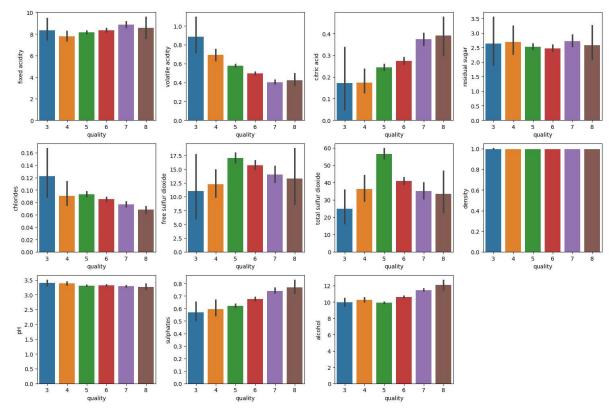
```
import numpy as np
In [1]:
          import pandas as pd
          import seaborn as sns
          from sklearn.svm import SVC
          import matplotlib.pyplot as plt
          from sklearn.linear_model import SGDClassifier
          from sklearn.preprocessing import LabelEncoder
          from sklearn.model_selection import GridSearchCV
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
          %matplotlib inline
          wine = pd.read csv('winequality-red.csv')
In [2]:
          wine.head()
Out[2]:
                                                           free
                                                                   total
              fixed volatile citric residual
                                              chlorides
                                                          sulfur
                                                                   sulfur
                                                                         density
                                                                                   pH sulphates alcohol
             acidity
                      acidity
                               acid
                                       sugar
                                                        dioxide dioxide
                               0.00
          0
                7.4
                        0.70
                                         1.9
                                                 0.076
                                                           11.0
                                                                    34.0
                                                                           0.9978 3.51
                                                                                             0.56
                                                                                                       9.4
          1
                7.8
                        0.88
                               0.00
                                                 0.098
                                                           25.0
                                                                           0.9968 3.20
                                                                                             0.68
                                         2.6
                                                                    67.0
                                                                                                       9.8
          2
                        0.76
                               0.04
                                                 0.092
                                                           15.0
                                                                    54.0
                                                                                             0.65
                7.8
                                         2.3
                                                                           0.9970 3.26
                                                                                                       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
          wine.describe()
In [3]:
                                  volatile
                                                                                    free sulfur
                                                                                                total sulfur
Out[3]:
                       fixed
                                                            residual
                                                                        chlorides
                                             citric acid
                      acidity
                                   acidity
                                                                                       dioxide
                                                                                                    dioxide
                                                              sugar
          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
                                              0.420000
                                                           2.600000
                                                                        0.090000
                                                                                    21.000000
                                 0.640000
                                                                                                  62.000000
           max
                   15.900000
                                 1.580000
                                              1.000000
                                                          15.500000
                                                                        0.611000
                                                                                     72.000000
                                                                                                 289.000000
          wine.info()
In [4]:
```

```
<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
    citric acid
                          1599 non-null
                                         float64
3
   residual sugar
                         1599 non-null
                                         float64
    chlorides
                                         float64
4
                          1599 non-null
    free sulfur dioxide
                         1599 non-null
                                         float64
    total sulfur dioxide 1599 non-null
                                        float64
6
                                        float64
7
    density
                          1599 non-null
8
                          1599 non-null
                                        float64
    рΗ
                          1599 non-null
9
    sulphates
                                         float64
10 alcohol
                          1599 non-null
                                         float64
11 quality
                          1599 non-null
                                         int64
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

```
In [5]: fig = plt.figure(figsize=(15,10))
        plt.subplot(3,4,1)
        sns.barplot(x='quality',y='fixed acidity',data=wine)
        plt.subplot(3,4,2)
        sns.barplot(x='quality',y='volatile acidity',data=wine)
        plt.subplot(3,4,3)
        sns.barplot(x='quality',y='citric acid',data=wine)
        plt.subplot(3,4,4)
        sns.barplot(x='quality',y='residual sugar',data=wine)
        plt.subplot(3,4,5)
        sns.barplot(x='quality',y='chlorides',data=wine)
        plt.subplot(3,4,6)
        sns.barplot(x='quality',y='free sulfur dioxide',data=wine)
        plt.subplot(3,4,7)
        sns.barplot(x='quality',y='total sulfur dioxide',data=wine)
        plt.subplot(3,4,8)
        sns.barplot(x='quality',y='density',data=wine)
        plt.subplot(3,4,9)
        sns.barplot(x='quality',y='pH',data=wine)
        plt.subplot(3,4,10)
        sns.barplot(x='quality',y='sulphates',data=wine)
        plt.subplot(3,4,11)
        sns.barplot(x='quality',y='alcohol',data=wine)
        plt.tight layout()
```



```
In [6]: wine['quality'].value_counts()
```

Out[6]: 5 681 6 638 7 199 4 53 8 18 3 10

Name: quality, dtype: int64

```
In [7]: ranges = (2,6.5,8)
    groups = ['bad','good']
    wine['quality'] = pd.cut(wine['quality'],bins=ranges,labels=groups)
    le = LabelEncoder()
    wine['quality'] = le.fit_transform(wine['quality'])
    wine.head()
```

Out[7]:		fixed acidity			residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcohol
	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 [8]: wine['quality'].value_counts()
```

Out[8]: 0 1382 1 217

Name: quality, dtype: int64

```
In [9]: good_quality = wine[wine['quality']==1]
bad_quality = wine[wine['quality']==0]

bad_quality = bad_quality.sample(frac=1)
bad_quality = bad_quality[:217]

new_df = pd.concat([good_quality,bad_quality])
new_df = new_df.sample(frac=1)
new_df
```

Out[9]:		fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	рН	sulphates	alcol
	1421	7.5	0.400	0.18	1.6	0.079	24.0	58.0	0.99650	3.34	0.58	
	549	9.0	0.530	0.49	1.9	0.171	6.0	25.0	0.99750	3.27	0.61	
	1193	6.4	0.885	0.00	2.3	0.166	6.0	12.0	0.99551	3.56	0.51	1
	124	7.8	0.500	0.17	1.6	0.082	21.0	102.0	0.99600	3.39	0.48	
	640	9.9	0.540	0.45	2.3	0.071	16.0	40.0	0.99910	3.39	0.62	
	•••										•••	
	1204	7.2	0.360	0.46	2.1	0.074	24.0	44.0	0.99534	3.40	0.85	1
	842	10.6	0.500	0.45	2.6	0.119	34.0	68.0	0.99708	3.23	0.72	1
	290	8.7	0.520	0.09	2.5	0.091	20.0	49.0	0.99760	3.34	0.86	1
	1440	7.2	0.370	0.32	2.0	0.062	15.0	28.0	0.99470	3.23	0.73	1

0.086

6.0

19.0 0.99880 3.22

0.69

1

434 rows × 12 columns

11.3

0.620

0.67

5.2

455

```
new_df['quality'].value_counts()
In [10]:
               217
Out[10]:
               217
         Name: quality, dtype: int64
In [11]:
          new_df.corr()['quality'].sort_values(ascending=False)
         quality
                                  1.000000
Out[11]:
          alcohol
                                  0.577559
         sulphates
                                  0.355054
          citric acid
                                  0.319310
         fixed acidity
                                  0.174802
                                 -0.001258
         residual sugar
         рΗ
                                 -0.069247
         free sulfur dioxide
                                 -0.088221
         chlorides
                                 -0.209602
         total sulfur dioxide
                                 -0.213407
         density
                                 -0.245622
         volatile acidity
                                 -0.457369
         Name: quality, dtype: float64
In [18]: from sklearn.model_selection import train_test_split
          X = new_df.drop('quality',axis=1)
          y = new_df['quality']
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_st
In [19]: param = {'n_estimators':[100,200,300,400,500,600,700,800,900,1000]}
         grid_rf = GridSearchCV(RandomForestClassifier(),param,scoring='accuracy',cv=10,)
         grid_rf.fit(X_train, y_train)
         print('Best parameters --> ', grid_rf.best_params_)
         # Wine Quality Prediction
         pred = grid_rf.predict(X_test)
         print(confusion_matrix(y_test,pred))
         print('\n')
         print(classification_report(y_test,pred))
         print('\n')
         print(accuracy_score(y_test,pred))
         Best parameters --> {'n_estimators': 900}
         [[55 19]
          [ 3 54]]
                                    recall f1-score
                       precision
                                                        support
                            0.95
                                       0.74
                                                 0.83
                                                             74
                    1
                             0.74
                                       0.95
                                                 0.83
                                                             57
             accuracy
                                                 0.83
                                                            131
                            0.84
                                       0.85
                                                 0.83
                                                            131
            macro avg
                                       0.83
                                                 0.83
                                                            131
         weighted avg
                            0.86
```

0.8320610687022901

In []: