Wine Quality Analysis and Prediction

```
In [1]: #importing the Libery
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

Data Collection

```
In [2]: #loding dataset in pandas dataframe
data = pd.read_csv('/content/winequality.csv')
```

In [3]: #check first five rows of the dataset
data.head()

Out[3]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulpha
0	white	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0
1	white	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0
2	white	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0
3	white	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0
4	white	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0
- 1											

http://localhost:8888/notebooks/Downloads/Untitled3.ipynb

In [4]: #check last five rows of the dataset
data.tail()

Out[4]:

	type	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulp
6492	red	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	
6493	red	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	
6494	red	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	
6495	red	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	
6496	red	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	

In [5]: #check shape of the dataset

data.shape

Out[5]: (6497, 13)

In [6]: #check infomation of the dataset
data.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	рН	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

In [7]: #check columns of the dataset data.columns

In [8]: #check mathamatic describe data.describe()

Out[8]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	tot
count	6487.000000	6489.000000	6494.000000	6495.000000	6495.000000	6497.000000	6497
mean	7.216579	0.339691	0.318722	5.444326	0.056042	30.525319	11{
std	1.296750	0.164649	0.145265	4.758125	0.035036	17.749400	56
min	3.800000	0.080000	0.000000	0.600000	0.009000	1.000000	ť
25%	6.400000	0.230000	0.250000	1.800000	0.038000	17.000000	77
50%	7.000000	0.290000	0.310000	3.000000	0.047000	29.000000	118
75%	7.700000	0.400000	0.390000	8.100000	0.065000	41.000000	156
max	15.900000	1.580000	1.660000	65.800000	0.611000	289.000000	44(

In [10]: #check coreation of the dataset data.corr()

Out[10]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	d€
fixed acidity	1.000000	0.220172	0.323736	-0.112319	0.298421	-0.283317	-0.329747	0.45
volatile acidity	0.220172	1.000000	-0.378061	-0.196702	0.377167	-0.353230	-0.414928	0.27
citric acid	0.323736	-0.378061	1.000000	0.142486	0.039315	0.133437	0.195218	90.0
residual sugar	-0.112319	-0.196702	0.142486	1.000000	-0.128902	0.403439	0.495820	0.55
chlorides	0.298421	0.377167	0.039315	-0.128902	1.000000	-0.195042	-0.279580	0.36
free sulfur dioxide	-0.283317	-0.353230	0.133437	0.403439	-0.195042	1.000000	0.720934	0.02
total sulfur dioxide	-0.329747	-0.414928	0.195218	0.495820	-0.279580	0.720934	1.000000	0.03
density	0.459204	0.271193	0.096320	0.552498	0.362594	0.025717	0.032395	1.00
рН	-0.251814	0.260660	-0.328689	-0.267050	0.044806	-0.145191	-0.237687	0.01
sulphates	0.300380	0.225476	0.057613	-0.185745	0.395332	-0.188489	-0.275381	0.25
alcohol	-0.095603	-0.038248	-0.010433	-0.359706	-0.256861	-0.179838	-0.265740	-0.68
quality	-0.077031	-0.265953	0.085706	-0.036825	-0.200886	0.055463	-0.041385	-0.30
1								

In [11]: #check missing value of the dataset
data.isnull().sum()

Out[11]: type

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

```
In [12]: #check duplicated value
data.duplicated().sum()
```

Out[12]: 1168

EDA of The Dataset

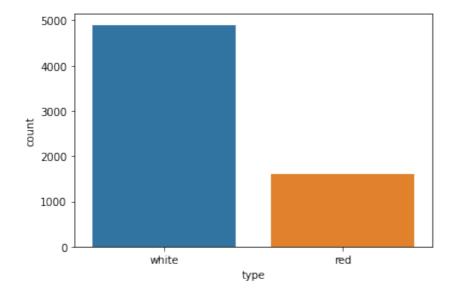
```
In [13]: #count the value of type
data['type'].value_counts()
```

Out[13]: white 4898 red 1599

Name: type, dtype: int64

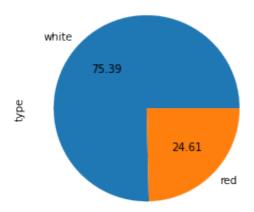
```
In [14]: #plot conutplot
sns.countplot(data['type'])
```

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6c0137a60>



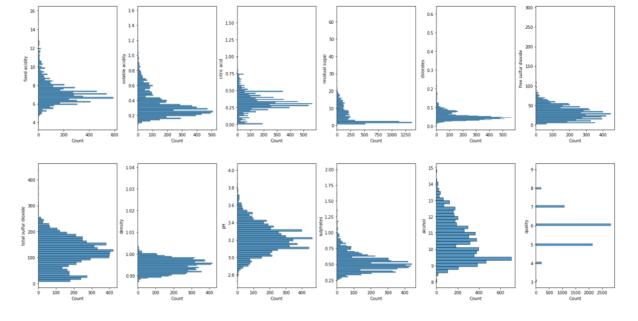
```
In [15]: #plot pie plot
data['type'].value_counts().plot(kind='pie',autopct='%.2f')
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bf8c8e50>



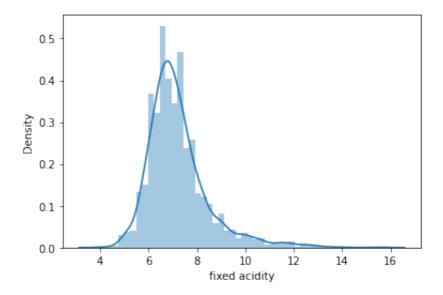
```
In [16]: # create histplot plots
fig, ax = plt.subplots(ncols=6, nrows=2, figsize=(20,10))
index = 0
ax = ax.flatten()

for col, value in data.items():
    if col != 'type':
        sns.histplot(y=col, data=data, ax=ax[index])
        index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```



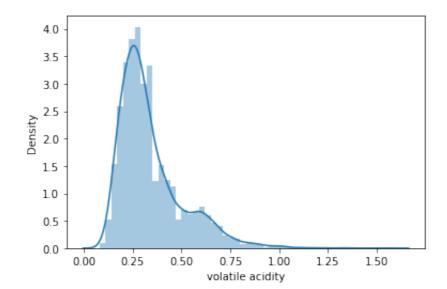
In [23]: #distplot for fixed acidity
sns.distplot(data['fixed acidity'])

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bec86520>



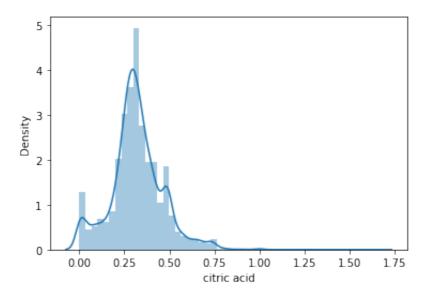
In [24]: #distplot for volatile acidity
sns.distplot(data['volatile acidity'])

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bee81ac0>



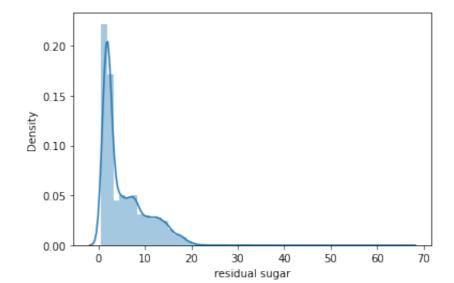
In [25]: #distplot for citric acid
sns.distplot(data['citric acid'])

Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bf4aa970>



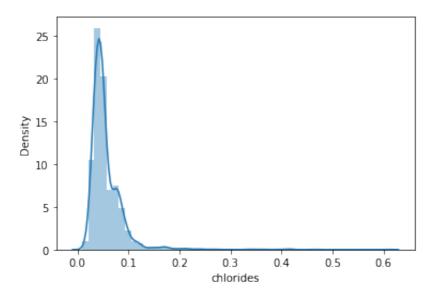
In [26]: #distplot for residual sugar
sns.distplot(data['residual sugar'])

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bf0d6fa0>



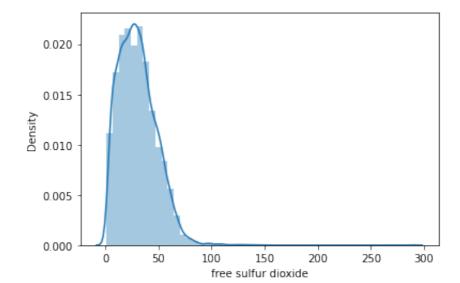
In [27]: #distplot for chlorides
sns.distplot(data['chlorides'])

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bf5531c0>



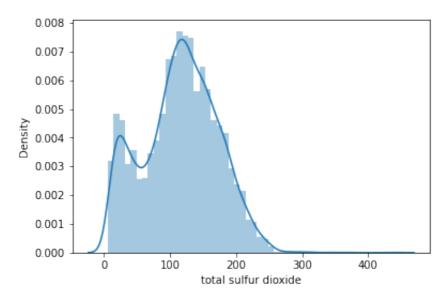
In [28]: #distplot for free sulfur dioxide
sns.distplot(data['free sulfur dioxide'])

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bf28f100>



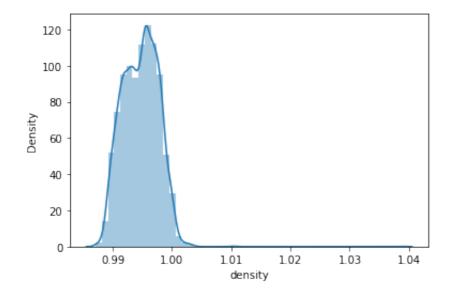
In [29]: #distplot for total sulfur dioxide
sns.distplot(data['total sulfur dioxide'])

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bf22d580>



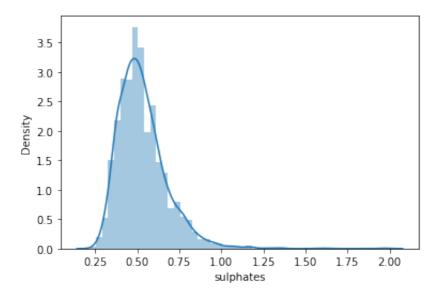
In [31]: #distplot for density
sns.distplot(data['density'])

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bfd46a90>



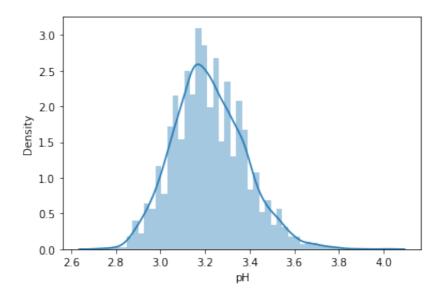
In [32]: #distplot for sulphates
sns.distplot(data['sulphates'])

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6ba7148b0>



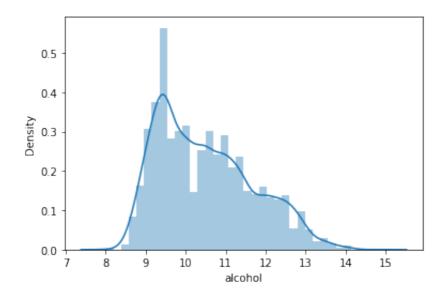
In [35]: #distplot for PH
sns.distplot(data['pH'])

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6ba1dea90>



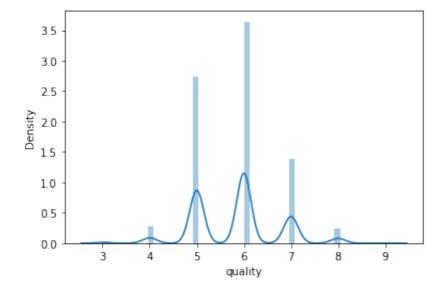
In [36]: #distplot for alcohol
sns.distplot(data['alcohol'])

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bec61bb0>



In [37]: #distplot for quality
sns.distplot(data['quality'])

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bed212b0>



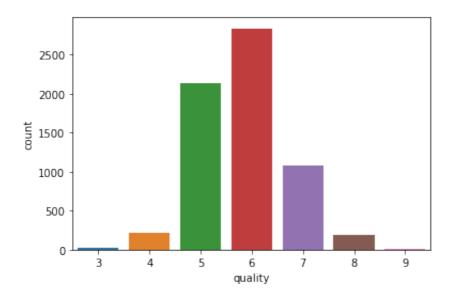
In [38]: #count the value quality
data['quality'].value_counts()

Out[38]: 6 2836 5 2138 7 1079 4 216 8 193 3 30 9 5

Name: quality, dtype: int64

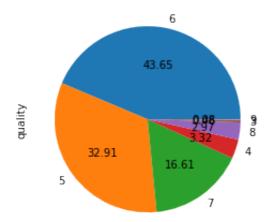
In [39]: #countplot value quality
sns.countplot(data['quality'])

Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6beca4160>



In [40]: #plot pie plot
data['quality'].value_counts().plot(kind='pie',autopct='%.2f')

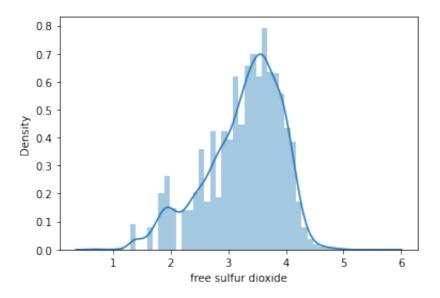
Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bf7aefd0>



```
In [41]: # log transformation
data['free sulfur dioxide'] = np.log(1 + data['free sulfur dioxide']
```

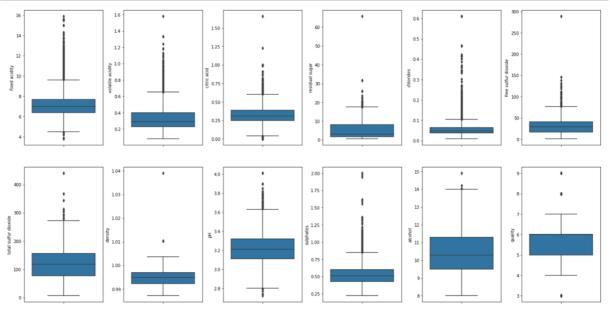
In [42]: sns.distplot(data['free sulfur dioxide'])

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bc0dedc0>



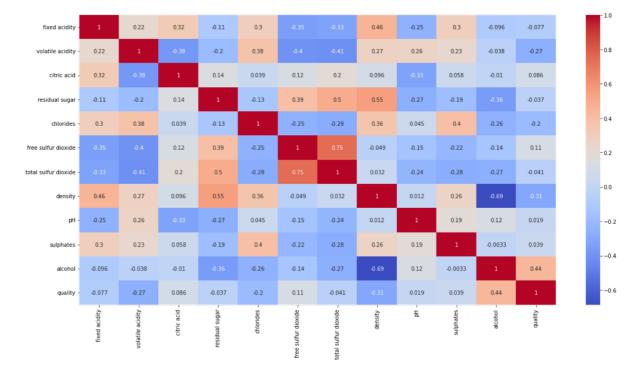
```
In [18]: # create box plots
fig, ax = plt.subplots(ncols=6, nrows=2, figsize=(20,10))
index = 0
ax = ax.flatten()

for col, value in data.items():
    if col != 'type':
        sns.boxplot(y=col, data=data, ax=ax[index])
        index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```



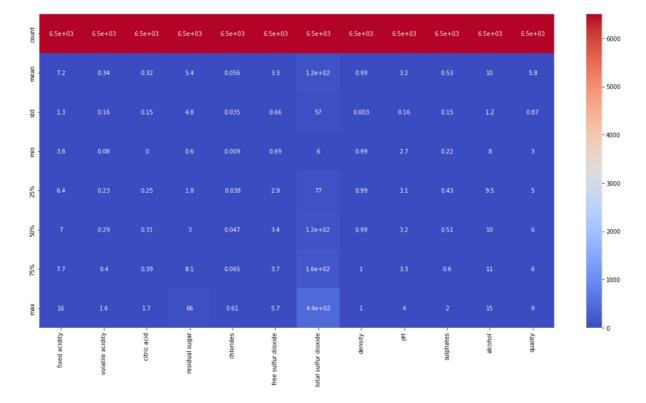
In [43]: #correaction of the dataset corr = data.corr() plt.figure(figsize=(20,10)) sns.heatmap(corr, annot=True, cmap='coolwarm')

Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bf1856a0>



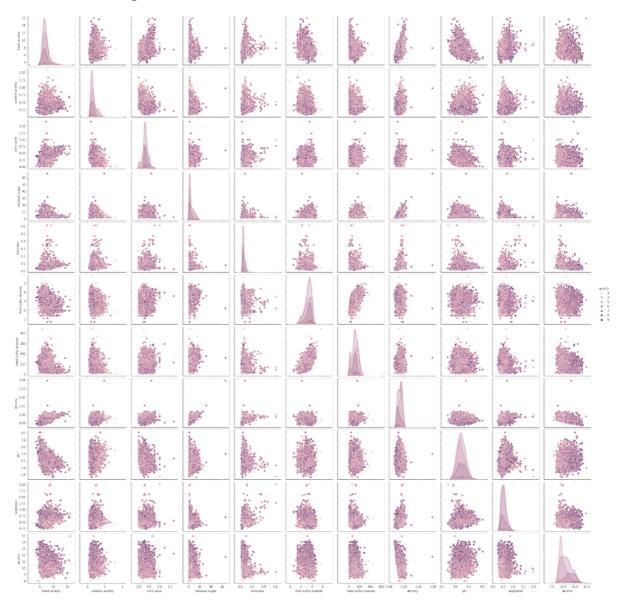
```
In [46]: desc = data.describe()
  plt.figure(figsize=(20,10))
  sns.heatmap(desc, annot=True, cmap='coolwarm')
```

Out[46]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe6bec22b50>



```
In [48]: #pairplot of the dataset
sns.pairplot(data,hue='quality')
```

Out[48]: <seaborn.axisgrid.PairGrid at 0x7fe6b64a2460>



```
In [55]: # fill the missing values
for col, value in data.items():
    if col != 'type':
        data[col] = data[col].fillna(data[col].mean())
```

```
In [56]: #after fill missing value check missing value
          data.isnull().sum()
Out[56]: 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
                                    0
          рΗ
          sulphates
                                    0
          alcohol
                                    0
          quality
                                    0
          dtype: int64
In [57]: #spliting the dataset in X and Y
          X = data.drop(columns=['type', 'quality'])
          Y = data['quality']
In [58]: print(X)
          print(Y)
                fixed acidity volatile acidity citric acid residual sugar
          chlorides \
                           7.0
                                            0.270
                                                            0.36
                                                                             20.7
          0
          0.045
                           6.3
          1
                                            0.300
                                                            0.34
                                                                              1.6
          0.049
                           8.1
                                            0.280
                                                            0.40
                                                                              6.9
          0.050
                           7.2
                                            0.230
                                                            0.32
                                                                              8.5
          3
          0.058
                           7.2
                                            0.230
                                                            0.32
                                                                              8.5
          4
          0.058
          . . .
                                                             . . .
          . . .
                           6.2
                                                                              2.0
          6492
                                            0.600
                                                            0.08
          0.090
                           5.9
                                            0.550
                                                            0.10
                                                                              2.2
          6493
          0.062
                           6.3
                                                                              2.3
          6494
                                            0.510
                                                            0.13
          0.076
          6495
                           5.9
                                            0.645
                                                            0.12
                                                                              2.0
          0.075
          6496
                           6.0
                                            0.310
                                                            0.47
                                                                              3.6
          0.067
```

free sulfur dioxide total sulfur dioxide density

lphates \

pH su

0	3.828641	170.0	1.00100	3.00
.450000 1	2.708050	132.0	0.99400	3.30
.490000 2	3.433987	97.0	0.99510	3.26
.440000 3	3.871201	186.0	0.99560	3.19
.400000 4	3.871201	186.0	0.99560	3.19
.400000	5.0/ ==0=			0.20
	• • • •		• • • •	• • •
6492 •580000	3.496508	44.0	0.99490	3.45
6493	3.688879	51.0	0.99512	3.52
.531215 6494	3.401197	40.0	0.99574	3.42
.750000 6495	3.496508	44.0	0.99547	3.57
.710000 6496 .660000	2.944439	42.0	0.99549	3.39
1 9 2 10 3 9 4 9 6492 10 6493 11 6494 11 6495 10 6496 11 [6497 rows 0 6 1 6 2 6 3 6 4 6	001 8.8 9.5 9.9 9.9 1.5 1.2 1.0 0.2 1.0 x 11 columns]			
6492 5 6493 6 6494 6 6495 5				

Name: quality, Length: 6497, dtype: int64

```
In [63]: Y.value_counts()
Out[63]: 6
              2836
         5
              2138
         7
              1079
         4
               216
         8
               193
         3
                 30
         9
                 5
         Name: quality, dtype: int64
In [64]: from imblearn.over_sampling import SMOTE
         oversample = SMOTE(k neighbors=4)
         # transform the dataset
         X, Y = oversample.fit_resample(X, Y)
In [68]: Y.value_counts()
Out[68]: 6
              2836
              2836
         7
              2836
         8
              2836
         4
              2836
         3
              2836
         9
              2836
         Name: quality, dtype: int64
In [59]: |#spliting the dataset in X_train and Y_train
         from sklearn.preprocessing import StandardScaler
         from sklearn.model selection import train test split
In [65]: # split the data to train and test set
         X_train, X_test, Y_train, Y_test = train_test_split(X, Y, train_size=0.8
In [66]: #print X_train and Y_train
         print(X_train.shape, X_test.shape, Y_train.shape, Y_test.shape)
         (16874, 11) (2978, 11) (16874,) (2978,)
In [67]: #usingg standardscaler
         scaler = StandardScaler()
         X_train =scaler.fit_transform(X_train)
```

Model Training

```
In [69]: # classify function
         from sklearn.model_selection import cross_val_score, train_test_spl
         def classify(model, X_train, Y_train):
             # train the model
             model.fit(X_train, Y_train)
             print("Accuracy:", model.score(X test, Y test) * 100)
             # cross-validation
             score = cross_val_score(model, X_train, Y_train, cv=5)
             print("CV Score:", np.mean(score)*100)
In [70]: #using LogisticRegression
         from sklearn.linear_model import LogisticRegression
         model = LogisticRegression()
         classify(model, X_train, Y_train)
         Accuracy: 8.059100067159166
         CV Score: 52,275715383433216
In [71]: from sklearn.tree import DecisionTreeClassifier
         model = DecisionTreeClassifier()
         classify(model, X_train, Y_train)
```

Accuracy: 13.834788448623236 CV Score: 79.01506860743376

In [72]: from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
classify(model, X_train, Y_train)

Accuracy: 15.547347212894561 CV Score: 87.37703308524885

In [73]: from sklearn.ensemble import ExtraTreesClassifier
model = ExtraTreesClassifier()
classify(model, X_train, Y_train)

Accuracy: 14.707857622565479 CV Score: 88.68078772311137

In []: