WineQualityPrediction - Binary classification by P.Pallavi

July 16, 2022

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import RobustScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix , classification_report ,␣
↪accuracy_score
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
import warnings;
warnings.filterwarnings('ignore');
```

[2]:
```
df_wine = pd.read_csv("QualityPrediction.csv")  # to read the csv file using␣
↪pandas
```

[3]:
```
df = df_wine.copy()  # to make a copy of dataframe
```

[4]:
```
df.info() # to see the information related to the dataset and observed no␣
↪missing values
```

```
<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
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
```

```
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```

[5]:
```
df.shape
```

[5]:
```
(1599, 12)
```

[6]:
```
df.describe()
```

[6]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    1599.000000       1599.000000  1599.000000     1599.000000
mean        8.319637          0.527821     0.270976        2.538806
std         1.741096          0.179060     0.194801        1.409928
min         4.600000          0.120000     0.000000        0.900000
25%         7.100000          0.390000     0.090000        1.900000
50%         7.900000          0.520000     0.260000        2.200000
75%         9.200000          0.640000     0.420000        2.600000
max        15.900000          1.580000     1.000000       15.500000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  1599.000000          1599.000000           1599.000000  1599.000000
mean      0.087467            15.874922             46.467792     0.996747
std       0.047065            10.460157             32.895324     0.001887
min       0.012000             1.000000              6.000000     0.990070
25%       0.070000             7.000000             22.000000     0.995600
50%       0.079000            14.000000             38.000000     0.996750
75%       0.090000            21.000000             62.000000     0.997835
max       0.611000            72.000000            289.000000     1.003690

                pH    sulphates      alcohol      quality
count  1599.000000  1599.000000  1599.000000  1599.000000
mean      3.311113     0.658149    10.422983     5.636023
std       0.154386     0.169507     1.065668     0.807569
min       2.740000     0.330000     8.400000     3.000000
25%       3.210000     0.550000     9.500000     5.000000
50%       3.310000     0.620000    10.200000     6.000000
75%       3.400000     0.730000    11.100000     6.000000
max       4.010000     2.000000    14.900000     8.000000
```

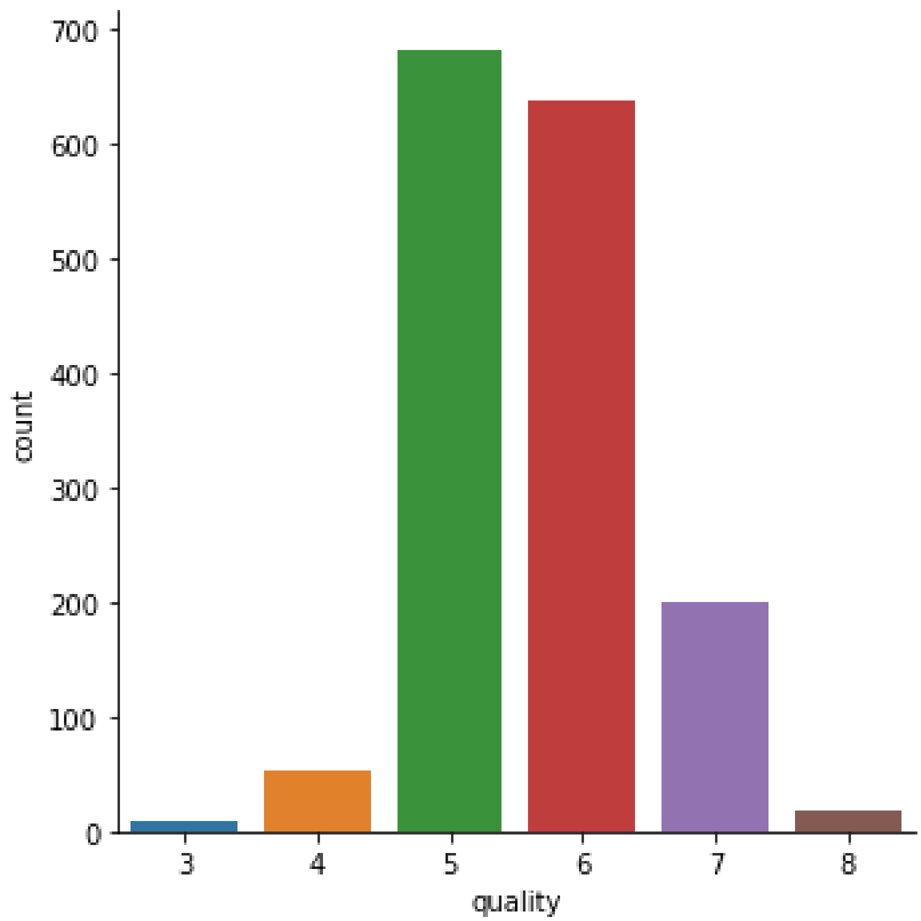
1 Exploratory Data Analysis(Data Visualization using Seaborn and Matplotlib)

[7]:
```
df['quality'].unique() # the target variable quality has unique categories of␣
↪3,4,5,6,7,8
```

[7]:
```
array([5, 6, 7, 4, 8, 3], dtype=int64)
```

[8]:
```
# The target variable 'quality' has high number of values in catagories 5,6 & 7␣
↪and lower
# number of values in catagories 3,4,8.
sns.catplot(x ='quality', data = df, kind='count')
```

[8]:
```
<seaborn.axisgrid.FacetGrid at 0x1a5315ae940>
```

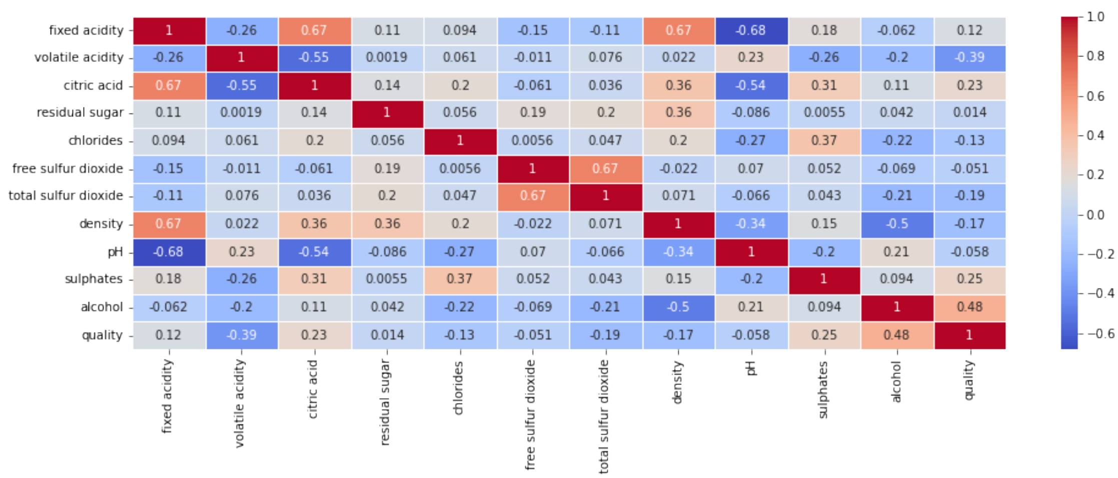


[9]:
```
df['quality'].value_counts()/len(df['quality']) # Shows that the categorical␣
↪data is unbalanced
```

[9]:
```
5    0.425891
6    0.398999
7    0.124453
4    0.033146
8    0.011257
3    0.006254
Name: quality, dtype: float64
```

[10]:
```python
# From the heatmap it is observed that fixed acidity and density are positive␣
↪moderately
# correlated with co-efficent of 0.67
plt.figure(figsize = (16,5))
sns.heatmap(df.corr(), annot = True, cmap="coolwarm",linewidths=1)
```

[10]:
```
<AxesSubplot:>
```

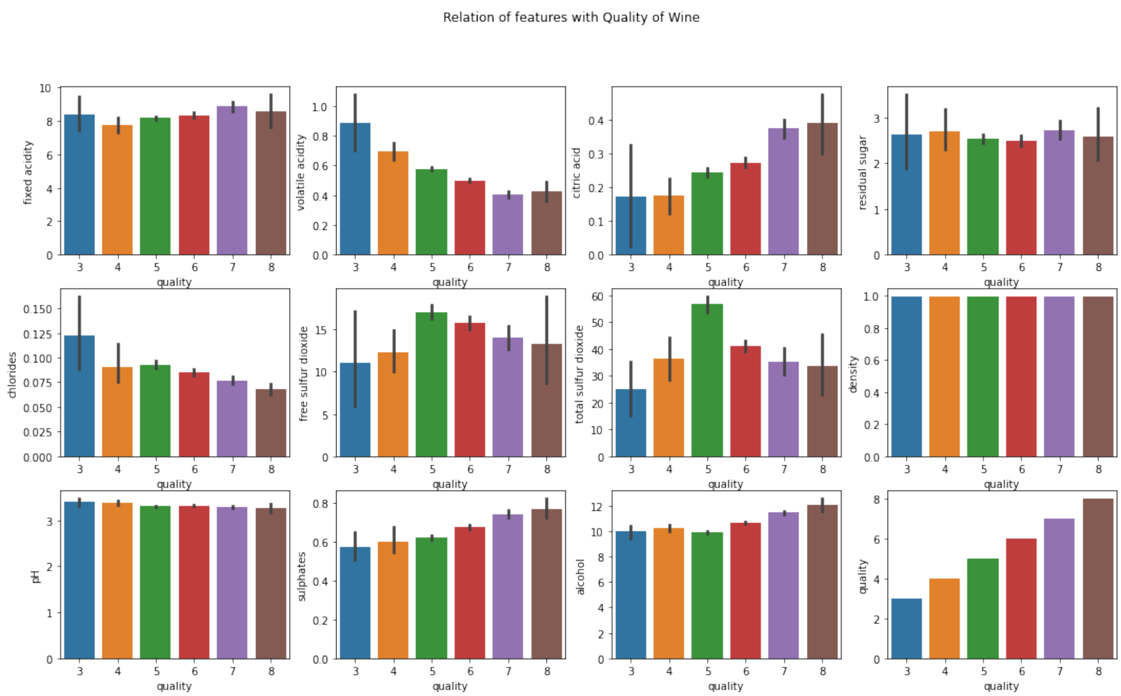


[11]:
```python
df.columns
```

[11]:
```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol', 'quality'],
      dtype='object')
```

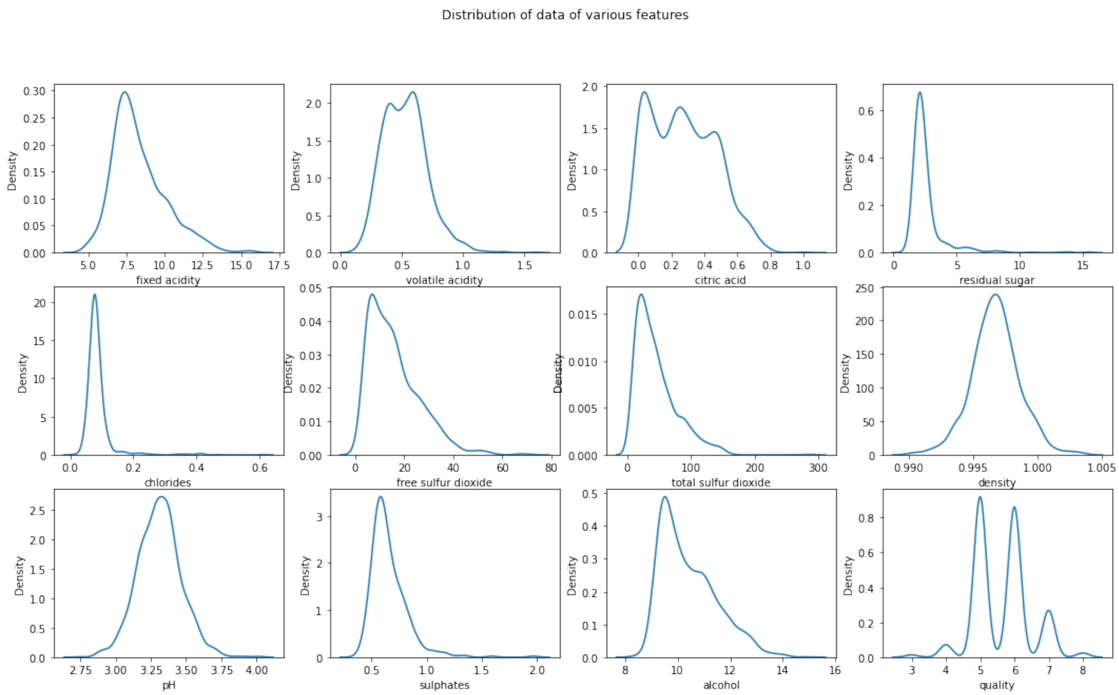
[12]:
```python
# The observations from the subplots are as follows
#1. Fixed acidity is not related to the quality of wine.
#2. Volatile acidity is inversely related to quality, higher the  quality,␣
↪lower
# the volatile acidity.
#3. Citric acidity and quality are directly related, higher the quality, higher␣
↪the
# citric acid composition.
```

```
#4. Residual Sugar composition is almost same irrespective of wine quality.
#5. Composition of chloride is less in higher quality wines.
#6. Density and pH value is almost same irrespective of wine quality.
#7. Sulphates and alcohol composition goes higher with increase in quality of␣
↪wine.
features = np.array(['fixed acidity', 'volatile acidity', 'citric acid',␣
↪'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol','quality'])
f = features.reshape(3,4)
fig, axes = plt.subplots(3, 4, figsize=(18, 10))
fig.suptitle('Relation of features with Quality of Wine')
for i in range(0,3):
    for j in range(0,4):
        sns.barplot(ax=axes[i, j], data = df, x = 'quality', y = f[i,j])
```

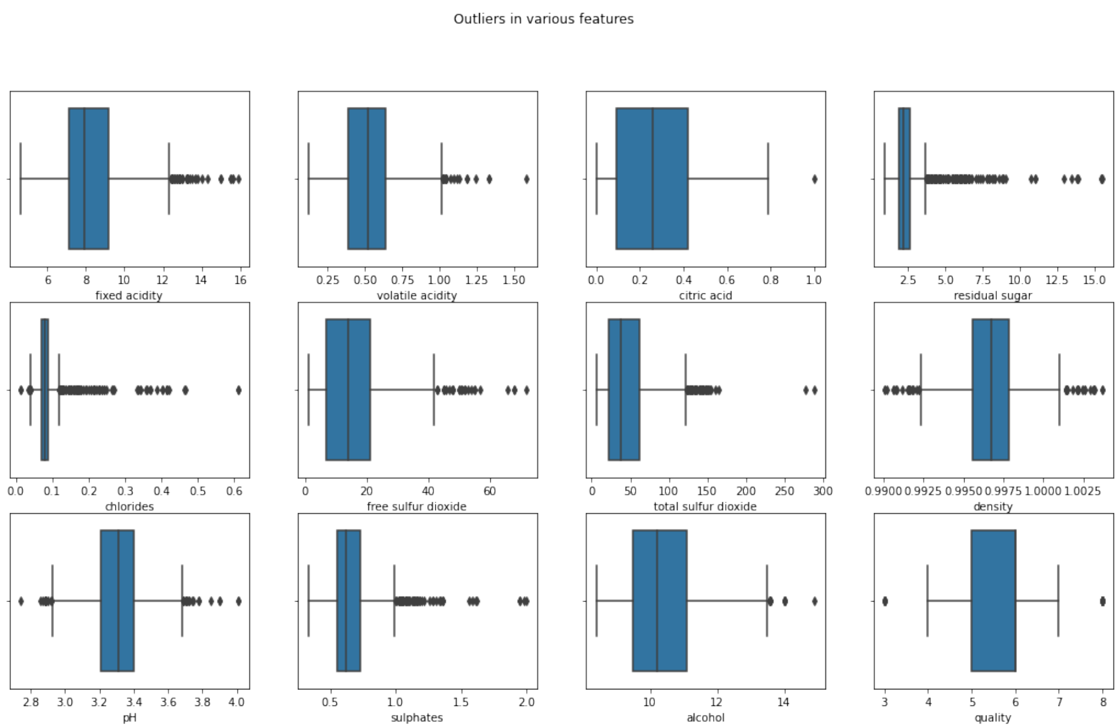


[13]:
```
# Except density and pH, all the features of the dataset are right skewed
features = np.array(['fixed acidity', 'volatile acidity', 'citric acid',␣
↪'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol','quality'])
f = features.reshape(3,4)
fig, axes = plt.subplots(3, 4, figsize=(18, 10))
```

```
fig.suptitle('Distribution of data of various features')
for i in range(0,3):
    for j in range(0,4):
        sns.kdeplot(ax=axes[i, j], data = df, x = f[i,j] )
```



[14]:
```
# All the features of the dataset has outliers
features = np.array(['fixed acidity', 'volatile acidity', 'citric acid',␣
↪'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol','quality'])
f = features.reshape(3,4)
fig, axes = plt.subplots(3, 4, figsize=(18, 10))
fig.suptitle('Outliers in various features')
for i in range(0,3):
    for j in range(0,4):
        sns.boxplot(ax=axes[i, j], data = df, x = f[i,j] )
```



2 2. Data preprocessing

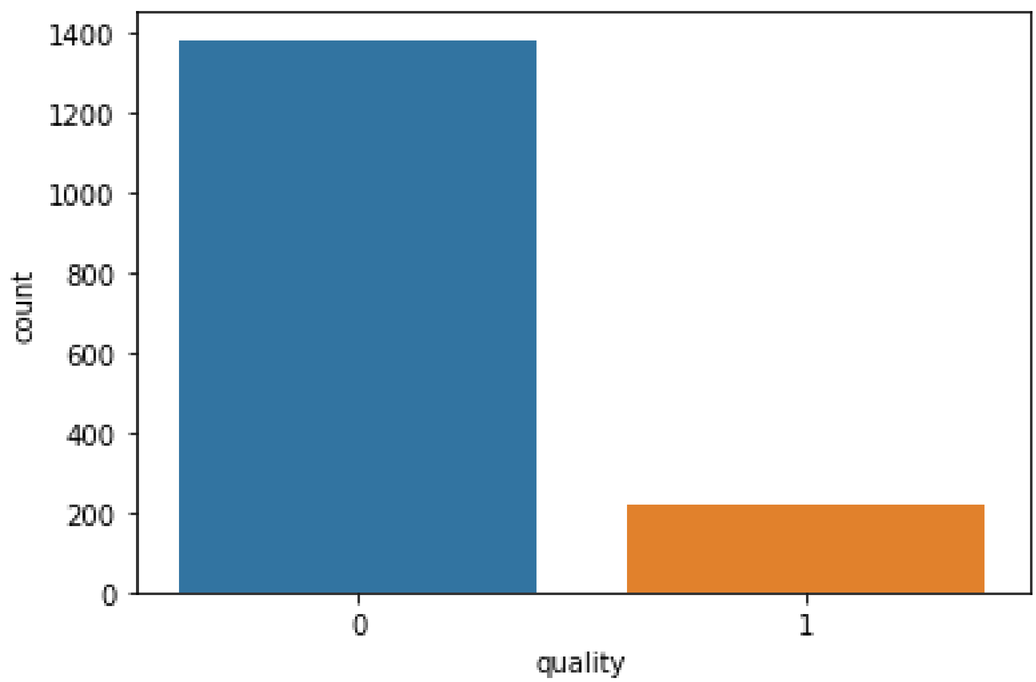
[16]:
```python
# The wine with ranking less than 6 considered as low quality wine designated␣
↪with
#'0' and ranking more than  6 considered as high quality wine designated with␣
↪'1'.
#The categorical target data quality encoded with '0' and '1's using mapping␣
↪function
df['quality'] = df['quality'].map({3:0,4:0,5:0,6:0,7:1,8:1})
df
```

[16]:
```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0               7.4             0.700         0.00             1.9      0.076
1               7.8             0.880         0.00             2.6      0.098
2               7.8             0.760         0.04             2.3      0.092
3              11.2             0.280         0.56             1.9      0.075
4               7.4             0.700         0.00             1.9      0.076
…               …               …           …                …          …
1594            6.2             0.600         0.08             2.0      0.090
1595            5.9             0.550         0.10             2.2      0.062
1596            6.3             0.510         0.13             2.3      0.076
1597            5.9             0.645         0.12             2.0      0.075
1598            6.0             0.310         0.47             3.6      0.067
```

```
      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                    11.0                  34.0  0.99780  3.51       0.56
1                    25.0                  67.0  0.99680  3.20       0.68
2                    15.0                  54.0  0.99700  3.26       0.65
3                    17.0                  60.0  0.99800  3.16       0.58
4                    11.0                  34.0  0.99780  3.51       0.56
…                     …                   …       …     …        …
1594                 32.0                  44.0  0.99490  3.45       0.58
1595                 39.0                  51.0  0.99512  3.52       0.76
1596                 29.0                  40.0  0.99574  3.42       0.75
1597                 32.0                  44.0  0.99547  3.57       0.71
1598                 18.0                  42.0  0.99549  3.39       0.66

      alcohol  quality
0         9.4        0
1         9.8        0
2         9.8        0
3         9.8        0
4         9.4        0
…       …      …
1594     10.5        0
1595     11.2        0
1596     11.0        0
1597     10.2        0
1598     11.0        0

[1599 rows x 12 columns]
```

[17]:
```
sns.countplot(df['quality'])
```

[17]: <AxesSubplot:xlabel='quality', ylabel='count'>



[18]:
```
# From the boxplot of EDA part, it is observed that, almost all the features of
# data are right skewed, hence using #RobustScaler() preprocessing method for
# feature scaling
df.columns
X = df.drop('quality',axis=1).values
scaler = RobustScaler()
df_scale= pd.DataFrame(scaler.fit_transform(X), columns = ['fixed acidity',␣
↪'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol'])
df_scale
```

[18]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	\
0	-0.238095	0.72	-0.787879	-0.428571	-0.15	
1	-0.047619	1.44	-0.787879	0.571429	0.95	
2	-0.047619	0.96	-0.666667	0.142857	0.65	
3	1.571429	-0.96	0.909091	-0.428571	-0.20	
4	-0.238095	0.72	-0.787879	-0.428571	-0.15	
…	…	…	…	…	…	
1594	-0.809524	0.32	-0.545455	-0.285714	0.55	
1595	-0.952381	0.12	-0.484848	0.000000	-0.85	
1596	-0.761905	-0.04	-0.393939	0.142857	-0.15	
1597	-0.952381	0.50	-0.424242	-0.285714	-0.20	
1598	-0.904762	-0.84	0.636364	2.000000	-0.60	

```
      free sulfur dioxide  total sulfur dioxide   density        pH  \
0               -0.214286                -0.100  0.469799  1.052632
1                0.785714                 0.725  0.022371 -0.578947
2                0.071429                 0.400  0.111857 -0.263158
3                0.214286                 0.550  0.559284 -0.789474
4               -0.214286                -0.100  0.469799  1.052632
…                     …                     …       …         …
1594             1.285714                 0.150 -0.827740  0.736842
1595             1.785714                 0.325 -0.729306  1.105263
1596             1.071429                 0.050 -0.451902  0.578947
1597             1.285714                 0.150 -0.572707  1.368421
1598             0.285714                 0.100 -0.563758  0.421053

      sulphates  alcohol
0     -0.333333  -0.5000
1      0.333333  -0.2500
2      0.166667  -0.2500
3     -0.222222  -0.2500
4     -0.333333  -0.5000
…          …       …
1594  -0.222222   0.1875
1595   0.777778   0.6250
1596   0.722222   0.5000
1597   0.500000   0.0000
1598   0.222222   0.5000

[1599 rows x 11 columns]
```

[19]:

```python
# Since more features are involved in the dataset, using VIF to evaluate
# multicollinearity. Fixed acidity and density are
# multicollinear with respect to other features in the dataset as the VIF > 5.

# VIF dataframe
vif_data = pd.DataFrame()
vif_data["Feature"] = df_scale.columns

# calculating VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(df_scale.values, i)
                          for i in range(len(df_scale.columns))]
vif_data = vif_data.sort_values(by = "VIF", ascending = False)

print(vif_data)
```

```
             Feature       VIF
0      fixed acidity  5.711998
7            density  5.250172
```

```
10              alcohol  3.088076
2           citric acid  2.991682
8                    pH  2.789818
6  total sulfur dioxide  2.148662
5   free sulfur dioxide  2.012653
1      volatile acidity  1.792550
3        residual sugar  1.611141
9             sulphates  1.454095
4             chlorides  1.442854
```

[21]:
```python
df_scale['quality_en']=df['quality'].values
df_scale
```

[21]:
```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0         -0.238095              0.72    -0.787879       -0.428571      -0.15
1         -0.047619              1.44    -0.787879        0.571429       0.95
2         -0.047619              0.96    -0.666667        0.142857       0.65
3          1.571429             -0.96     0.909091       -0.428571      -0.20
4         -0.238095              0.72    -0.787879       -0.428571      -0.15
…               …                 …            …              …          …
1594      -0.809524              0.32    -0.545455       -0.285714       0.55
1595      -0.952381              0.12    -0.484848        0.000000      -0.85
1596      -0.761905             -0.04    -0.393939        0.142857      -0.15
1597      -0.952381              0.50    -0.424242       -0.285714      -0.20
1598      -0.904762             -0.84     0.636364        2.000000      -0.60

      free sulfur dioxide  total sulfur dioxide   density        pH  \
0               -0.214286                -0.100  0.469799  1.052632
1                0.785714                 0.725  0.022371 -0.578947
2                0.071429                 0.400  0.111857 -0.263158
3                0.214286                 0.550  0.559284 -0.789474
4               -0.214286                -0.100  0.469799  1.052632
…                     …                    …        …        …
1594             1.285714                 0.150 -0.827740  0.736842
1595             1.785714                 0.325 -0.729306  1.105263
1596             1.071429                 0.050 -0.451902  0.578947
1597             1.285714                 0.150 -0.572707  1.368421
1598             0.285714                 0.100 -0.563758  0.421053

      sulphates  alcohol  quality_en
0     -0.333333  -0.5000           0
1      0.333333  -0.2500           0
2      0.166667  -0.2500           0
3     -0.222222  -0.2500           0
4     -0.333333  -0.5000           0
…           …        …         …
1594  -0.222222   0.1875           0
```

```
1595    0.777778    0.6250          0
1596    0.722222    0.5000          0
1597    0.500000    0.0000          0
1598    0.222222    0.5000          0

[1599 rows x 12 columns]
```

3 Prediction using various ML models for binary classification.

As the target variable is available in the dataset, I am using supervised ML models to predict the output and target variable is categorical data, i am using classification models such linear regression, Decision tree, Random forest, KNN, Naive Bayes and Support Vector Machine learning models for prediction. As scaling is not required for Decision tree,NB and Random forest models, so using unscaled data for prediction. For remaining all the models except Decision,NB and Random forest, I am using scaled data for prediction(Scaled data is represented with X and Y), unscaled data represented with x and y.

4 1. Logistic Regression ML model

Logistic Regression ML model is distance based model, using scaled data into the model for prediction

[23]:
```
X = df_scale.drop('quality_en',axis=1).values
```

[24]:
```
Y = df_scale['quality_en'].values
```

[25]:
```
# X_train, X_test represents scaled data
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size=0.
↪25,random_state=0)
```

[26]:
```
# instanstiation of LogisticRegression
log_reg = LogisticRegression(random_state=0)
log_reg.fit(X_train,Y_train)
print(log_reg.fit(X_train,Y_train))
```

```
LogisticRegression(random_state=0)
```

[27]:
```
Y_pred_LR=log_reg.predict(X_test)
```

[28]:
```
# the confusion matrix shows the same format everytime: (TN , FP, FN , TP) with␣
↪actuals
# being the rows and predicted being the columns.

from sklearn.metrics import confusion_matrix
conf_matrix = confusion_matrix(Y_test,Y_pred_LR)
conf_matrix      #Check   ()
```

[28]:
```
array([[341,  14],
       [ 29,  16]], dtype=int64)
```

[29]:
```
print("Accuracy: ",accuracy_score(Y_test,Y_pred_LR))   #  (TP + TN )/ Total
```

```
Accuracy:  0.8925
```

[30]:
```
print(classification_report(Y_test,Y_pred_LR))
```

```
              precision    recall  f1-score   support

           0       0.92      0.96      0.94       355
           1       0.53      0.36      0.43        45

    accuracy                           0.89       400
   macro avg       0.73      0.66      0.68       400
weighted avg       0.88      0.89      0.88       400
```

[31]:
```
from sklearn.model_selection import cross_val_score

scores = cross_val_score(log_reg, X_train, Y_train, cv=5)
scores.mean()
```

[31]:
```
0.8690620641562063
```

The accuracy obtained using Logistic Regression ML model is 89%.

5 2. Decision tree ML model using Hyperparameter tuning

As the Decision tree and Random forest models does not depend upon scaling, hence using unscaled data into the model

[32]:
```
df
```

[32]:
```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0               7.4             0.700         0.00             1.9      0.076
1               7.8             0.880         0.00             2.6      0.098
2               7.8             0.760         0.04             2.3      0.092
3              11.2             0.280         0.56             1.9      0.075
4               7.4             0.700         0.00             1.9      0.076
…                 …                 …          …               …          …
1594            6.2             0.600         0.08             2.0      0.090
1595            5.9             0.550         0.10             2.2      0.062
1596            6.3             0.510         0.13             2.3      0.076
1597            5.9             0.645         0.12             2.0      0.075
1598            6.0             0.310         0.47             3.6      0.067
```

```
      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                    11.0                  34.0  0.99780  3.51       0.56
1                    25.0                  67.0  0.99680  3.20       0.68
2                    15.0                  54.0  0.99700  3.26       0.65
3                    17.0                  60.0  0.99800  3.16       0.58
4                    11.0                  34.0  0.99780  3.51       0.56
…                     …                     …       …     …         …
1594                 32.0                  44.0  0.99490  3.45       0.58
1595                 39.0                  51.0  0.99512  3.52       0.76
1596                 29.0                  40.0  0.99574  3.42       0.75
1597                 32.0                  44.0  0.99547  3.57       0.71
1598                 18.0                  42.0  0.99549  3.39       0.66

      alcohol  quality
0         9.4        0
1         9.8        0
2         9.8        0
3         9.8        0
4         9.4        0
…         …       …
1594     10.5        0
1595     11.2        0
1596     11.0        0
1597     10.2        0
1598     11.0        0

[1599 rows x 12 columns]
```

[48]:
```
x = df.drop('quality',axis=1).values
y = df['quality'].values
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
↪25,random_state=0)
```

[49]:
```
# Set the random state for reproducibility
fit_dt = DecisionTreeClassifier()
```

[50]:
```
# Providing the different values of hyperparameters
param_dist_dt = {'max_depth': [2, 3, 4, 8, 16],
              'max_features': ['auto', 'sqrt', 'log2'],
               'criterion': ['gini', 'entropy'],
             'max_leaf_nodes':[4,8,16,32,64],
             "random_state":[0,1,2,3,4,5]}

# Running gridsearchCV to check for all the different PnCs of these parameter␣
↪values
cv_dt= GridSearchCV(fit_dt,cv = 10,
                     param_grid=param_dist_dt,
```

```
                     n_jobs = 3)

#Fitting the train set , so that grid search is executed on this dataset
cv_dt.fit(x_train, y_train)

#Printing the best parameters by using best_params
print('Best Parameters using grid search: \n', cv_dt.best_params_)
```

```
Best Parameters using grid search:
 {'criterion': 'gini', 'max_depth': 16, 'max_features': 'auto',
'max_leaf_nodes': 64, 'random_state': 4}
```

[51]:

```
#Finally the best parameters are specified

fit_dt.set_params(criterion = 'gini',
                  max_features = 'auto',
                  max_leaf_nodes = 64,
                  max_depth = 16,
                  random_state = 4)
```

[51]:

```
DecisionTreeClassifier(max_depth=16, max_features='auto', max_leaf_nodes=64,
                       random_state=4)
```

[52]:

```
fit_dt.fit(x_train, y_train)
y_pred_dt = fit_dt.predict(x_test)
```

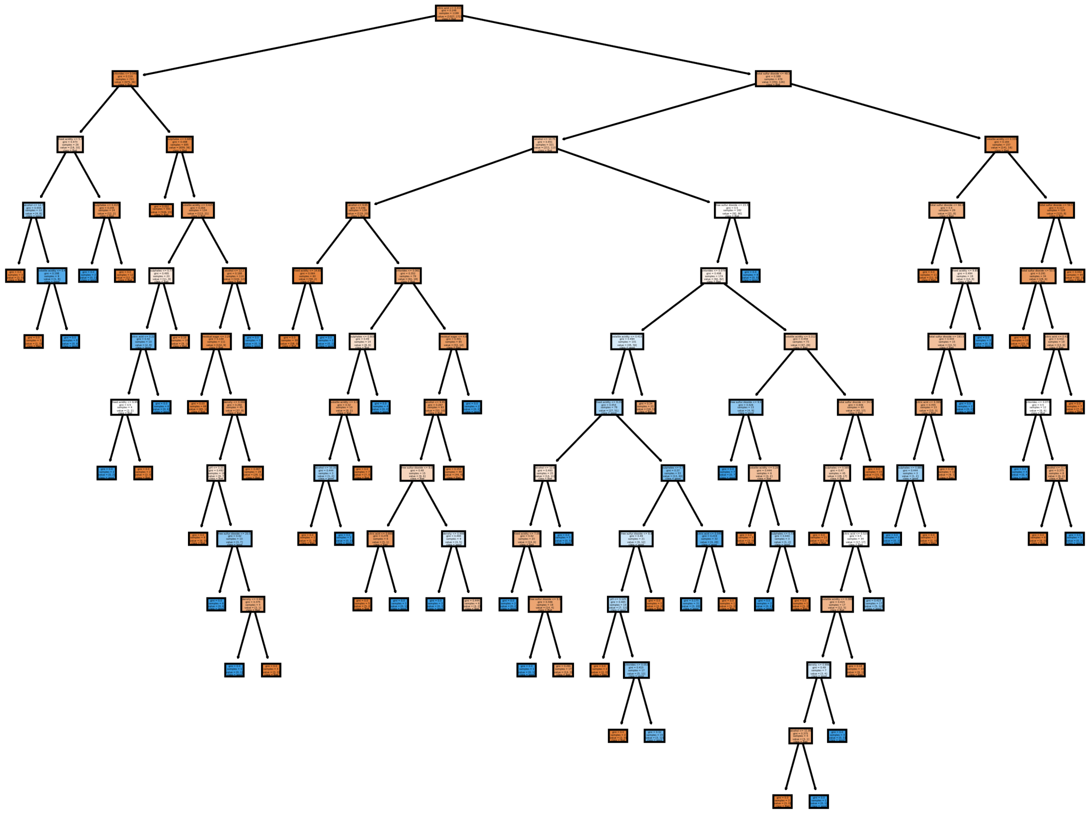
[53]:

```
print(confusion_matrix(y_test,y_pred_dt))
```

```
[[334  21]
 [ 26  19]]
```

[54]:

```
from sklearn import tree
df1=pd.DataFrame(df.drop(['quality'],axis=1))
column_names=list(df1.columns)
fn=column_names
cn=['Bad','good']

fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (10,8), dpi=300)

tree.plot_tree(fit_dt,
           feature_names = fn,
           class_names=cn,
           filled = True);

fig.savefig('DecisionTree.png')
```



[55]:
```
print(classification_report(y_test,y_pred_dt))
```

```
              precision    recall  f1-score   support

           0       0.93      0.94      0.93       355
           1       0.47      0.42      0.45        45

    accuracy                           0.88       400
   macro avg       0.70      0.68      0.69       400
weighted avg       0.88      0.88      0.88       400
```

[56]:
```
print(accuracy_score(y_test,y_pred_dt))
```

```
0.8825
```

[57]:
```
from sklearn.model_selection import cross_val_score

scores = cross_val_score(DecisionTreeClassifier(max_depth=2), x_train, y_train,␣
 ↪cv=5)
```

```
scores.mean()
```

[57]: 0.8757426778242678

The accuracy obtained using Decision tree ML model is 88%.

6 3. Random Forest ML model using hyperparameter tuning

[58]:
```
# instantiation
fit_rf = RandomForestClassifier()
```

[59]:
```
# Providing the different values of hyperparameters
param_dist = {'max_depth': [2, 3, 4],
              'max_features': ['auto', 'sqrt', 'log2', None],
                'bootstrap' : [True, False],
              'criterion': ['gini', 'entropy'],
             'random_state':[0,1,2,3,4,5]}

# Running gridsearchCV to check for all the different PnCs of these parameter␣
↪values
cv_rf = GridSearchCV(fit_rf, cv = 10,
                     param_grid=param_dist,
                     n_jobs = 3)

#Fitting the train set , so that grid search is executed on this dataset
cv_rf.fit(x_train, y_train)

#Printing the best parameters by using best_params
print('Best Parameters using grid search: \n', cv_rf.best_params_)
```

```
Best Parameters using grid search:
 {'bootstrap': True, 'criterion': 'gini', 'max_depth': 4, 'max_features': None,
'random_state': 4}
```

[60]:
```
#Finally the best parameters are specified

fit_rf.set_params(criterion = 'gini',
                  max_features = None,
                  bootstrap = True,
                  max_depth = 4, random_state= 4 )
```

[60]: RandomForestClassifier(max_depth=4, max_features=None, random_state=4)

[61]:
```
fit_rf.fit(x_train, y_train)
y_pred_rf = fit_rf.predict(x_test)
```

[62]:
```
print(confusion_matrix(y_test,y_pred_rf))
```

```
[[342  13]
 [ 28  17]]
```

[63]:
```
print(accuracy_score(y_test,y_pred_rf))
```

```
0.8975
```

[64]:
```
print(classification_report(y_test,y_pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.92      0.96      0.94       355
           1       0.57      0.38      0.45        45

    accuracy                           0.90       400
   macro avg       0.75      0.67      0.70       400
weighted avg       0.88      0.90      0.89       400
```

[65]:
```
#  To crossvalidate the dataset

from sklearn.model_selection import cross_val_score

scores = cross_val_score(fit_rf, x_train, y_train, cv=5)
scores.mean()
```

[65]: 0.8799093444909344

The accuracy of Random forest ML model is 90%.

7 4. K-Nearest Neighbours ML model

(As KNN is distance based model,so using scaled input data for prediction, X_train and Y_train)

[66]:
```
knn = KNeighborsClassifier()
# Providing the different values of hyperparameters
param_dist = {'n_neighbors': list(range(2,40)),
              }

# Running gridsearchCV to check for all the different PnCs of these parameter␣
↪values
cv_knn = GridSearchCV(knn, cv = 10,
                      param_grid=param_dist,
                      n_jobs = 3)
```

```python
#Fitting the train set , so that grid search is executed on this dataset
cv_knn.fit(X_train, Y_train)

#Printing the best parameters by using best_params
print('Best Parameters using grid search: \n', cv_knn.best_params_)
```

```
Best Parameters using grid search:
 {'n_neighbors': 31}
```

[67]:
```python
#Finally using the optimum value of K = 31
knn = KNeighborsClassifier(n_neighbors = 31)
knn.fit(X_train,Y_train)                                  #fit
Y_pred_knn = knn.predict(X_test)                          #Predict

print(confusion_matrix(Y_test,Y_pred_knn))
```

```
[[343  12]
 [ 31  14]]
```

[68]:
```python
print(accuracy_score(Y_test,Y_pred_knn))
```

```
0.8925
```

[69]:
```python
print(classification_report(Y_test,Y_pred_knn))
```

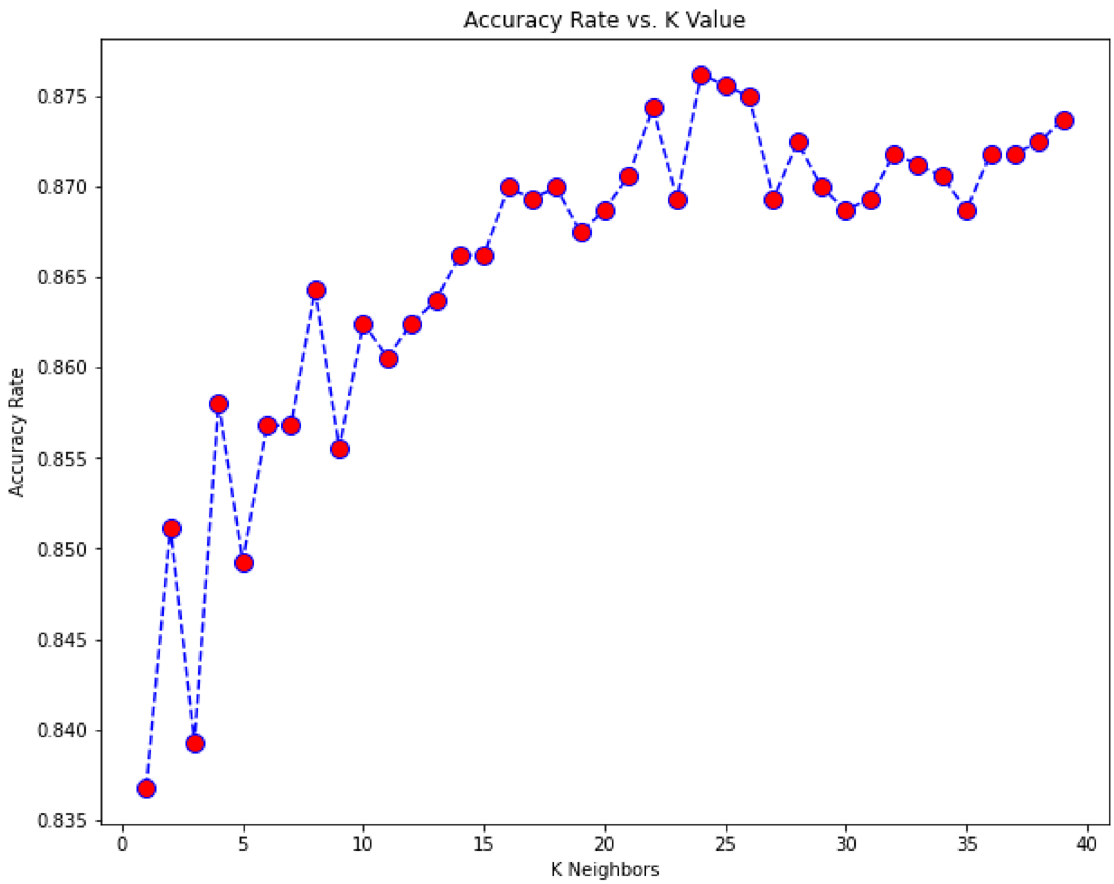
```
              precision    recall  f1-score   support

           0       0.92      0.97      0.94       355
           1       0.54      0.31      0.39        45

    accuracy                           0.89       400
   macro avg       0.73      0.64      0.67       400
weighted avg       0.87      0.89      0.88       400
```

[70]:
```python
accuracy_rate = []
for i in range(1,40):     # May take some time
    knn = KNeighborsClassifier(n_neighbors=i)
    score=cross_val_score(knn,df_scale.iloc[:, df_scale.columns !=
 ↪'quality_en'],df_scale['quality_en'],cv=10)
    accuracy_rate.append(score.mean())

#For different number of neighbors the model is run several times using FOR loop
# cross_val_score returns the accuracy score of all the 10 validations done
 ↪since cv = 10
# In the Accuracy list the mean of all 10 scores is stored.
```

```
#Hence we have the mean accuracy score for each iteration.
```

[71]:
```
#Plotting the mean accuracy socre against all the K values

plt.figure(figsize = (10,8))
plt.plot(range(1,40),accuracy_rate,color='blue', linestyle='dashed', marker='o',
         markerfacecolor='red', markersize=10)
plt.title('Accuracy Rate vs. K Value')
plt.xlabel('K Neighbors')
plt.ylabel('Accuracy Rate')
```

[71]: Text(0, 0.5, 'Accuracy Rate')



The accuracy obtained using KNN ML model is 89%

8 5. Prediction using Naive Bayes ML model

[72]:
```
# Instanstiation of the Gaussian Classifier
model = GaussianNB()

# Train the model
model.fit(x_train, y_train)
```

[72]: GaussianNB()

[73]:
```
# Predict Output
y_pred_nb = model.predict(x_test)
print(confusion_matrix(y_test, y_pred_nb))
```

```
[[298  57]
 [ 13  32]]
```

[74]:
```
print(accuracy_score(y_test,y_pred_nb))
```

```
0.825
```

[75]:
```
print(classification_report(y_test,y_pred_nb))
```

```
              precision    recall  f1-score   support

           0       0.96      0.84      0.89       355
           1       0.36      0.71      0.48        45

    accuracy                           0.82       400
   macro avg       0.66      0.78      0.69       400
weighted avg       0.89      0.82      0.85       400
```

The accuracy obtained using Naive Bayes ML model is 82%.

9 6. Prediction using SVM ML model

As model is distance based,using scaled data into the model

[76]:
```
from sklearn.svm import SVC     #support Vector Classifier
                                #default kernel is rbf
svc = SVC(random_state = 5)
svc.fit(X_train,Y_train)
Y_pred_svc = svc.predict(X_test)
```

[82]:
```
print(confusion_matrix(Y_test,Y_pred_svc))
```

```
[[351   4]
 [ 32  13]]
```

[83]:
```python
print(accuracy_score(Y_test,Y_pred_svc))
```

```
0.91
```

[84]:
```python
print(classification_report(Y_test,Y_pred_svc))
```

```
              precision    recall  f1-score   support

           0       0.92      0.99      0.95       355
           1       0.76      0.29      0.42        45

    accuracy                           0.91       400
   macro avg       0.84      0.64      0.69       400
weighted avg       0.90      0.91      0.89       400
```

The accuracy of SVM ML model is 91%

As the multicollinearity of features affects the accuracy of models, hereby dropping the features which are multicollinear with respect to other features in dataset and also dropping the features which does not affect the target variable. observed the accuracy of Logistic regression Model as 90%.

[85]:
```python
df_scale_M = df_scale.drop(['fixed acidity','density','residual sugar','free␣
↪sulfur dioxide'],axis=1)
df_scale_M
```

[85]:
```
      volatile acidity  citric acid  chlorides  total sulfur dioxide  \
0                 0.72    -0.787879      -0.15                -0.100
1                 1.44    -0.787879       0.95                 0.725
2                 0.96    -0.666667       0.65                 0.400
3                -0.96     0.909091      -0.20                 0.550
4                 0.72    -0.787879      -0.15                -0.100
…                    …          …         …                    …
1594              0.32    -0.545455       0.55                 0.150
1595              0.12    -0.484848      -0.85                 0.325
1596             -0.04    -0.393939      -0.15                 0.050
1597              0.50    -0.424242      -0.20                 0.150
1598             -0.84     0.636364      -0.60                 0.100

            pH  sulphates  alcohol  quality_en
0     1.052632  -0.333333  -0.5000           0
1    -0.578947   0.333333  -0.2500           0
2    -0.263158   0.166667  -0.2500           0
3    -0.789474  -0.222222  -0.2500           0
4     1.052632  -0.333333  -0.5000           0
```

```
...        ...        ...      ...          ...
1594  0.736842  -0.222222   0.1875            0
1595  1.105263   0.777778   0.6250            0
1596  0.578947   0.722222   0.5000            0
1597  1.368421   0.500000   0.0000            0
1598  0.421053   0.222222   0.5000            0

[1599 rows x 8 columns]
```

[86]:
```python
X_M = df_scale_M.drop('quality_en',axis=1).values
```

[87]:
```python
Y_M = df_scale_M['quality_en'].values
```

[88]:
```python
X_train,X_test,Y_train,Y_test = train_test_split(X_M,Y_M,test_size=0.
 ↪25,random_state=0)
```

[89]:
```python
# instanstiation of LogisticRegression
log_reg = LogisticRegression(random_state=0)
log_reg.fit(X_train,Y_train)
print(log_reg.fit(X_train,Y_train))
```

```
LogisticRegression(random_state=0)
```

[90]:
```python
Y_pred_LR=log_reg.predict(X_test)
```

[91]:
```python
# the confusion matrix shows the same format everytime: (TN , FP, FN , TP) with␣
 ↪actuals
# being the rows and predicted being the columns
conf_matrix = confusion_matrix(Y_test,Y_pred_LR)
conf_matrix      #Check   ()
```

[91]:
```
array([[344,  11],
       [ 30,  15]], dtype=int64)
```

[92]:
```python
print("Accuracy: ",accuracy_score(Y_test,Y_pred_LR))   #  (TP + TN )/ Total
```

```
Accuracy:  0.8975
```

[93]:
```python
print(classification_report(Y_test,Y_pred_LR))
```

```
              precision    recall  f1-score   support

           0       0.92      0.97      0.94       355
           1       0.58      0.33      0.42        45

    accuracy                           0.90       400
   macro avg       0.75      0.65      0.68       400
```

```
weighted avg       0.88      0.90      0.89       400
```

The accuracy of Logistic Regression model improved from 89% to 90% after removing multicollinear features from data set

The accuracy observed from the different models for binary classification are as follows 1. Logistic regression model - 89% 2. Decision tree model - 88% 3. Random forest model - 90% 4. KNN model - 89% 5. Naive Bayes - 87% 6. Support Vector ML - 91%

Conclusion :1) It is already observed from the EDA, that the target variable 'quality' of the dataset is imbalanced having multiple categories with majority classes(5,6) and minority classes(3,4,7,8) . This imbalance leads to improper training of the model,i.e, model is trained better with majority class than minority class. So, the model can predict the majority class accurately and fails to predict the minority class. This lead to major fall in the accuracy of all ML models. All ML models for target multiclassification recorded an accuracy around 63-71%. Among all the ML models for classification, Random forest model recorded high accuracy of 70% than other models.

In order to increase the count of minority class in the target, divided the target classes 3,4,5,6,7,8 into two classes good and bad based on the wine quality ranking. 3,4,5,6 are designated with '0'(majority class) - Bad quality wine and 7, 8 are designated with '1'(minority class) good quaity wine. This lead to binary classification of target variable and also observed that the target is still imbalanced. But the count of minority class increased. This lead to increase in the accuracy of machine learning models to 89-91%. All the models unable to reach maximum accuracy due to imbalance target classes i.e, all the models can predict majority classes accurately and fails to predict minority classes. Among all the ML models for classification, SVC ML model recorded high accuracy of 91% than other models.

2) Some of the features in the dataset, doesnot affect the target variable. The features which are multicollinear with(VIF > 5) and the features which does not affect the target feature may be dropped for prediction of target variable.

3) Among the all the ML models, Random Forest and Support vector Classifier ML are best models for good prediction and accuracy.