```
In [1]:
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [2]:

```
data=pd.read_csv('WINE DATA\\winequality-white.csv',delimiter = ";")
```

In [3]:

data

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.00100	3.00	0.45	8.8	6
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9.5	6
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10.1	6
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9.9	6
											•••	
4893	6.2	0.21	0.29	1.6	0.039	24.0	92.0	0.99114	3.27	0.50	11.2	6
4894	6.6	0.32	0.36	8.0	0.047	57.0	168.0	0.99490	3.15	0.46	9.6	5
4895	6.5	0.24	0.19	1.2	0.041	30.0	111.0	0.99254	2.99	0.46	9.4	6
4896	5.5	0.29	0.30	1.1	0.022	20.0	110.0	0.98869	3.34	0.38	12.8	7
4897	6.0	0.21	0.38	0.8	0.020	22.0	98.0	0.98941	3.26	0.32	11.8	6

4898 rows × 12 columns

In [4]:

data.columns

Out[4]:

In [5]:

data.describe()

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulph
count	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.000000	4898.00
mean	6.854788	0.278241	0.334192	6.391415	0.045772	35.308085	138.360657	0.994027	3.188267	0.48
std	0.843868	0.100795	0.121020	5.072058	0.021848	17.007137	42.498065	0.002991	0.151001	0.11
min	3.800000	0.080000	0.000000	0.600000	0.009000	2.000000	9.000000	0.987110	2.720000	0.22
25%	6.300000	0.210000	0.270000	1.700000	0.036000	23.000000	108.000000	0.991723	3.090000	0.41
50%	6.800000	0.260000	0.320000	5.200000	0.043000	34.000000	134.000000	0.993740	3.180000	0.47

```
7.300000
                                         0.390000
                                                                     0.050000
                                                                                                                0.996100
                                                                                                                              3.280000
                                                                                                                                            0.55
                           0.320000
                                                       9-200000
                                                                                  46e 90000
                                                                                               167a P 90000
         fixed acidity
                                        citric acid
                                                                     chlorides
                                                                                                                 density
                                                                                                                                           sulph
                                                                                 289.000000
                           1. foodby
                                                                                               440.000000
                                                      65.800000
           14.200000
                                         1.660000
                                                                     0.346000
                                                                                                                1.038980
                                                                                                                              3.820000
                                                                                                                                            1.08
   max
4
                                                                                                                                              F
```

In [6]:

```
print("Total quantity of wine quality 3 : ",len([a for a in data['quality'] if a==3]))
print("Total quantity of wine quality 4 : ",len([a for a in data['quality'] if a==4]))
print("Total quantity of wine quality 5 : ",len([a for a in data['quality'] if a==5]))
print("Total quantity of wine quality 6 : ",len([a for a in data['quality'] if a==6]))
print("Total quantity of wine quality 7 : ",len([a for a in data['quality'] if a==7]))
print("Total quantity of wine quality 8 : ",len([a for a in data['quality'] if a==8]))
print("Total quantity of wine quality 9 : ",len([a for a in data['quality'] if a==9]))
```

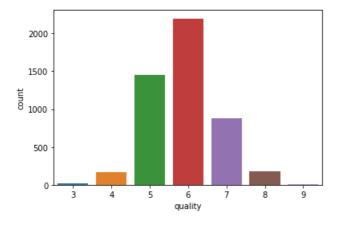
```
Total quantity of wine quality 3: 20
Total quantity of wine quality 4: 163
Total quantity of wine quality 5: 1457
Total quantity of wine quality 6: 2198
Total quantity of wine quality 7: 880
Total quantity of wine quality 8: 175
Total quantity of wine quality 9: 5
```

In [7]:

```
sns.countplot(x='quality', data=data)
```

Out[7]:

<matplotlib.axes. subplots.AxesSubplot at 0x1a5d7067da0>



In [11]:

```
reviews = []
for i in data['quality']:
    if i <= 5:
        reviews.append(0)
    elif (i==6):
        reviews.append(1)
    elif (i>6):
        reviews.append(2)
data['Reviews'] = reviews
```

In [12]:

```
sns.countplot(x='Reviews', data=data)
```

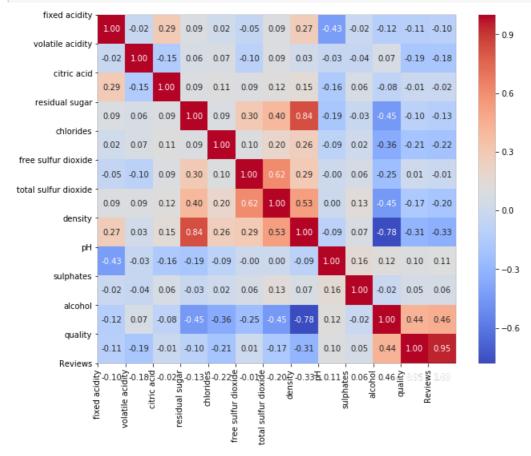
Out[12]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a5d73fd2e8>

```
2000 -
```

In [13]:

```
corr = data.corr()
#Plot figsize
fig, ax = plt.subplots(figsize=(10, 8))
#Generate Heat Map, allow annotations and place floats in map
sns.heatmap(corr, cmap='coolwarm', annot=True, fmt=".2f")
#Apply xticks
plt.xticks(range(len(corr.columns)), corr.columns);
#Apply yticks
plt.yticks(range(len(corr.columns)), corr.columns)
#show plot
plt.show()
```



In [14]:

data.head()

Out[14]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol	quality	Reviews
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45	8.8	6	1
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49	9.5	6	1
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44	10.1	6	1
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6	1

```
residual
sugar
                                                 free sulfur
dioxide
                                                             total sulfur
dioxide density 3pM sulphates alcohol quality Reviews
      fixed
                                      chlo@ide8
     acidity
In [15]:
data.tail()
Out[15]:
        fixed
                volatile
                         citric
                                residual
                                                  free sulfur
                                                             total sulfur
                                        chlorides
                                                                               pH sulphates alcohol quality Reviews
                                                                       density
       acidity
                 acidity
                                                     dioxide
                                                                dioxide
                                  sugar
                                                                                                                  1
 4893
          6.2
                   0.21
                          0.29
                                    1.6
                                           0.039
                                                       24 0
                                                                  92.0 0.99114 3.27
                                                                                                11.2
                                                                                                         6
                                                                                        0.50
                                                                                                                  0
 4894
          6.6
                   0.32
                          0.36
                                    8.0
                                            0.047
                                                       57.0
                                                                  168.0 0.99490 3.15
                                                                                        0.46
                                                                                                 9.6
                                                                                                         5
 4895
          6.5
                   0.24
                          0.19
                                    1.2
                                            0.041
                                                       30.0
                                                                  111.0 0.99254 2.99
                                                                                        0.46
                                                                                                 9.4
                                                                                                         6
                                                                                                                  1
 4896
          5.5
                   0.29
                          0.30
                                    1.1
                                            0.022
                                                       20.0
                                                                  110.0 0.98869 3.34
                                                                                        0.38
                                                                                                12.8
                                                                                                         7
                                                                                                                  2
 4897
          6.0
                   0.21
                          0.38
                                    8.0
                                            0.020
                                                       22.0
                                                                  98.0 0.98941 3.26
                                                                                        0.32
                                                                                                11.8
                                                                                                         6
In [16]:
X = data.iloc[:,0:11]
y = data.iloc[:,12]
y mul = data.iloc[:,11]
In [20]:
from sklearn.preprocessing import MinMaxScaler
minmax = MinMaxScaler()
X_s = minmax.fit_transform(X)
In [21]:
from sklearn.model_selection import train test split
X train, X test, y train, y test = train test split(X s,y,test size = 0.3, random state = 42)
In [22]:
print(X train.shape)
print(X test.shape)
(3428, 11)
(1470, 11)
In [23]:
from sklearn.svm import SVC
from sklearn.metrics import accuracy score, classification report, confusion matrix
In [38]:
svc lin = SVC(kernel = 'linear',class weight = 'balanced')
svc_lin.fit(X_train, y_train)
y_pred_svc_lin=svc_lin.predict(X_test)
lin svc conf matrix = confusion matrix(y test, y pred svc lin)
lin svc_clf = classification_report(y_test, y_pred_svc_lin)
print(lin svc conf matrix)
print(lin_svc_clf)
[[334 86 53]
 [236 202 230]
 [ 47 56 226]]
                             recall f1-score support
                precision
```

0

0.54

0.59

0.71

0.30

0.61

0.40

473

668

```
0.44 0.69 0.54
                                                 329
                                      0.52
                                               1470
   accuracy
                                    0.52 1470
0.50 1470
                 0.52 0.57
  macro avg
                 0.54
                           0.52
weighted avg
In [39]:
svc_rbf = SVC(kernel = 'rbf',class_weight = 'balanced')
svc rbf.fit(X_train, y_train)
y_pred_svc_rbf=svc_rbf.predict(X_test)
rbf_svc_conf_matrix = confusion_matrix(y_test, y_pred_svc_rbf)
rbf svc_clf = classification_report(y_test, y_pred_svc_rbf)
print(rbf_svc_conf_matrix)
print(rbf_svc_clf)
[[334 104 35]
 [191 262 215]
 [ 34 68 227]]
             precision recall f1-score support
                          0.71
0.39
                                    0.65
0.48
          0
                  0.60
                                                  473
          1
                  0.60
                                                 668
                                     0.56
           2
                  0.48
                           0.69
                                                 329
                                            1470
1470
                                     0.56
   accuracy
                        0.60
                                  0.56
0.55
                  0.56
  macro avq
weighted avg
                  0.57
                            0.56
                                                1470
In [42]:
svc_poly = SVC(kernel = 'poly',class_weight = 'balanced')
svc poly.fit(X_train, y_train)
y pred svc poly = svc poly.predict(X test)
poly_svc_conf_matrix = confusion_matrix(y_test, y_pred_svc_poly)
poly_svc_clf = classification_report(y_test, y_pred_svc_poly)
print(poly svc conf matrix)
print(poly_svc_clf)
[[350 93 30]
[212 265 191]
 [ 24 85 220]]
             precision
                        recall f1-score support
          0
                  0.60
                           0.74
                                     0.66
          1
                  0.60
                           0.40
                                    0.48
                                                 668
                                     0.57
                  0.50
                           0.67
                                                 329

    0.57
    1470

    0.56
    0.60
    0.57
    1470

    0.58
    0.57
    0.56
    1470

   accuracy
  macro avq
weighted avg
In [46]:
svc sigmoid = SVC(kernel = 'sigmoid')
svc_sigmoid.fit(X_train, y_train)
y pred svc sigmoid=svc sigmoid.predict(X test)
sigmoid svc conf matrix = confusion matrix(y test, y pred svc sigmoid)
```

```
0.15
                         0.20
                                    0.17
                                               329
                                    0.31
                                             1470
   accuracy
                0.32 0.30
                                   0.29
                                             1470
  macro avg
                0.36
                          0.31
                                    0.31
                                             1470
weighted avg
In [49]:
from sklearn.model_selection import cross_val_score
clf = SVC(kernel='linear', C=1)
scores = cross_val_score(clf, X_s, y, cv=5)
print(scores)
print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std() * 2))
[0.49183673 0.51938776 0.56326531 0.53626149 0.56588355]
Accuracy: 0.54 (+/- 0.06)
In [37]:
from sklearn.model_selection import cross val score
clf = SVC(kernel='rbf', C=1)
scores = cross_val_score(clf, X_s, y, cv=5)
print(scores)
print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std() * 2))
[0.54489796 0.56734694 0.61632653 0.58937692 0.57814096]
Accuracy: 0.58 (+/- 0.05)
In [50]:
from sklearn.model_selection import cross val score
clf = SVC(kernel='poly',C=1)
scores = cross_val_score(clf, X_s, y, cv=5)
print(scores)
print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std() * 2))
Accuracy: 0.57 (+/- 0.06)
In [48]:
from sklearn.model selection import cross val score
clf = SVC(kernel='sigmoid',C=1)
scores = cross val score(clf, X s, y, cv=5)
print(scores)
print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std() * 2))
[0.3755102  0.41632653  0.39387755  0.35955056  0.29213483]
Accuracy: 0.37 (+/- 0.08)
In [ ]:
```