In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
```

In [2]:
```
wine=pd.read_csv(r'C:\Users\mayur/winequality-red.csv')
wine.head()
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quali
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	

In [3]:
```
wine.describe()
```

Out[3]:

	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	1599
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	1

In [4]:
```
wine.isnull().sum()
```

Out[4]:
```
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 [5]:
```
wine.transpose()
```

Out[5]:

	0	1	2	3	4	5	6	7	8	9	...	
fixed acidity	7.4000	7.8000	7.800	11.200	7.4000	7.4000	7.9000	7.3000	7.8000	7.5000	...	
volatile acidity	0.7000	0.8800	0.760	0.280	0.7000	0.6600	0.6000	0.6500	0.5800	0.5000	...	
citric acid	0.0000	0.0000	0.040	0.560	0.0000	0.0000	0.0600	0.0000	0.0200	0.3600	...	
residual sugar	1.9000	2.6000	2.300	1.900	1.9000	1.8000	1.6000	1.2000	2.0000	6.1000	...	
chlorides	0.0760	0.0980	0.092	0.075	0.0760	0.0750	0.0690	0.0650	0.0730	0.0710	...	
free sulfur dioxide	11.0000	25.0000	15.000	17.000	11.0000	13.0000	15.0000	15.0000	9.0000	17.0000	...	2
total sulfur dioxide	34.0000	67.0000	54.000	60.000	34.0000	40.0000	59.0000	21.0000	18.0000	102.0000	...	7
density	0.9978	0.9968	0.997	0.998	0.9978	0.9978	0.9964	0.9946	0.9968	0.9978	...	
pH	3.5100	3.2000	3.260	3.160	3.5100	3.5100	3.3000	3.3900	3.3600	3.3500	...	
sulphates	0.5600	0.6800	0.650	0.580	0.5600	0.5600	0.4600	0.4700	0.5700	0.8000	...	
alcohol	9.4000	9.8000	9.800	9.800	9.4000	9.4000	9.4000	10.0000	9.5000	10.5000	...	
quality	5.0000	5.0000	5.000	6.000	5.0000	5.0000	5.0000	7.0000	7.0000	5.0000	...	

12 rows × 1599 columns

In [6]:
```
wine.corr()
```

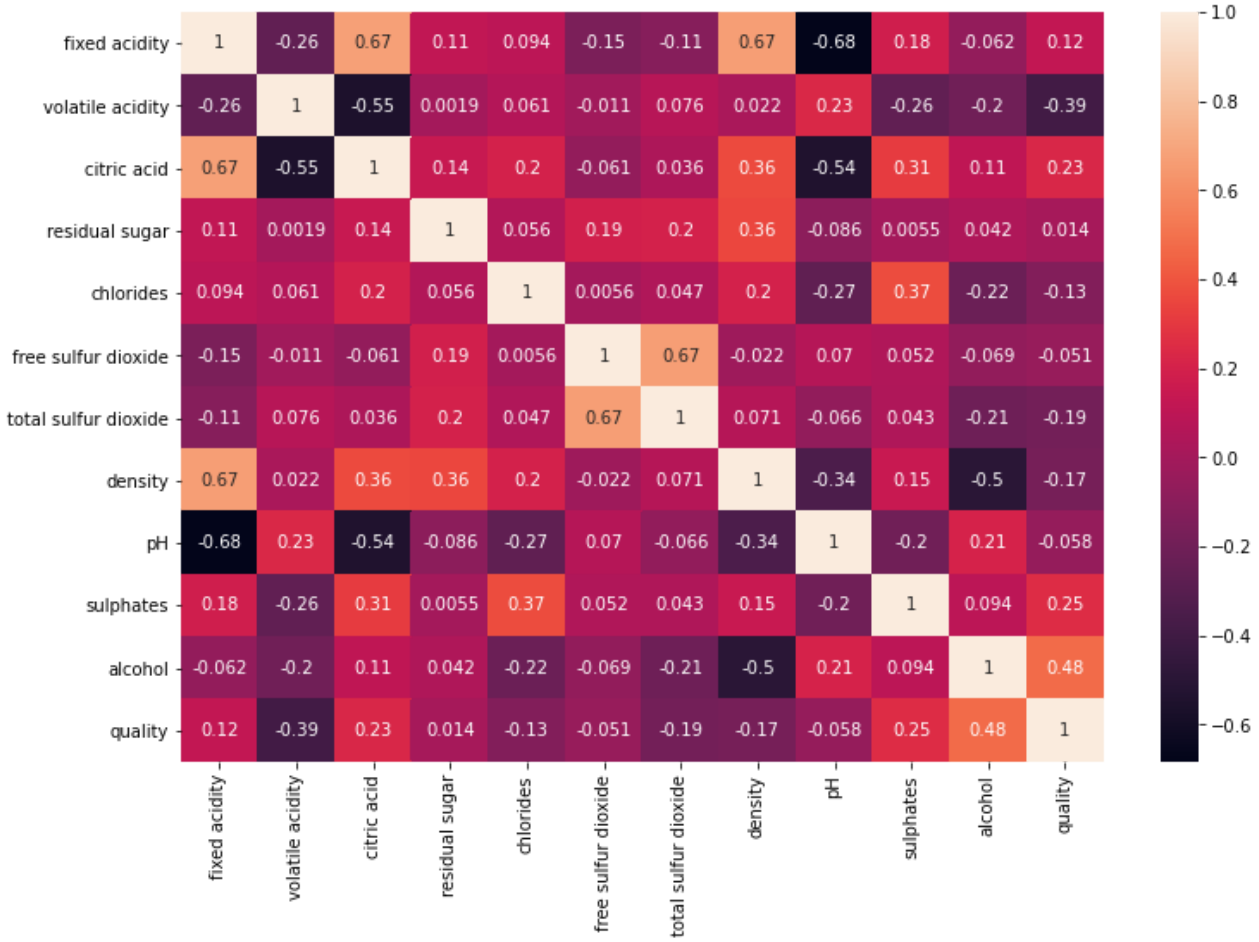
Out[6]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	p
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-0.6829
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026	0.2349

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	p
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947	-0.5419(
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-0.0856
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-0.2650
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946	0.0703
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269	-0.0664
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000	-0.3416
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699	1.0000(
sulphates	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.148506	-0.1966
alcohol	-0.061668	-0.202288	0.109903	0.042075	-0.221141	-0.069408	-0.205654	-0.496180	0.2056
quality	0.124052	-0.390558	0.226373	0.013732	-0.128907	-0.050656	-0.185100	-0.174919	-0.0577

In [7]:
```
plt.figure(figsize = (12,8))
sns.heatmap(wine.corr(),annot = True)
```

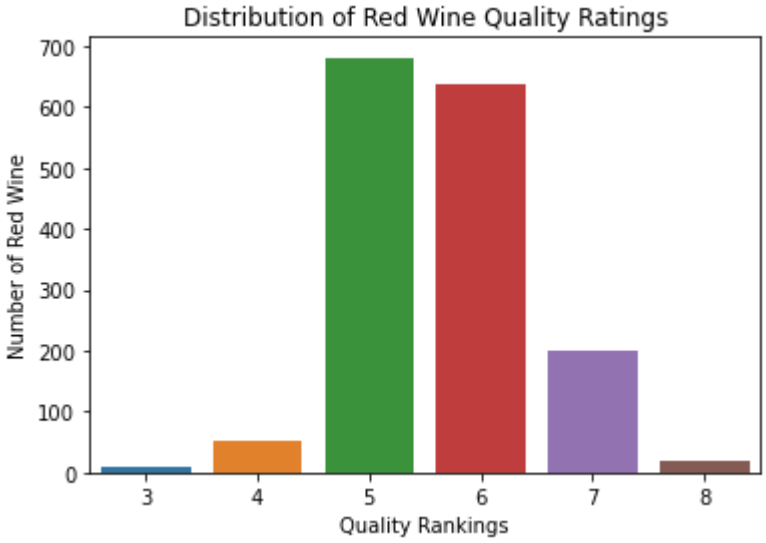
Out[7]: <AxesSubplot:>



In [8]:

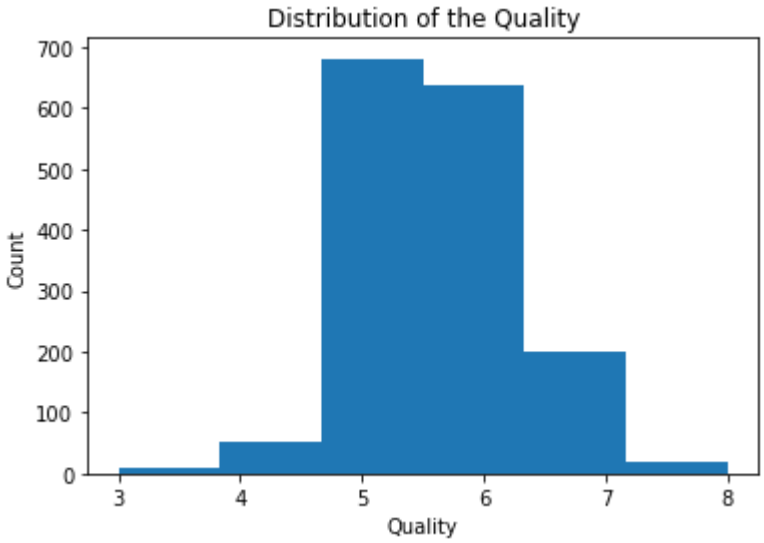
```
sns.barplot(wine['quality'].unique(),wine['quality'].value_counts())
plt.xlabel("Quality Rankings")
plt.ylabel("Number of Red Wine")
plt.title("Distribution of Red Wine Quality Ratings")
plt.show()
```

```
C:\Users\mayur\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid posit
ional argument will be `data`, and passing other arguments without an explicit keyword w
ill result in an error or misinterpretation.
  warnings.warn(
```



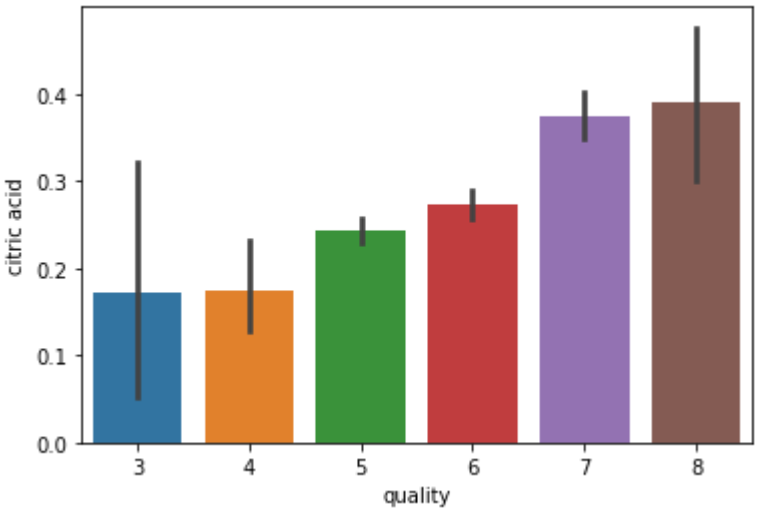
In [9]:
```
plt.hist(wine.quality,bins=6,histtype='bar')

plt.title('Distribution of the Quality')
plt.xlabel('Quality')
plt.ylabel('Count')
plt.show()
```



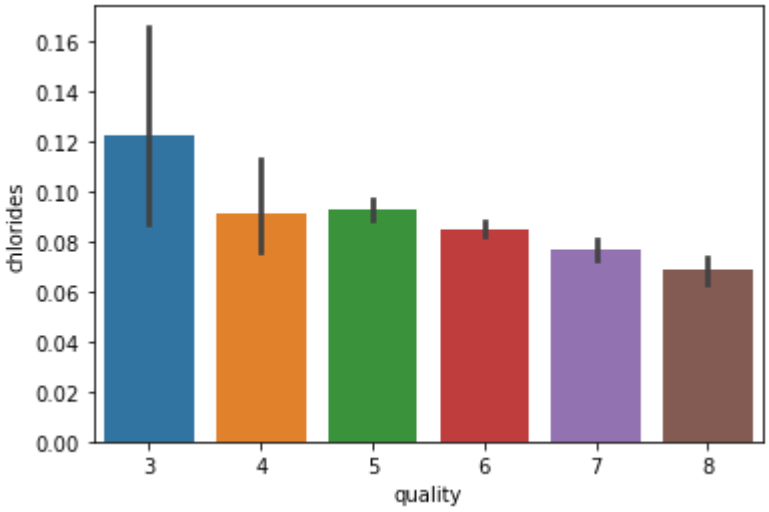
In [10]:
```
sns.barplot(x = 'quality', y = 'citric acid', data = wine)
```

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



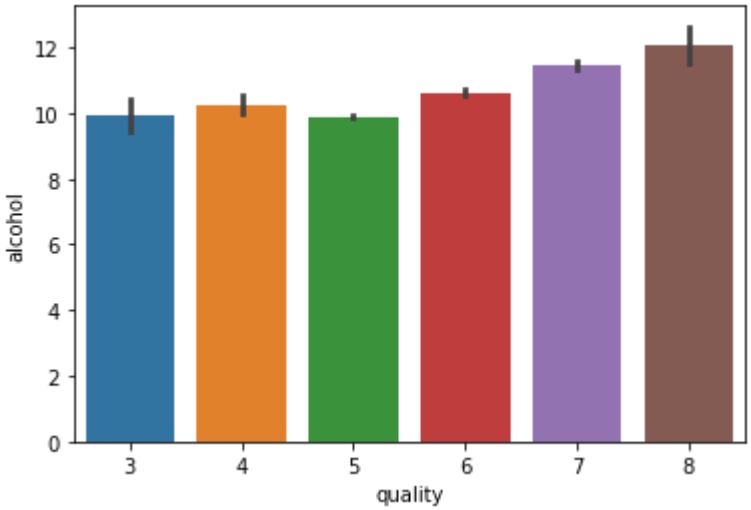
In [11]:
```
sns.barplot(x = 'quality', y = 'chlorides', data = wine)
```

Out[11]: <AxesSubplot:xlabel='quality', ylabel='chlorides'>



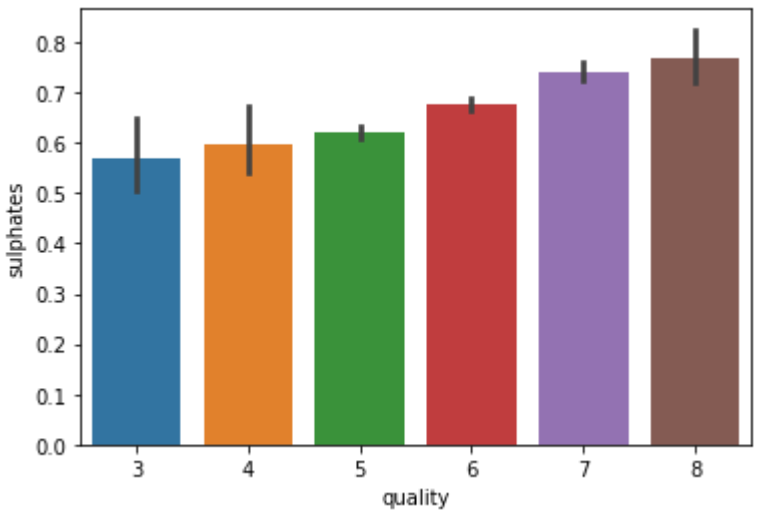
In [12]:
```
sns.barplot(x = 'quality', y = 'alcohol', data = wine)
```

Out[12]: <AxesSubplot:xlabel='quality', ylabel='alcohol'>



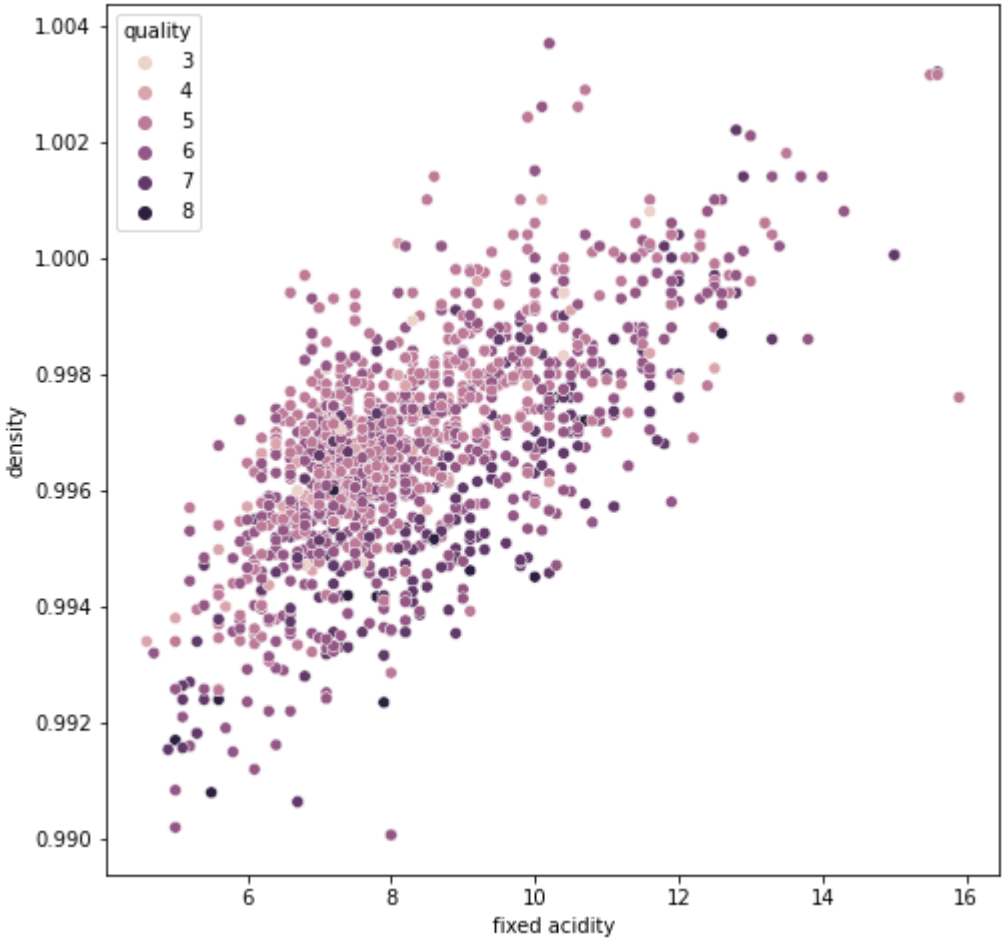
In [13]:
```
sns.barplot(x = 'quality', y = 'sulphates', data = wine)
```

Out[13]: <AxesSubplot:xlabel='quality', ylabel='sulphates'>



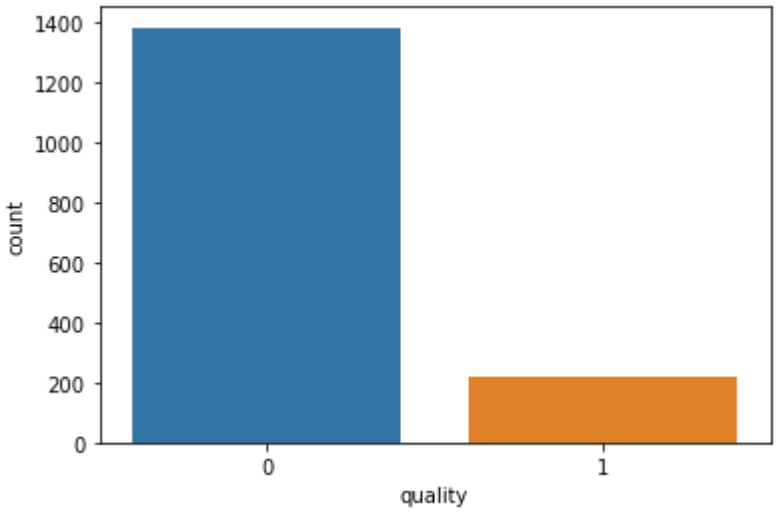
In [14]:
```
plt.figure(figsize = (8,8))
sns.scatterplot(x = 'fixed acidity', y = 'density', hue = 'quality' ,data = wine)
```

Out[14]: <AxesSubplot:xlabel='fixed acidity', ylabel='density'>



In [15]:
```
wine['quality'] = wine.quality.apply(lambda x : 1 if x > 6.5 else 0)
```

In [16]:
```
sns.countplot(data = wine, x = 'quality')
plt.show()
```



In [17]:
```
X=wine.drop('quality',axis=1)
y=wine['quality']
```

In [18]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=4 )
display(X_train.head(),y_train.head(),'Testing Data',X_test.head(),y_test.head())
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
998	8.9	0.840	0.34	1.40	0.050	4.0	10.0	0.99554	3.12	0.48	9.1
575	12.3	0.270	0.49	3.10	0.079	28.0	46.0	0.99930	3.20	0.80	10.2
731	8.9	0.875	0.13	3.45	0.088	4.0	14.0	0.99940	3.44	0.52	11.5
1299	7.6	1.580	0.00	2.10	0.137	5.0	9.0	0.99476	3.50	0.40	10.9
675	9.3	0.410	0.39	2.20	0.064	12.0	31.0	0.99840	3.26	0.65	10.2

```
998     0
575     0
731     0
1299    0
675     0
Name: quality, dtype: int64
'Testing Data'
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
289	11.6	0.42	0.53	3.3	0.105	33.0	98.0	1.00100	3.20	0.95	9.2
962	6.6	0.57	0.02	2.1	0.115	6.0	16.0	0.99654	3.38	0.69	9.5
826	7.5	0.27	0.34	2.3	0.050	4.0	8.0	0.99510	3.40	0.64	11.0
495	10.7	0.35	0.53	2.6	0.070	5.0	16.0	0.99720	3.15	0.65	11.0
57	7.5	0.63	0.12	5.1	0.111	50.0	110.0	0.99830	3.26	0.77	9.4

```
289    0
962    0
826    1
495    1
57     0
Name: quality, dtype: int64
```

In [28]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.ensemble import AdaBoostClassifier
```

In [29]:
```
wine_base=DecisionTreeClassifier(max_depth=10,random_state=4)
wine_base.fit(X_train,y_train)
AdaBoost= AdaBoostClassifier(base_estimator=wine_base,n_estimators=300,learning_rate=1)
```

In [31]:
```
y_pred=wine_base.predict(X_test)
boost_model=AdaBoost.fit(X_train,y_train)
```

In [34]:
```
y_pred1=boost_model.predict(X_test)
pred1=metrics.accuracy_score(y_test,y_pred1)
print("accuracy with Ada Boost",pred1*100)
```

```
accuracy with Ada Boost 91.04166666666667
```

In [22]:
```
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
print(accuracy_score(y_test, y_pred))
```

```
[[391  27]
 [ 28  34]]
              precision    recall  f1-score   support

           0       0.93      0.94      0.93       418
           1       0.56      0.55      0.55        62

    accuracy                           0.89       480
   macro avg       0.75      0.74      0.74       480
weighted avg       0.88      0.89      0.89       480

0.8854166666666666
```

In [23]:
```
acc = metrics.accuracy_score(y_test,y_pred)
print(acc)
```

```
0.8854166666666666
```

In [25]:
```
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier(n_estimators=100)
clf.fit(X_train,y_train)
```

Out[25]:
```
RandomForestClassifier()
```

In [ ]:
```
y_pred1 = clf.predict(x_test)
from sklearn import metrics
print('Accuracy: ', metrics.accuracy_score(y_test,y_pred1))
```

In [ ]:
```

```