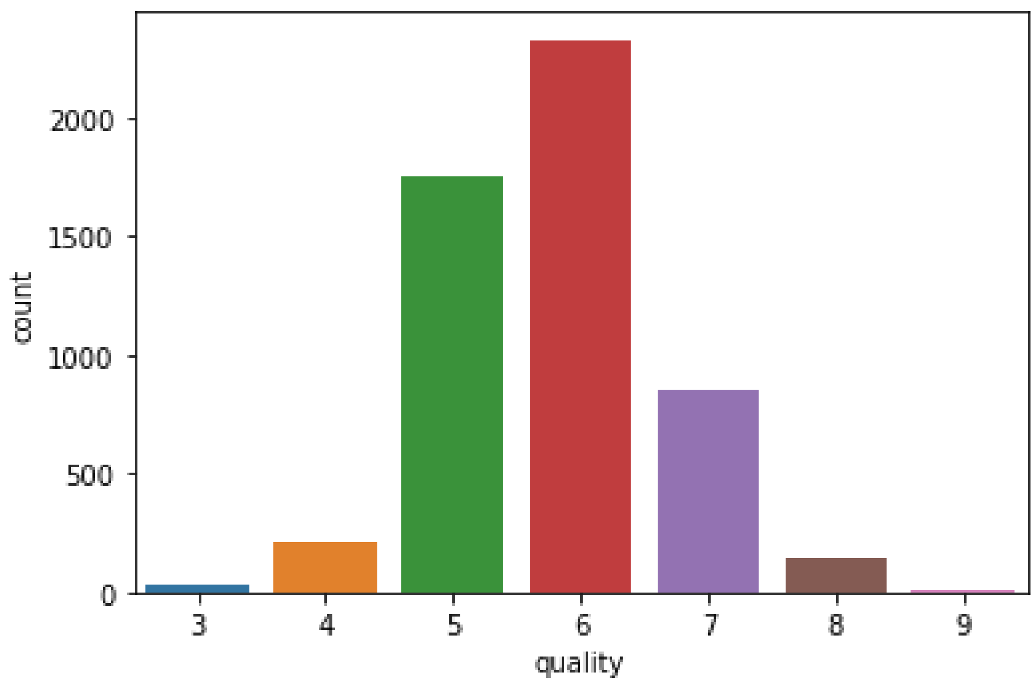
```
#print the no. of labels for each class
print(Winedata.quality.value_counts())
```

```
6    2820
5    2128
7    1074
4     214
8     192
3      30
9       5
Name: quality, dtype: int64
```

Data Visualization - Exploratory Data Analysis

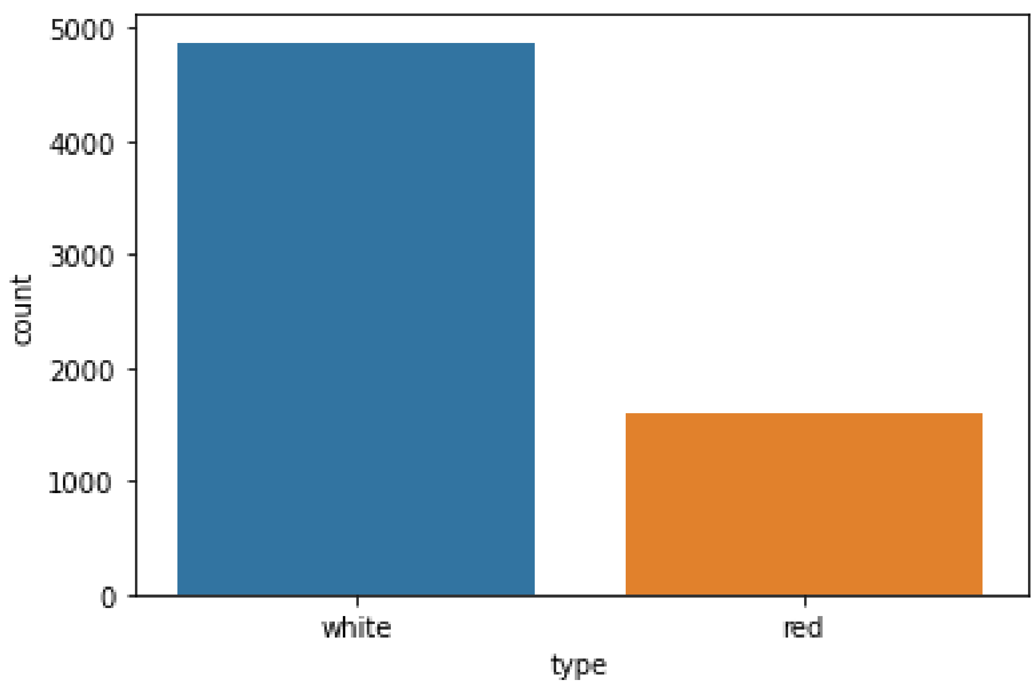
```
sb.countplot(Winedata['quality'])

plt.show()
```

```
C:\Users\nidhi\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other
arguments without an explicit keyword will result in an error or
misinterpretation.
  warnings.warn(
```



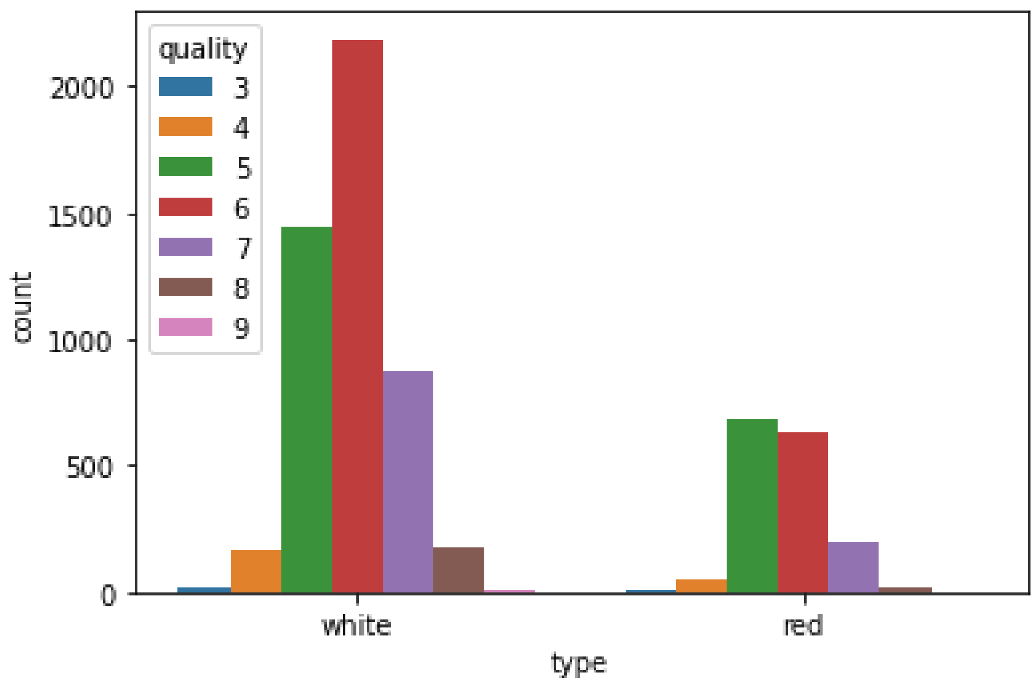

```
# to check the count of Red wine and white wine in the dataset
sb.countplot(x='type',data=Winedata)
```

<AxesSubplot:xlabel='type', ylabel='count'>




```
# plotting the data on the basis of type - univariate anlaysis
sb.countplot(x = 'type', hue = 'quality', data = Winedata)
```

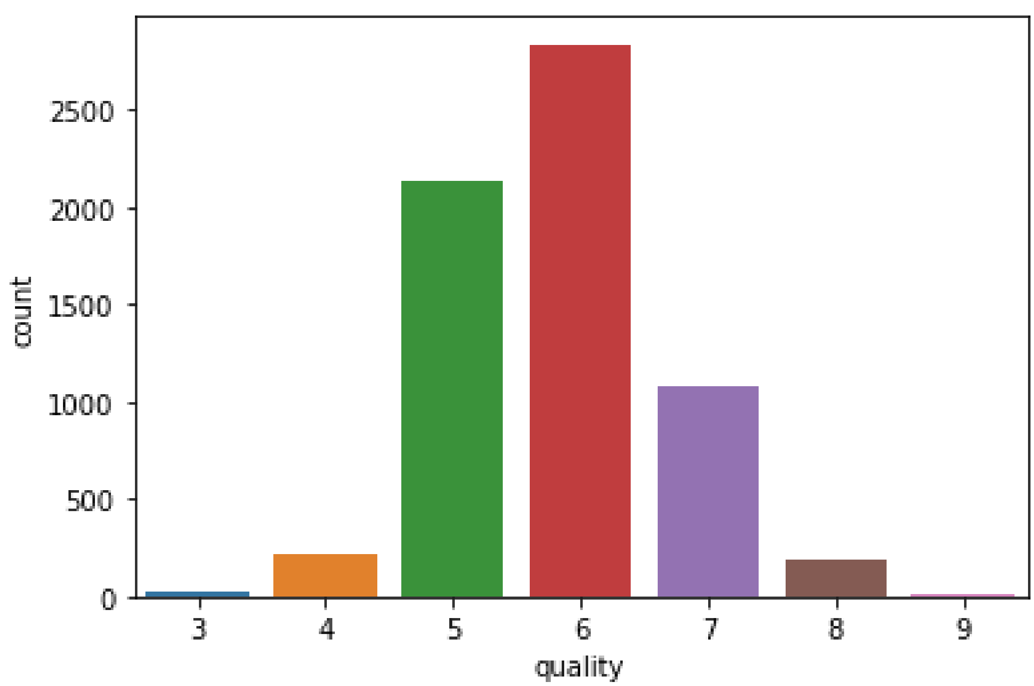
```
<AxesSubplot:xlabel='type', ylabel='count'>
```



- Dataset contains more information about white wine than red wine**

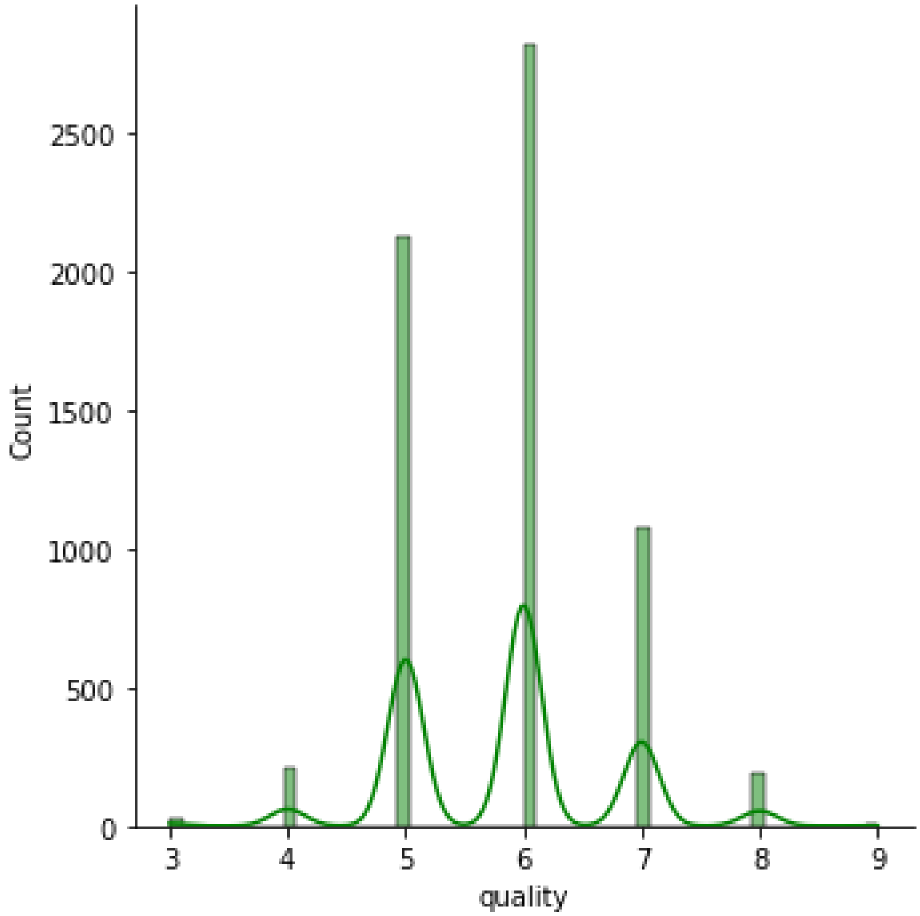
```
sb.countplot(x='quality', data=Winedata)
```

```
<AxesSubplot:xlabel='quality', ylabel='count'>
```



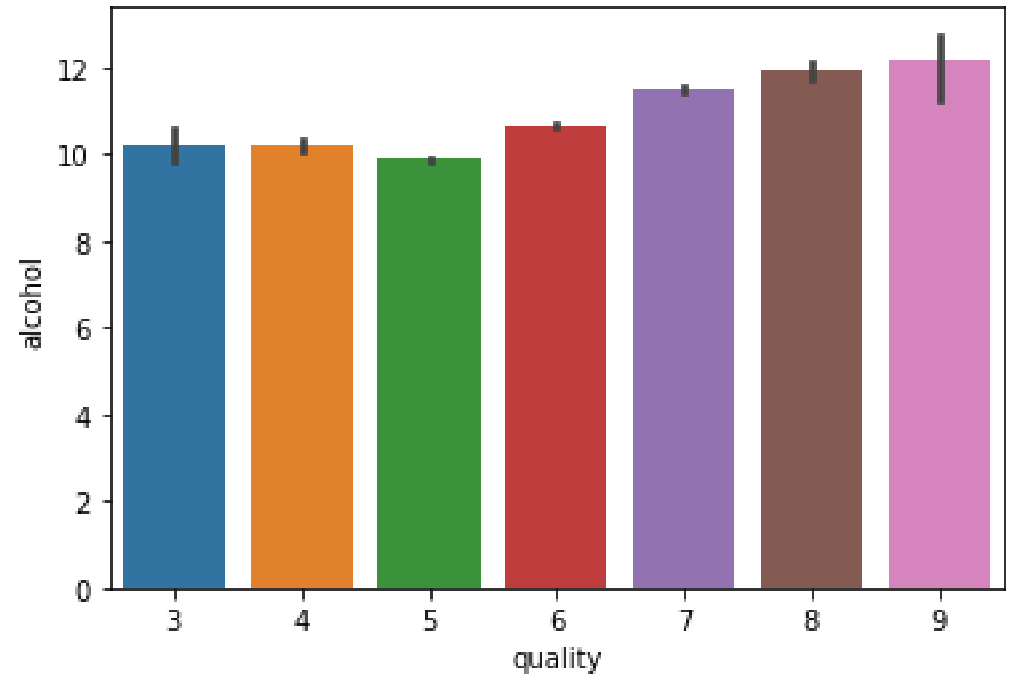
```python
# plotting the data to check the quality
sb.displot(x = Winedata['quality'], kde = True, color = 'green')
```

```
<seaborn.axisgrid.FacetGrid at 0x1fc52413280>
```



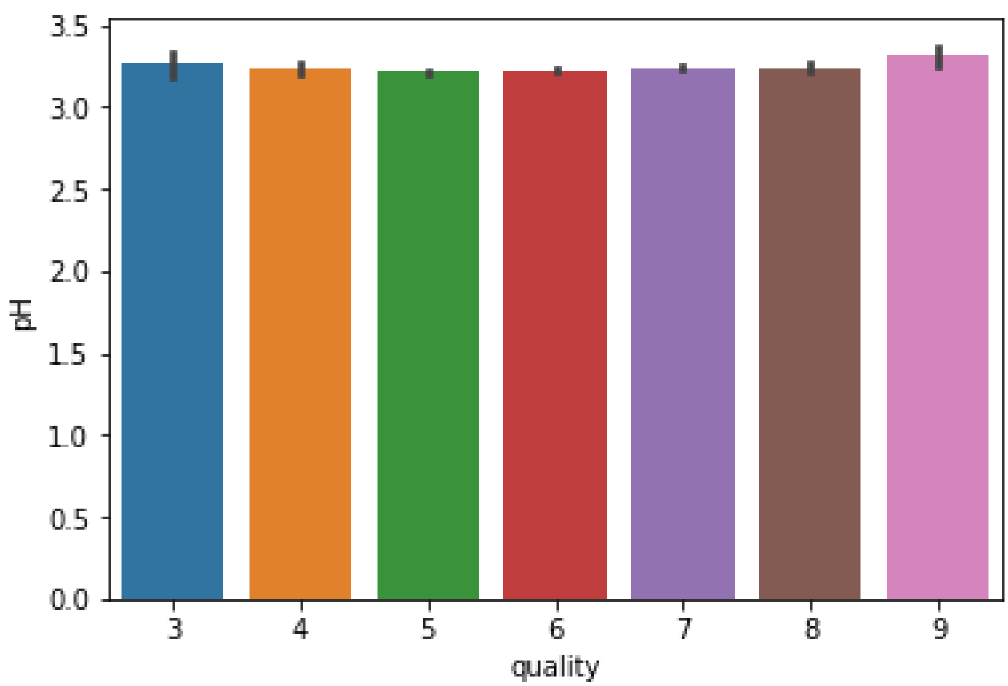

```python
sb.barplot(x='quality',y='alcohol',data=Winedata)
```

```
<AxesSubplot:xlabel='quality', ylabel='alcohol'>
```



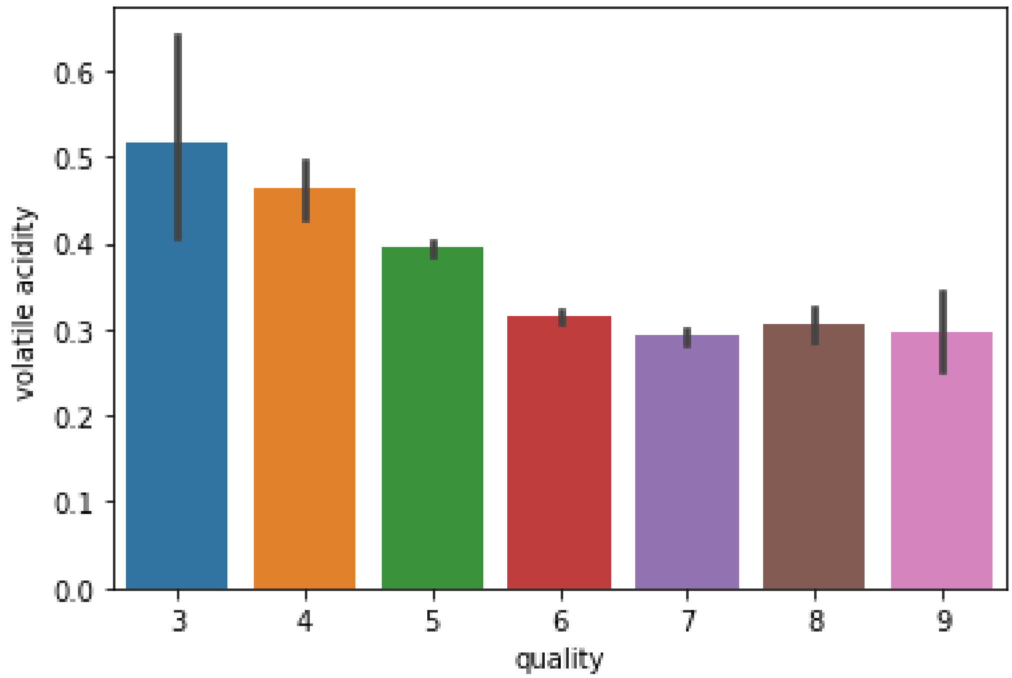

```
sb.barplot(x='quality',y='pH',data=Winedata)
```

```
<AxesSubplot:xlabel='quality', ylabel='pH'>
```




```
sb.barplot(x='quality',y='volatile acidity',data=Winedata)
```

```
<AxesSubplot:xlabel='quality', ylabel='volatile acidity'>
```

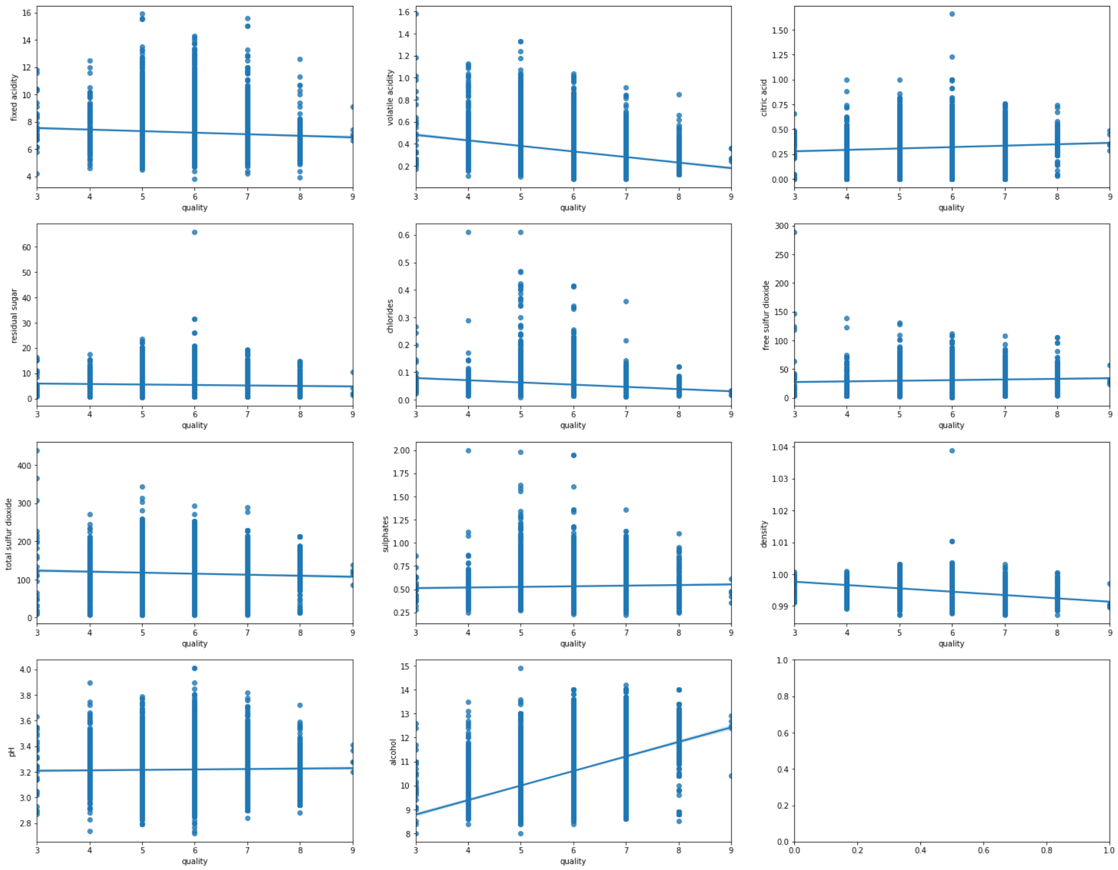



```
# As we can see, Mostly wine is of average quality 6
```

> ANALYSIS OF QUALITY WITH OTHER VARIOUS FACTORS

```
# to check the quality of wine with all other attributes
f, x = plt.subplots(4, 3, figsize = (25, 20))
sb.regplot(x = Winedata['quality'], y = Winedata['fixed acidity'], ax = x[0,
0])
sb.regplot(x = Winedata['quality'], y = Winedata['volatile acidity'], ax =
x[0, 1])
sb.regplot(x = Winedata['quality'], y = Winedata['citric acid'], ax = x[0,
2])
sb.regplot(x = Winedata['quality'], y = Winedata['residual sugar'], ax = x[1,
0])
sb.regplot(x = Winedata['quality'], y = Winedata['chlorides'], ax = x[1, 1])
sb.regplot(x = Winedata['quality'], y = Winedata['free sulfur dioxide'], ax =
x[1, 2])
sb.regplot(x = Winedata['quality'], y = Winedata['total sulfur dioxide'], ax
= x[2, 0])
sb.regplot(x = Winedata['quality'], y = Winedata['sulphates'], ax = x[2, 1])
sb.regplot(x = Winedata['quality'], y = Winedata['density'], ax = x[2, 2])
sb.regplot(x = Winedata['quality'], y = Winedata['pH'], ax = x[3, 0])
sb.regplot(x = Winedata['quality'], y = Winedata['alcohol'], ax = x[3, 1])
```

```
<AxesSubplot:xlabel='quality', ylabel='alcohol'>
```



Observations from the above plot:

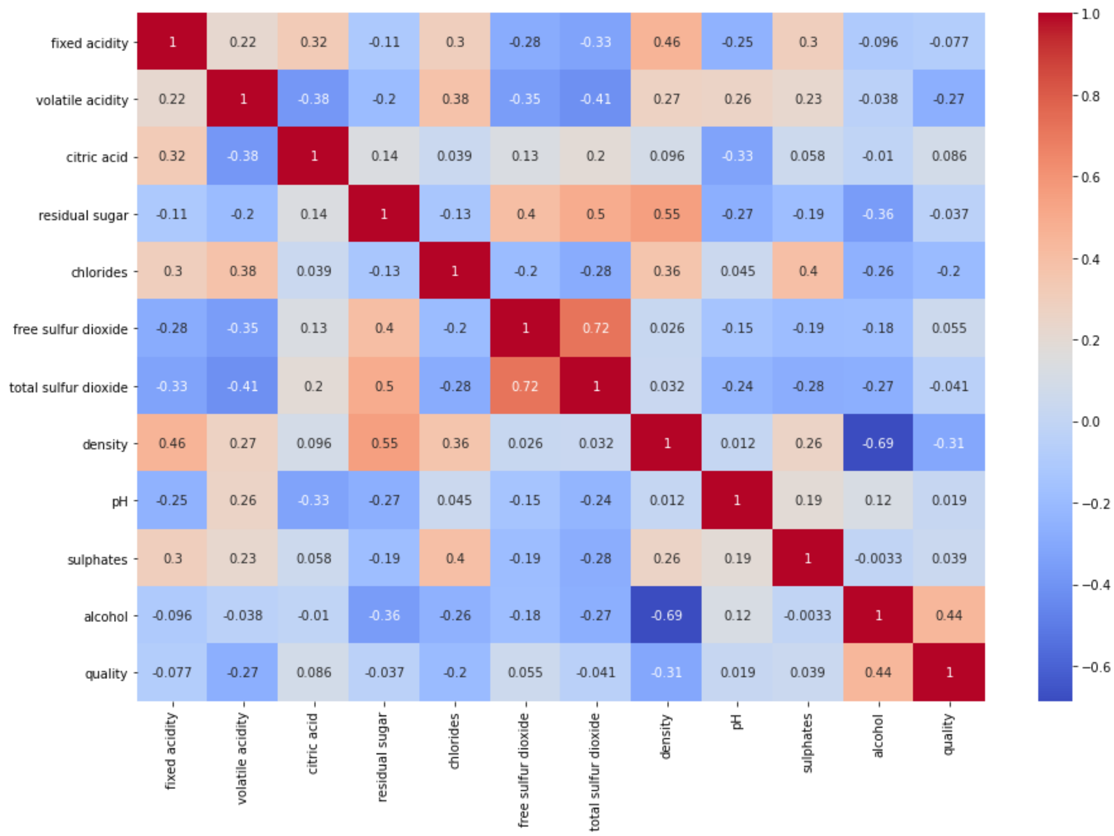
- Quality increases sharply with decrease in volatile acidity
- Quality increases with increase in citric acid
- Quality increases sharply with increase in alcohol

```
#to see the correlation
Winedata.corr()
```

```
                      fixed acidity  volatile acidity  citric acid  \
fixed acidity              1.000000          0.216524     0.329252
volatile acidity           0.216524          1.000000    -0.382750
citric acid                0.329252         -0.382750     1.000000
residual sugar            -0.106084         -0.164438     0.146528
chlorides                  0.289903          0.368266     0.055266
free sulfur dioxide       -0.282025         -0.349784     0.130802
total sulfur dioxide      -0.328631         -0.401231     0.194231
density                    0.478920          0.308416     0.095824
pH                        -0.269624          0.245329    -0.342648
sulphates                  0.307044          0.226537     0.062121
alcohol                   -0.103657         -0.066781    -0.005124
quality                   -0.049871         -0.143663     0.060059

                      residual sugar  chlorides  free sulfur dioxide  \
```

```
fixed acidity              -0.106084   0.289903             -0.282025
volatile acidity           -0.164438   0.368266             -0.349784
citric acid                 0.146528   0.055266              0.130802
residual sugar              1.000000  -0.123115              0.399579
chlorides                  -0.123115   1.000000             -0.187312
free sulfur dioxide         0.399579  -0.187312              1.000000
total sulfur dioxide        0.487534  -0.270009              0.721308
density                     0.520194   0.372126              0.005827
pH                         -0.233319   0.025963             -0.141368
sulphates                  -0.174663   0.405771             -0.199005
alcohol                    -0.305311  -0.270196             -0.169854
quality                    -0.083970  -0.160716              0.011845

                      total sulfur dioxide   density        pH  sulphates  \
fixed acidity                    -0.328631  0.478920 -0.269624   0.307044
volatile acidity                 -0.401231  0.308416  0.245329   0.226537
citric acid                       0.194231  0.095824 -0.342648   0.062121
residual sugar                    0.487534  0.520194 -0.233319  -0.174663
chlorides                        -0.270009  0.372126  0.025963   0.405771
free sulfur dioxide               0.721308  0.005827 -0.141368  -0.199005
total sulfur dioxide              1.000000  0.005974 -0.222003  -0.275389
density                           0.005974  1.000000  0.034979   0.283042
pH                               -0.222003  0.034979  1.000000   0.166139
sulphates                        -0.275389  0.283042  0.166139   1.000000
alcohol                          -0.247779 -0.668950  0.096615  -0.019008
quality                          -0.067750 -0.294350  0.048157   0.037557

                       alcohol   quality
fixed acidity        -0.103657 -0.049871
volatile acidity     -0.066781 -0.143663
citric acid          -0.005124  0.060059
residual sugar       -0.305311 -0.083970
chlorides            -0.270196 -0.160716
free sulfur dioxide  -0.169854  0.011845
total sulfur dioxide -0.247779 -0.067750
density              -0.668950 -0.294350
pH                    0.096615  0.048157
sulphates            -0.019008  0.037557
alcohol               1.000000  0.418605
quality               0.418605  1.000000
```

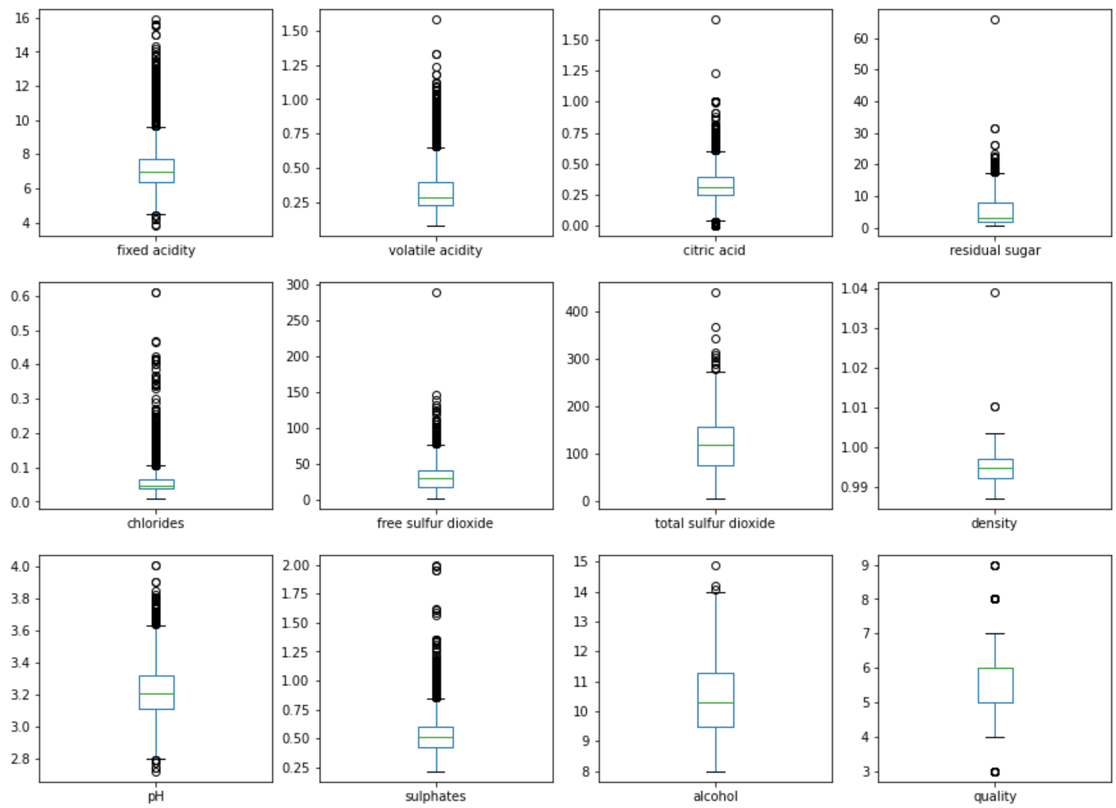
```python
# plotting a heatmap to see the correlation of wine quality with other
factors
plt.figure(figsize = (15, 10))
sb.heatmap(Winedata.corr(), annot = True,cmap='coolwarm')
plt.show()
```



Observation:

1. total sulfur dioxide is highly correlated with free sulfur dioxide
2. fixed acidity is highly correlated with density and citric acid
3. alcohol is highly correlated with quality
4. citric acid is inversely correlated with pH and volatile acidity

```
#checking outliers using box plot
Winedata.plot(kind="box",subplots=True,layout=(4,4),figsize=(15,15))

fixed acidity             AxesSubplot(0.125,0.71587;0.168478x0.16413)
volatile acidity       AxesSubplot(0.327174,0.71587;0.168478x0.16413)
citric acid            AxesSubplot(0.529348,0.71587;0.168478x0.16413)
residual sugar         AxesSubplot(0.731522,0.71587;0.168478x0.16413)
chlorides                AxesSubplot(0.125,0.518913;0.168478x0.16413)
free sulfur dioxide   AxesSubplot(0.327174,0.518913;0.168478x0.16413)
total sulfur dioxide  AxesSubplot(0.529348,0.518913;0.168478x0.16413)
density               AxesSubplot(0.731522,0.518913;0.168478x0.16413)
pH                       AxesSubplot(0.125,0.321957;0.168478x0.16413)
sulphates             AxesSubplot(0.327174,0.321957;0.168478x0.16413)
alcohol               AxesSubplot(0.529348,0.321957;0.168478x0.16413)
quality               AxesSubplot(0.731522,0.321957;0.168478x0.16413)
dtype: object
```



Observation from box plot:

“fixed.acidity” is a measure of inside liquid concentration. The histogram a right-skewed distributed with some outliers located at right side. The most frequent values are between 7-8. “volatile.acidity” is measure of acidity above-surface of liquid. The histogram is right-skewed distributed with some outliers located at right side. The most frequent values are between 0.4-0.6. “citric.acid” is right-skewed distributed with some outliers located at very right side. The most frequent values 0. It’s also interesting a lot of wine have citric.acid = 0 “residual.sugar” is right-skewed distributed “chlorides” is right-skewed distributed The most frequent values are between 0.05-0.1 “free.sulfur.dioxide” is right-skewed distributed “sulphates” is a right-skewed distributed

Data Modeling:

```
# importing all the required libraries for machine learning models

import sklearn
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split, GridSearchCV,
cross_val_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
```

```
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# let's categorize the quality column to apply classification model
# 1 is good qualit y and 0 is bad quality
Winedata['quality']=Winedata['quality'].apply (lambda x:1 if x > 6 else 0 )
Winedata.head()
```

```
    type  fixed acidity  volatile acidity  citric acid  residual sugar  \
0  white            7.0              0.27         0.36            20.7
1  white            6.3              0.30         0.34             1.6
2  white            8.1              0.28         0.40             6.9
3  white            7.2              0.23         0.32             8.5
4  white            7.2              0.23         0.32             8.5

   chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
0      0.045                 45.0                 170.0   1.0010  3.00
1      0.049                 14.0                 132.0   0.9940  3.30
2      0.050                 30.0                  97.0   0.9951  3.26
3      0.058                 47.0                 186.0   0.9956  3.19
4      0.058                 47.0                 186.0   0.9956  3.19

   sulphates  alcohol  quality
0       0.45      8.8        0
1       0.49      9.5        0
2       0.44     10.1        0
3       0.40      9.9        0
4       0.40      9.9        0
```

```
Winedata.sample(10)
```

```
       type  fixed acidity  volatile acidity  citric acid  residual sugar  \
4945    red            8.7             0.290         0.52            1.60
912   white            6.3             0.340         0.19            5.80
548   white            6.5             0.180         0.31            1.70
350   white            6.3             0.120         0.36            2.10
5949    red            8.5             0.460         0.59            1.40
1127  white            6.4             0.125         0.29            5.85
1140  white            8.5             0.160         0.33            1.00
4395  white            6.6             0.240         0.22           12.30
4040  white            6.3             0.240         0.29            1.60
15    white            6.6             0.170         0.38            1.50

      chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
4945      0.113                 12.0                  37.0  0.99690  3.25
```

```
912       0.041                22.0                  145.0  0.99430  3.15
548       0.044                30.0                  127.0  0.99280  3.49
350       0.044                47.0                  146.0  0.99140  3.27
5949      0.414                16.0                   45.0  0.99702  3.03
1127      0.042                24.0                   99.0  0.99200  3.23
1140      0.076                17.0                   57.0  0.99210  3.14
4395      0.051                35.0                  146.0  0.99676  3.10
4040      0.052                48.0                  185.0  0.99340  3.21
15        0.032                28.0                  112.0  0.99140  3.25

      sulphates  alcohol  quality
4945       0.58      9.5        0
912        0.63      9.9        0
548        0.50     10.2        1
350        0.74     11.4        1
5949       1.34      9.2        0
1127       0.32     12.0        1
1140       0.46     10.6        0
4395       0.67      9.4        0
4040       0.50      9.4        0
15         0.55     11.4        1
```

```
x.head()
```

```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.0              0.27         0.36            20.7      0.045
1            6.3              0.30         0.34             1.6      0.049
2            8.1              0.28         0.40             6.9      0.050
3            7.2              0.23         0.32             8.5      0.058
6            6.2              0.32         0.16             7.0      0.045

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 45.0                 170.0   1.0010  3.00       0.45
1                 14.0                 132.0   0.9940  3.30       0.49
2                 30.0                  97.0   0.9951  3.26       0.44
3                 47.0                 186.0   0.9956  3.19       0.40
6                 30.0                 136.0   0.9949  3.18       0.47

   alcohol
0      8.8
1      9.5
2     10.1
3      9.9
6      9.6
```

```
y.head()
```

```
0    6
1    6
2    6
```

```
3    6
6    6
Name: quality, dtype: int64
```

```
# divinding dataset into independent and dependent variables
#input split - DISCRETE(X) AND CATEGORICAL VARIABLE(Y)

x=Winedata.drop(['quality','type'], axis = 1)
y=Winedata['quality']
```

```
x.shape
```

```
(5329, 11)
```

Splitting the data into training and testing model

```
from sklearn.model_selection import train_test_split
```

```
#model splitting with 30% test data and 70% train dataset


x_train,x_test,y_train,y_test =
train_test_split(x,y,test_size=0.3,random_state=10)
```

```
#Feature scaling - standardize the data to same scale
sc=StandardScaler()
x_train=sc.fit_transform(x_train)
x_test=sc.fit_transform(x_test)
```

```
x_train
```

```
array([[-6.09071343e-01, -4.95364455e-01,  5.43707332e-01, ...,
        -8.37121346e-01,  2.89828723e-02, -3.93493362e-01],
       [-3.09907999e-01, -7.34440057e-01,  2.52161486e-03, ...,
        -1.51668423e-01,  2.25858629e-01,  1.96222690e-01],
       [-6.09071343e-01, -5.55133355e-01, -2.68071244e-01, ...,
        -8.37121346e-01,  2.91483881e-01,  1.88112569e+00],
       ...,
       [-6.09071343e-01, -5.55133355e-01,  2.84374663e+00, ...,
        -8.93545212e-02, -7.58520155e-01, -1.15169971e+00],
       [ 4.38000360e-01,  3.38961408e+00, -1.68868375e+00, ...,
         1.78006254e+00, -6.92894902e-01,  1.11977539e-01],
       [ 7.37163704e-01, -7.34440057e-01,  1.15254126e+00, ...,
        -1.27331866e+00, -1.34914742e+00,  2.77323892e-02]])
```

```
x_test.shape
```

```
(1599, 11)
```

```
x_train.shape
```

```
(3730, 11)
```

Machine Learning Supervised model - classification method

```
#classify function - classification methods/models
def classify(model, x, y):
    x_train,x_test,y_train,y_test =
train_test_split(x,y,test_size=0.3,random_state=42)
    #train the model
    model.fit(x_train,y_train)
    print("Accuracy:", model.score(x_test,y_test) * 100)
```

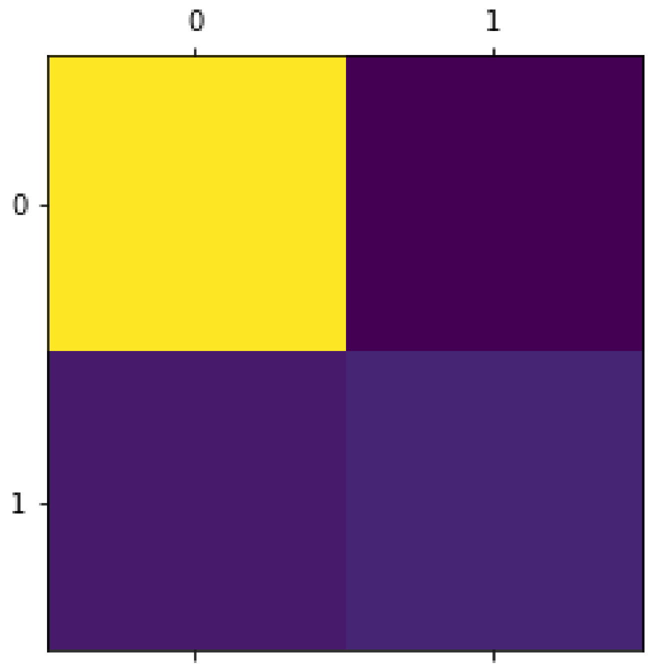
```
## model 1 - Random forest

reg=RandomForestClassifier(n_estimators=80)

reg.fit(x_train,y_train)
y_pred=reg.predict(x_test)
classify(reg,x,y)
```

```
Accuracy: 88.03506962351729
```

```
cm=confusion_matrix(y_test,y_pred)
print(cm)

plt.matshow(cm)
```

```
[[1506   60]
 [ 162  211]]
```

```
<matplotlib.image.AxesImage at 0x1fc524ec850>
```




```
# model 2 - Decision tree

DT=DecisionTreeClassifier()
classify(DT,x,y)
```

```
Accuracy: 82.98091799896854
```

```
### model 3 Naive bayes
nb = GaussianNB()
nb.fit(x_train,y_train)
nb_predict=nb.predict(x_test)
```

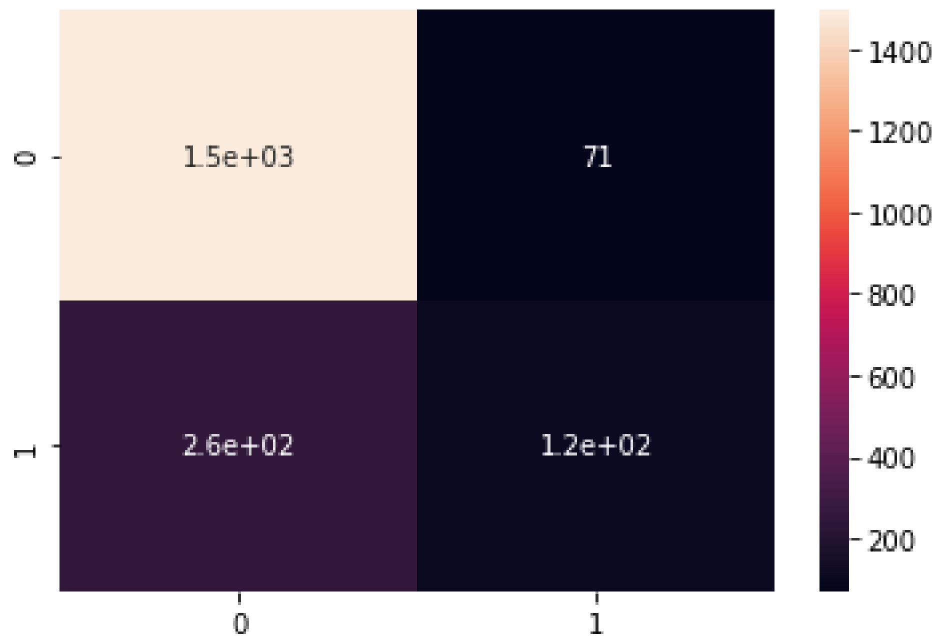
```
#print confusion matrix and accuracy score
nb_conf_matrix = confusion_matrix(y_test, nb_predict)
nb_acc_score = accuracy_score(y_test, nb_predict)
print(nb_conf_matrix)
print(nb_acc_score*100)
```

```
[[1223  343]
 [ 138  235]]
75.19339865910263
```

```
### model 4- LOGISTIC REGRESSION MODEL

#creating a instance for LR
LRmodel=LogisticRegression()

#fitting the model with  training data
LRmodel=LogisticRegression().fit(x_train,y_train)
```

```
#predicting the model with test data
pred_LR=LRmodel.predict(x_test)

#evalutaing the model
cm2=confusion_matrix(y_test,pred_LR)
print(cm2)
#plotting the CM
ax2=sb.heatmap(cm2,annot=True)
plt.show()
```

```
[[1495   71]
 [ 258  115]]
```




```
#evaluating the MODEL predictions
classification_report(y_test,pred_LR)
```

```
'              precision    recall  f1-score   support\n\n           0
0.85      0.95      0.90      1566\n           1       0.62      0.31
0.41       373\n\n    accuracy                           0.83      1939\n
macro avg       0.74      0.63      0.66      1939\nweighted avg       0.81
0.83      0.81      1939\n'
```

```
#evaluating the predictions
accuracy_score(y_test,pred_LR)
accuracy_score(y_test,pred_LR)*100
```

```
83.03249097472924
```

RESULT:

1. The data was downloaded from UCI Machine Learning Repository.
2. The datasets contains 25% red and 75 % white variants of the Portuguese "Vinho Verde" wine.
3. Mostly wine is of the average quality 6. There are low poor and excellent quality wine
4. Quality increases sharply with decrease in volatile acidity
5. Quality increases with increase in citric acid
6. Quality increases sharply with increase in alcohol. Alcohol is highly correlated with quality
7. total sulfur dioxide is highly correlated with free sulfur dioxide
8. fixed acidity is highly correlated with density and citric acid
9. citric acid is inversely correlated with pH and volatile acidity
10. We used 4 classification machine learning algorithms for the model prediction
11. Random Forest classifier gives the highest accuracy of 88%
12. Logistic Regression gives the accuracy of 83%
13. Decision Tree gives the accuracy of 82.7%
14. Naive Bayes gives 75% accuracy of the model
15. We have also used feature scaling for standardizing the data to the same scale.
16. We have viewed the results using classification report and the confusion matrix.

Wine Recommendation:

Château Lafite Rothschild (Bordeaux, France) Domaine de la Romanée-Conti (Burgundy, France) Domaine Etienne Guigal (Rhone, France)