Objective

- The main objective of this project is to predict wine quality using machine learning algorithms and analyze which model provides better accuracy by comparing the results.
- The first step will be doing an Exploratory Data Analysis and preparing the dataset for ML algos by splitting the dataset into train and test datasets.
- Later, different ML algorithms will be trained on the training dataset and then used for prediction on the test dataset.
- Finally, all the results will be compared on the accuracy to identify the best-suited model to predict the wine quality.

1. Importing the required libraries and modules

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import confusion_matrix, accuracy_score

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

2. Loading the dataset and basic exploration

In [2]:
```
df = pd.read_csv("QualityPrediction.csv")
df.head() #verifying the dataset
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

get the basic info about the dataset, such as no of records, no of features, and data type of the features

In [3]:
```
df.info()
```

```
<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
```

Observations:

- there are 1599 records and 11 (Independent Variables) + 1 (Target Variable) features.

- all features are numeric and in float expect quality which is the target variable.

based on info() it seems there are no missing values, lets's confirm it

In [4]:
```
df.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]:
```
df.describe()
```

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
count	1599.000000	1599.000000	1599.000000	1599.000000	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	0.996747	3.311113	0.658149	10.422983
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324	0.001887	0.154386	0.169507	1.065668
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000	0.990070	2.740000	0.330000	8.400000
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000	0.995600	3.210000	0.550000	9.500000
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000	0.996750	3.310000	0.620000	10.200000
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000	0.997835	3.400000	0.730000	11.100000
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000	1.003690	4.010000	2.000000	14.900000

3. Let's explore target variable - quality

In [6]:
```
df.quality.value_counts()
```

Out[6]:
```
5    681
6    638
7    199
4     53
8     18
3     10
Name: quality, dtype: int64
```

In [7]:
```
#Calculating the percentages for each unique quality value
df.quality.value_counts()/len(df) * 100
```

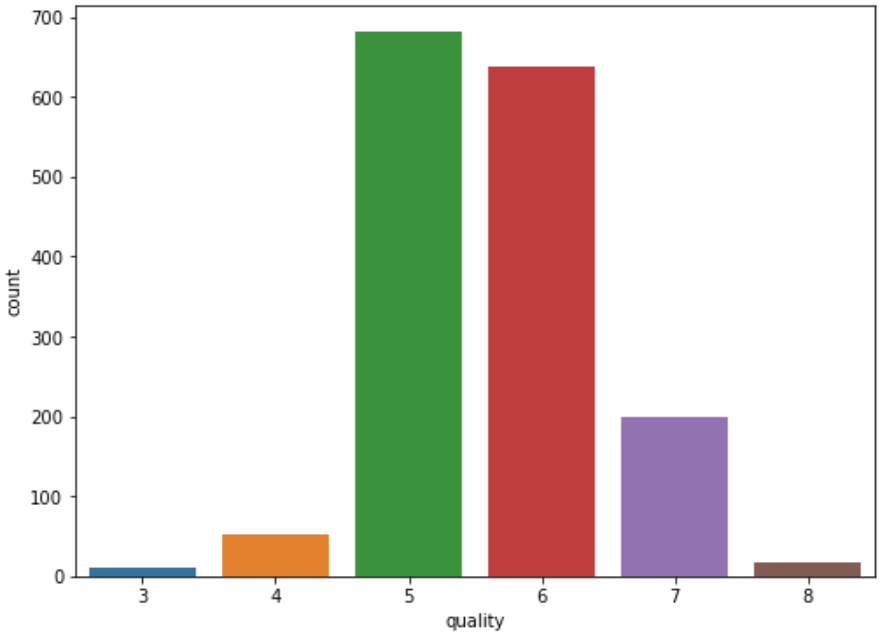
Out[7]:
```
5    42.589118
6    39.899937
7    12.445278
4     3.314572
8     1.125704
3     0.625391
Name: quality, dtype: float64
```

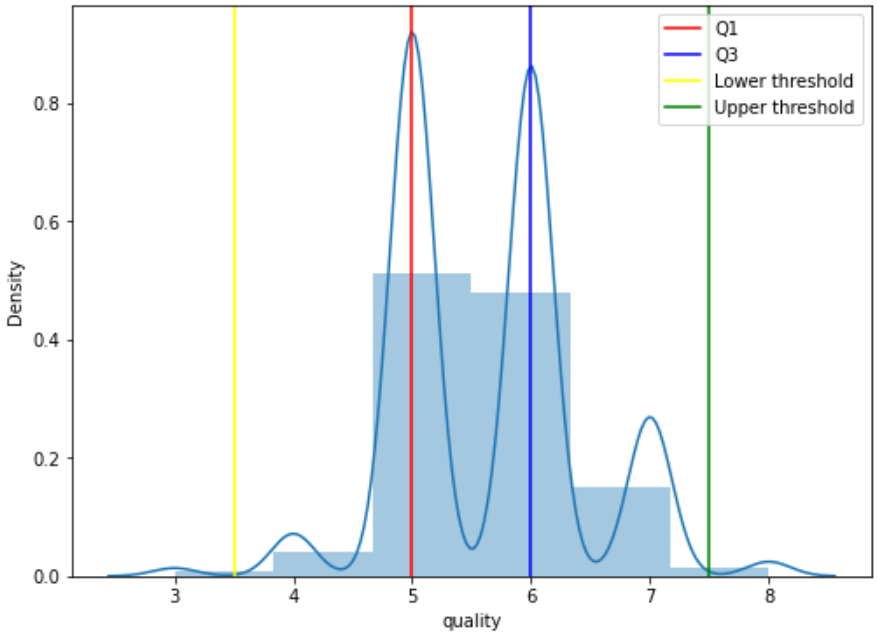
Creating a function to plot histogram so that we can use it easily multiple times for diff features

In [8]:
```
def get_distplot(col):
    ax = sns.distplot(df[col], bins = 6)
    Q1 = np.percentile(df[col],25)
    Q3 = np.percentile(df[col],75)
    IQR=Q3-Q1
    lower_threshold = Q1 - 1.5*IQR
    upper_threshold = Q3 + 1.5*IQR

    ax.axvline(Q1, color='red', linestyle='-', label="Q1")
    ax.axvline(Q3, color='blue', linestyle='-', label="Q3")
    ax.axvline(lower_threshold, color='yellow', linestyle='-', label="Lower threshold")
    ax.axvline(upper_threshold, color='green', linestyle='-', label="Upper threshold")
    ax.legend()
```

Visualization

In [9]:
```
fig = plt.figure(figsize=(18,6))

ax1 = fig.add_subplot(121)
ax1 = sns.countplot(df['quality'])
ax2 = fig.add_subplot(122)
ax2 = get_distplot('quality')
plt.show()
```





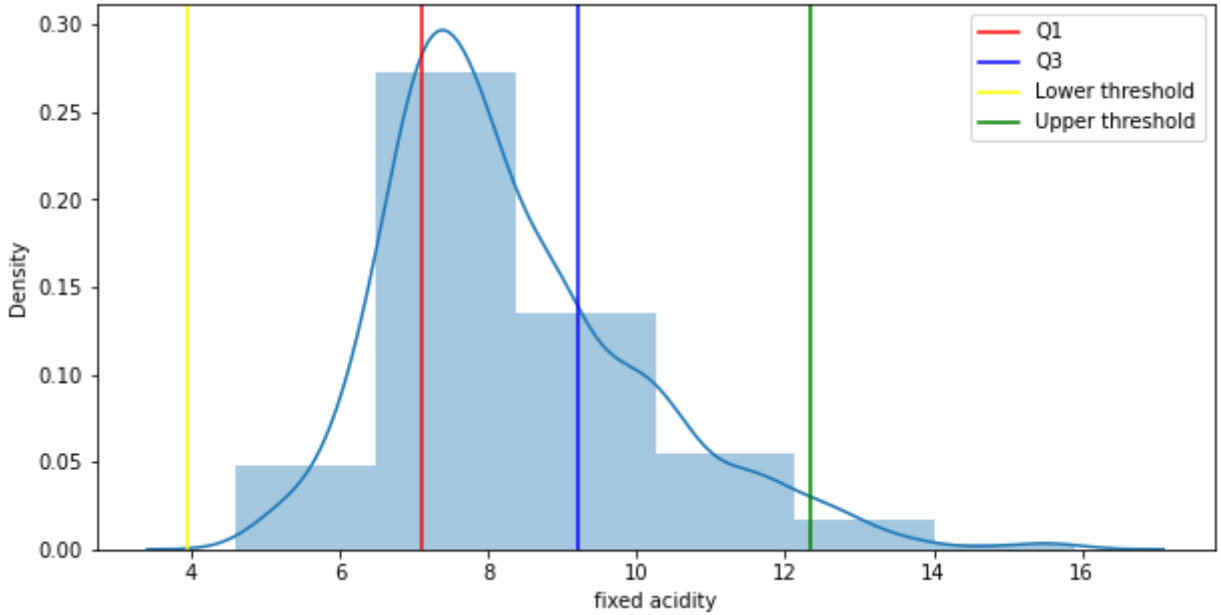
Observations:

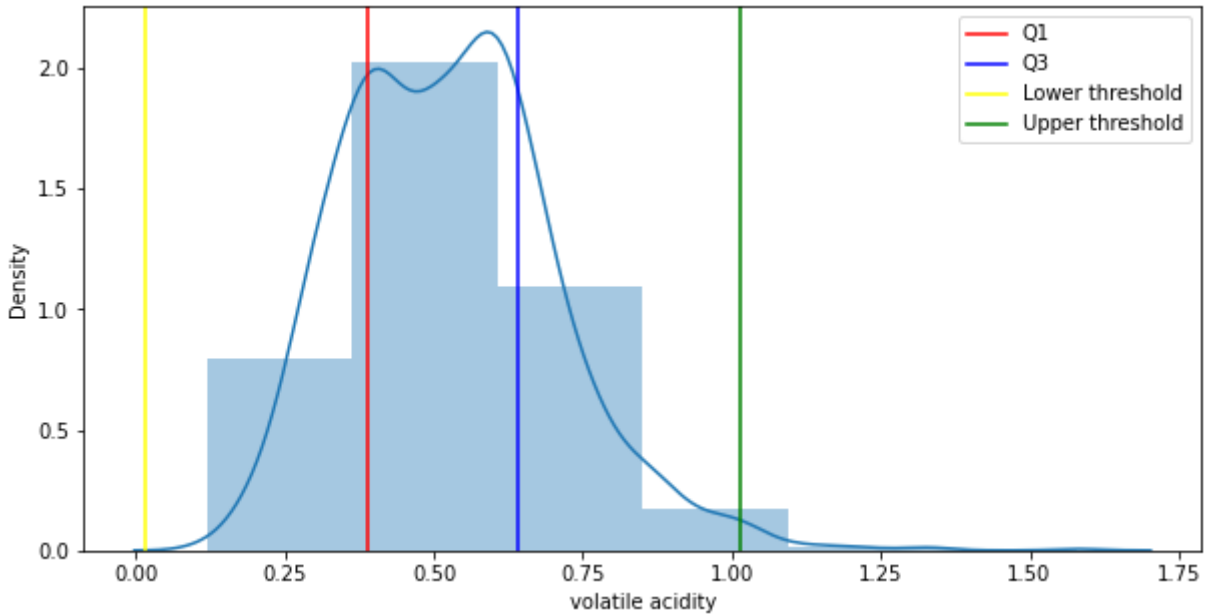
- Almost most of the wine in the dataset is of 5 or 6 quality.
- A very small portion of the wine is rated 3 similarly small portions are rated 8
- there are no wines with quality 1,2,9 or 10
- there is an imbalance in the dataset, extreme values high or low both are underrepresented
- mean and median are very close to each other

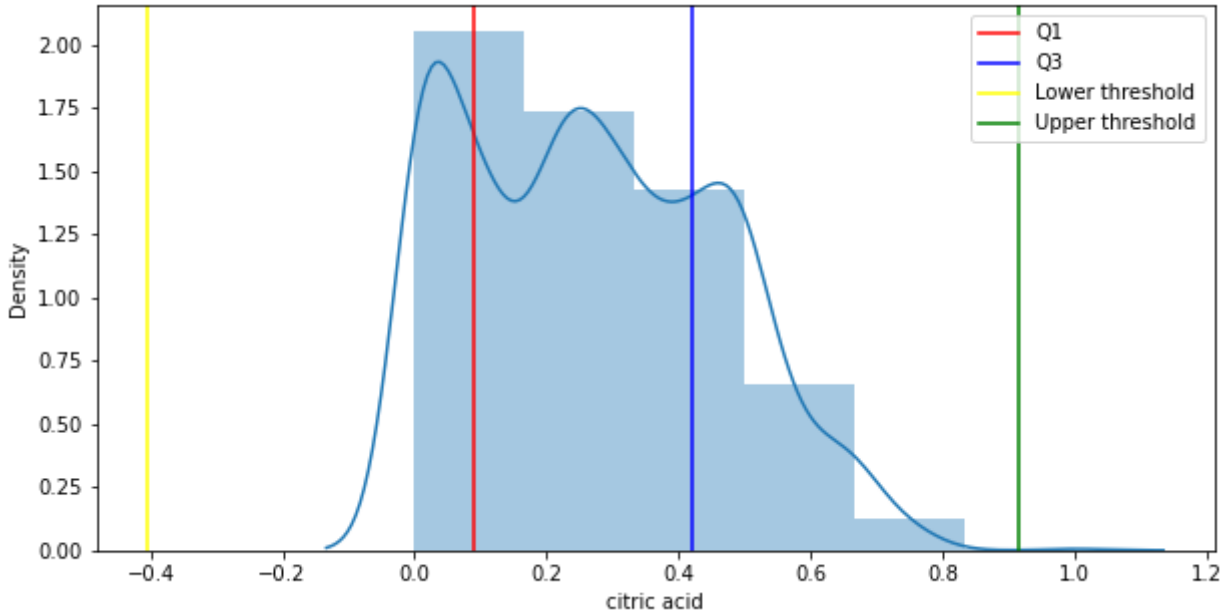
4. Univariate Exploaration

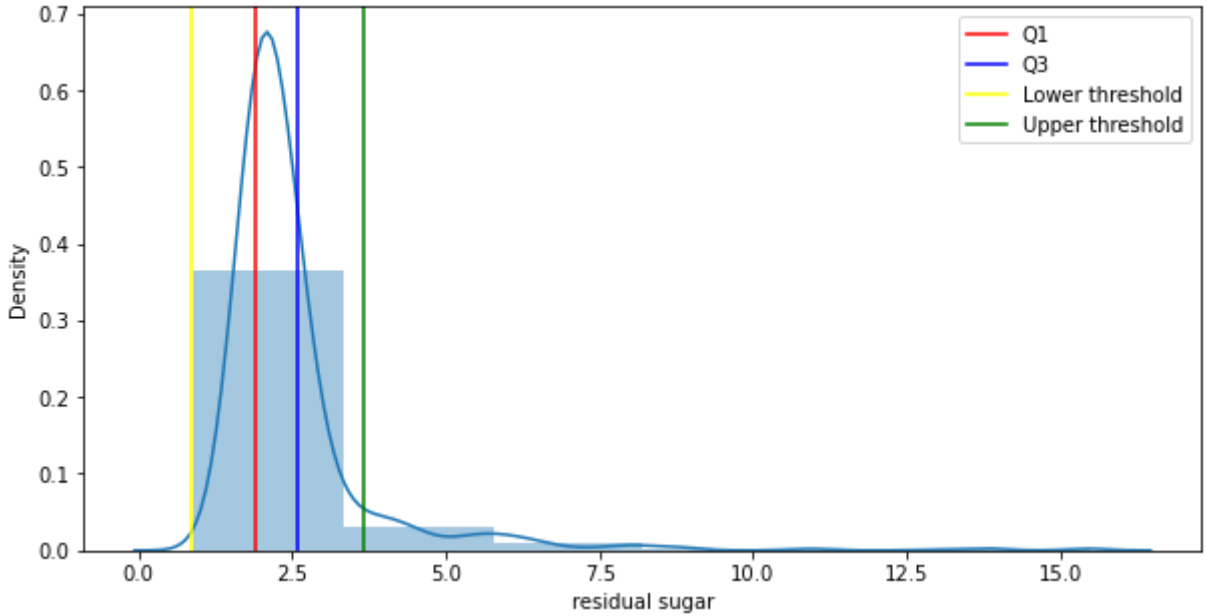
Let's check the distribution of each of the features by using a histogram

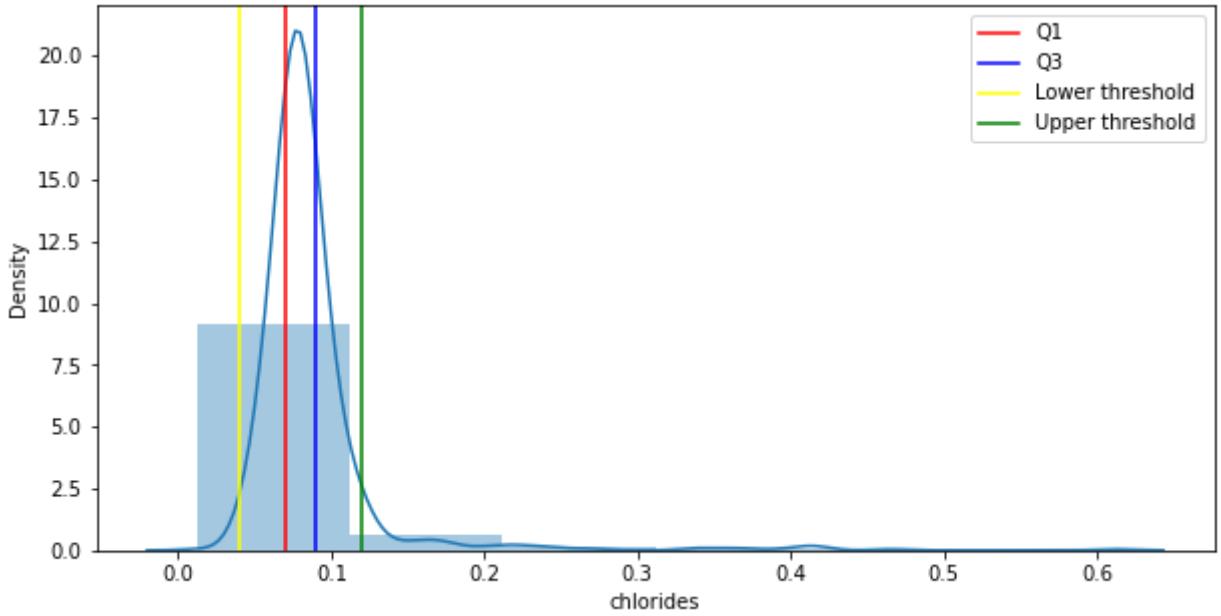
In [10]:
```
for i in df.columns:
    f, (ax1) = plt.subplots(1,1,figsize=(10,5))
    ax1 = get_distplot(i)
```

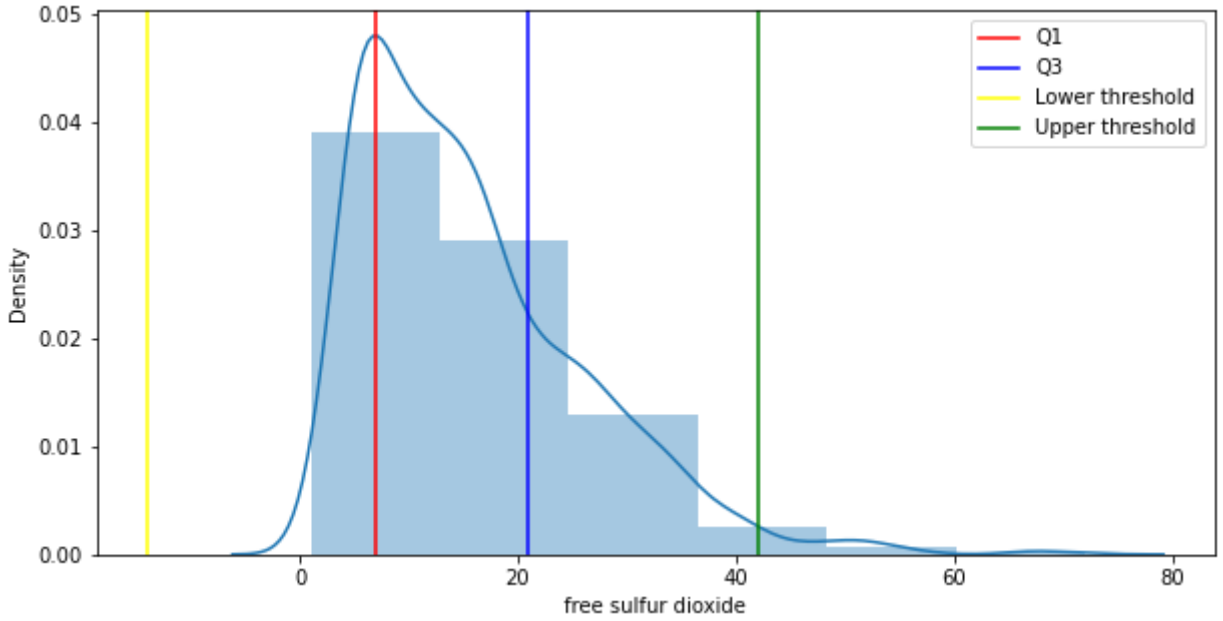


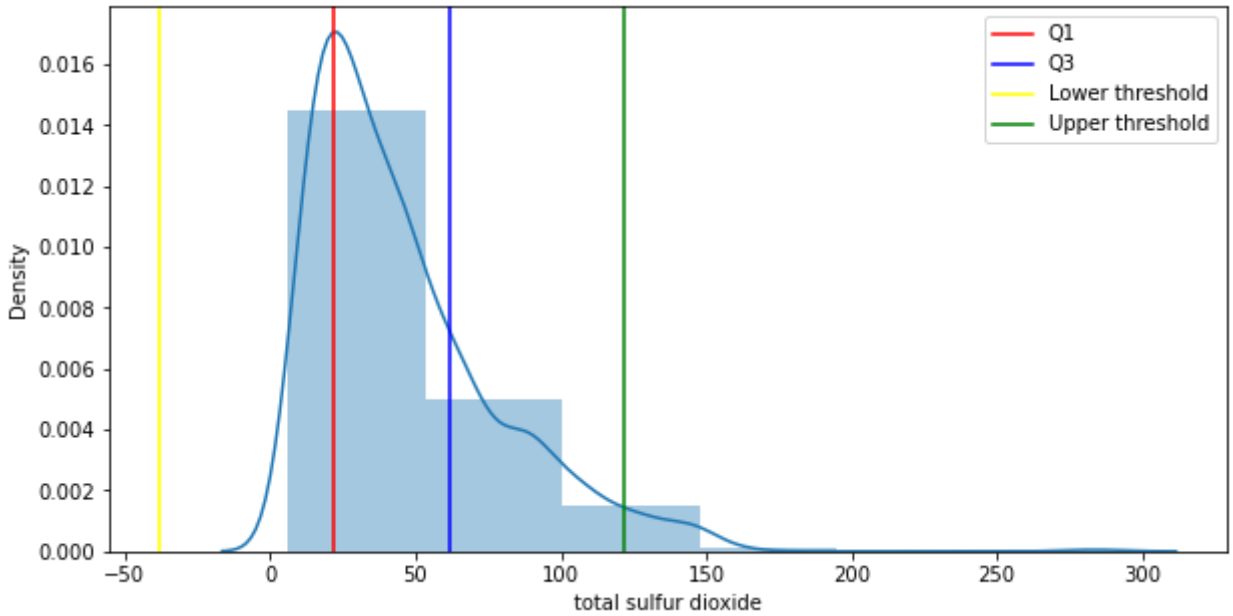

Q1
Q3
Lower threshold
Upper threshold
Density
volatile acidity
0.0
0.5
1.0
1.5
2.0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75

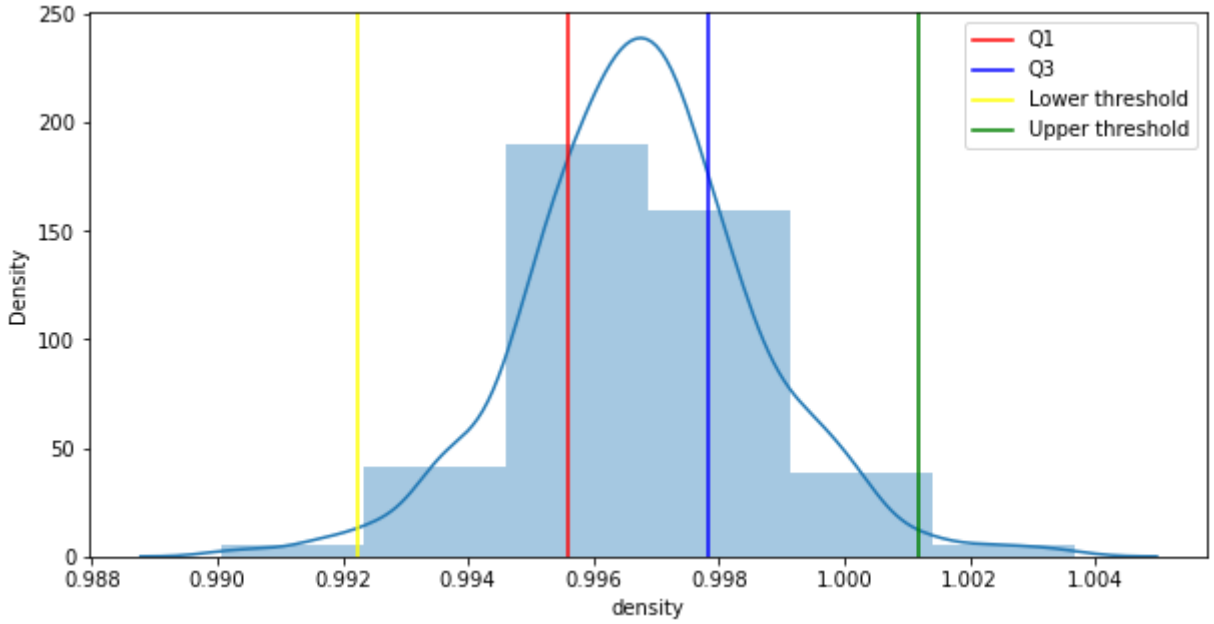

Q1
Q3
Lower threshold
Upper threshold
Density
citric acid
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2

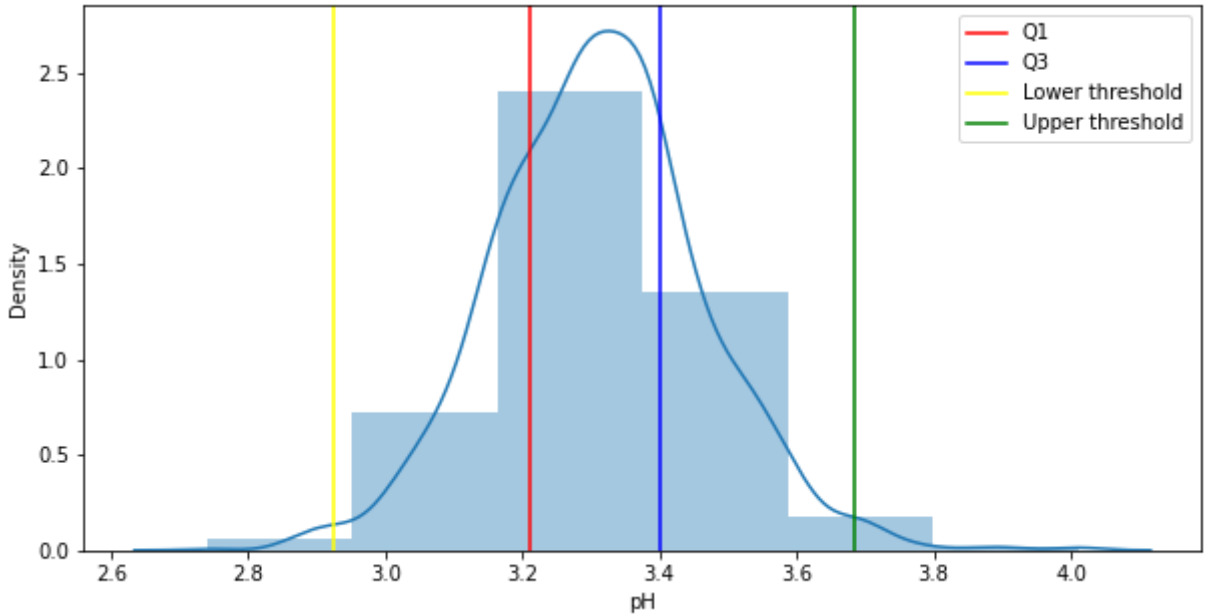

Q1
Q3
Lower threshold
Upper threshold
Density
residual sugar
0.0
2.5
5.0
7.5
10.0
12.5
15.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

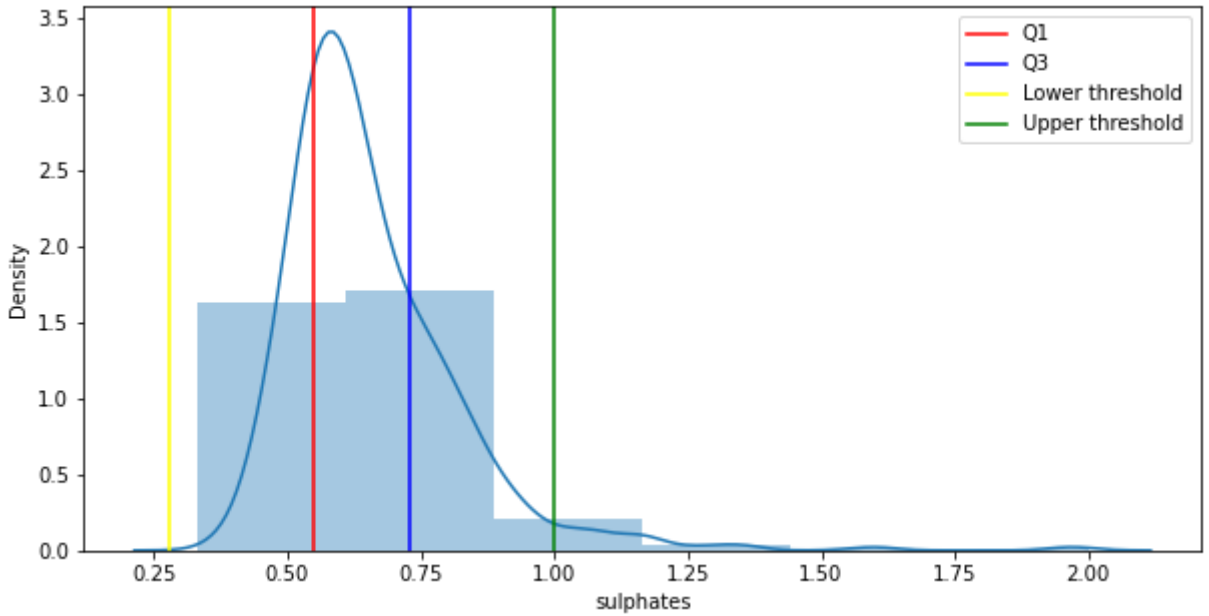

Q1
Q3
Lower threshold
Upper threshold
Density
chlorides
0.0
0.1
0.2
0.3
0.4
0.5
0.6
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

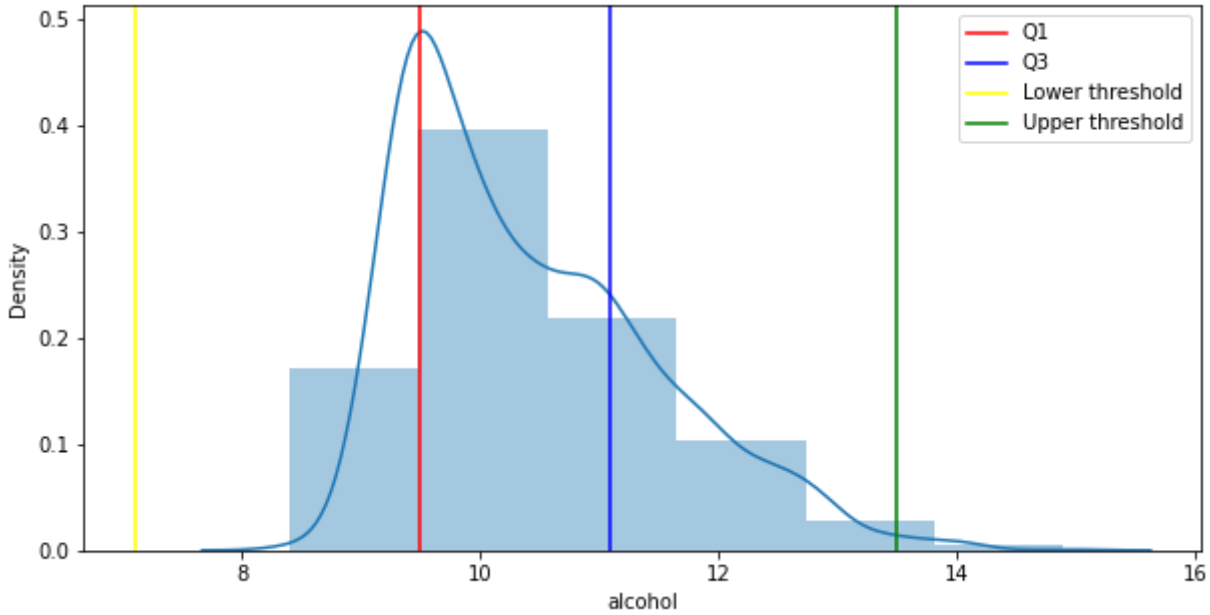

Q1
Q3
Lower threshold
Upper threshold
Density
free sulfur dioxide

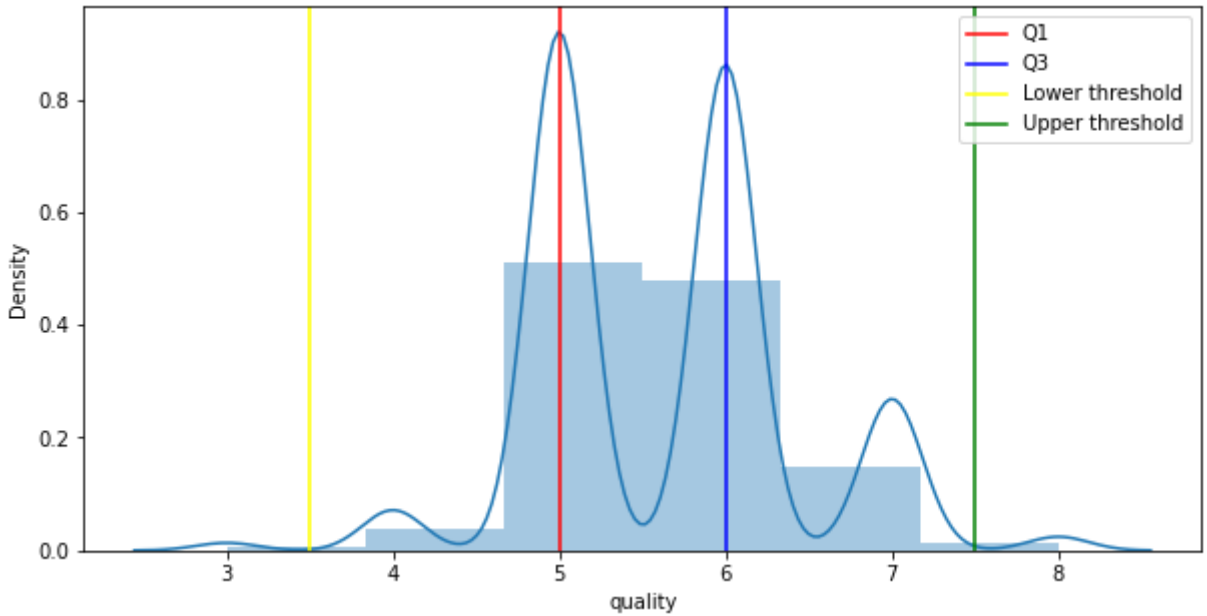

Q1
Q3
Lower threshold
Upper threshold
Density
total sulfur dioxide


Q1
Q3
Lower threshold
Upper threshold
Density
density
250
200
150
100
50
0
0.988
0.990
0.992
0.994
0.996
0.998
1.000
1.002
1.004


Q1
Q3
Lower threshold
Upper threshold
Density
pH
2.5
2.0
1.5
1.0
0.5
0.0
2.6
2.8
3.0
3.2
3.4
3.6
3.8
4.0

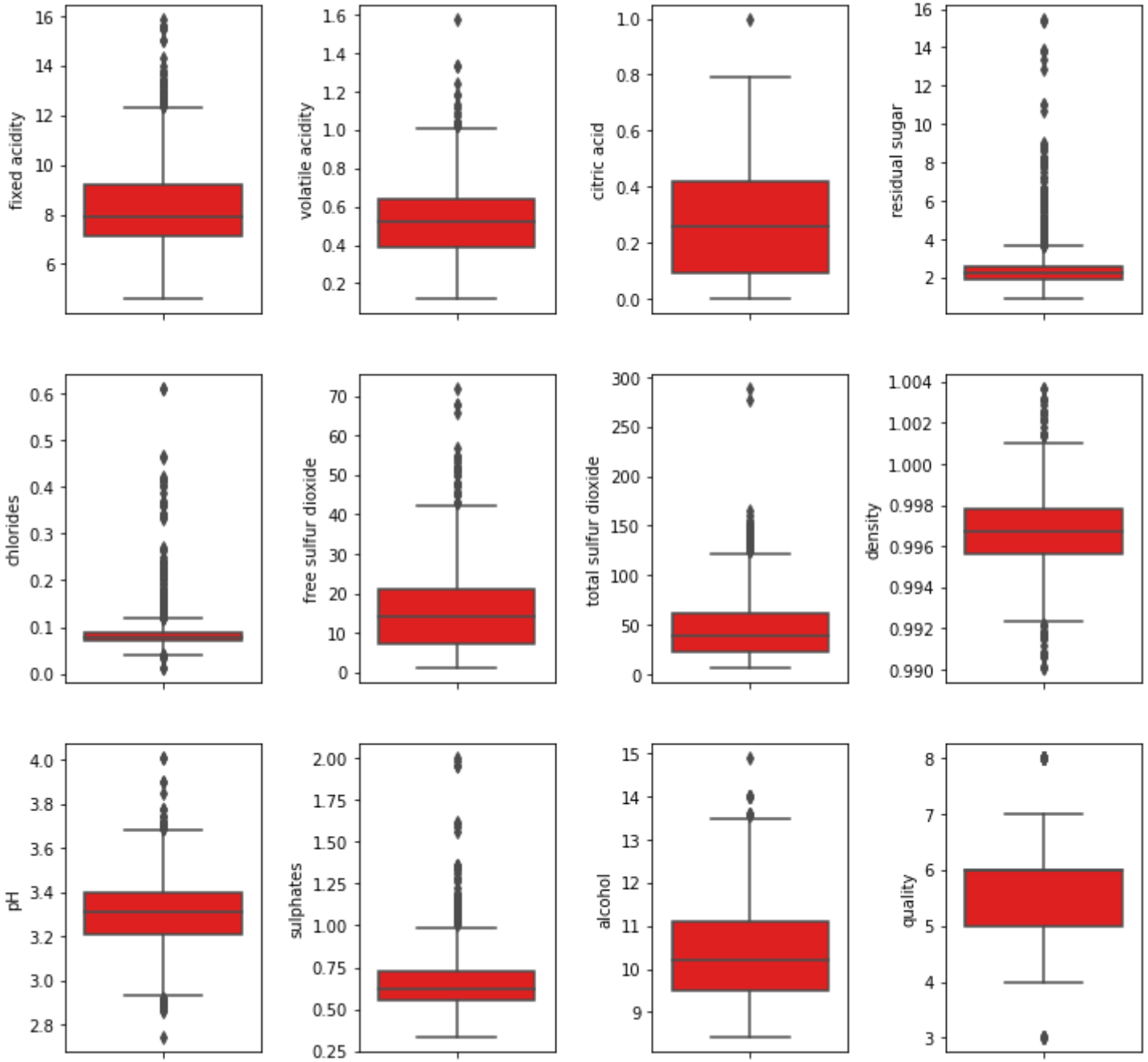

Q1
Q3
Lower threshold
Upper threshold
Density
sulphates
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00


Q1
Q3
Lower threshold
Upper threshold
Density
alcohol
0.0
0.1
0.2
0.3
0.4
0.5
8
10
12
14
16



Let's check the outliers using boxplot

In [11]:
```
# create box plots
fig, ax = plt.subplots(ncols=4, nrows=3, figsize=(12,12))
index = 0
ax = ax.flatten()

for col in df.columns:
    sns.boxplot(y=col, data=df, ax=ax[index], color='r')
    plt.subplots_adjust(wspace = .5)
    index += 1
```


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

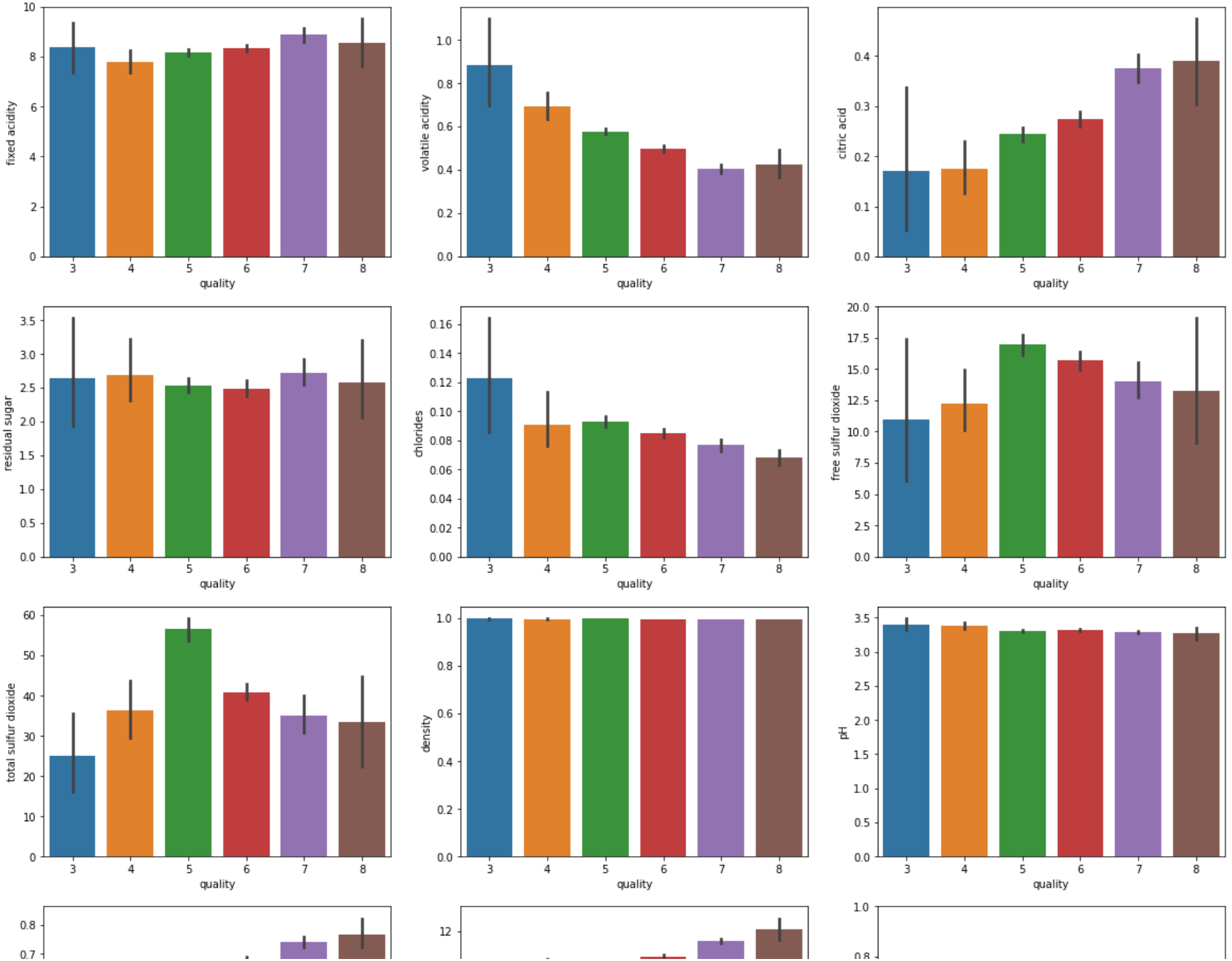
Observations :

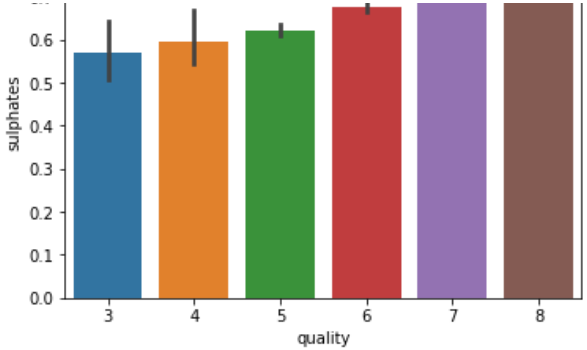
- From the histogram, we can see that feature density and pH are normally distributed
- Most of the remaining features are right-skewed.
- From boxplot its observed that outliers can be observed in almost all the features
- alcohol, citric acid, and volatile acidity has a very small no of outliers so safe to assume it won't affect the model

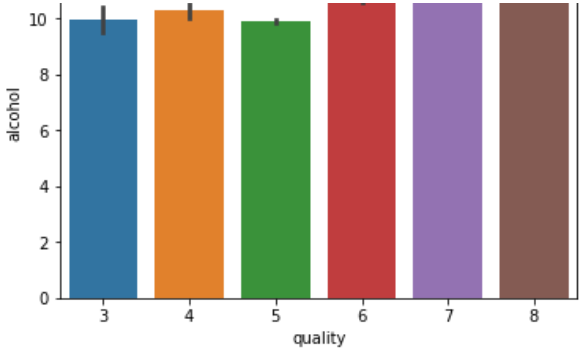
5. Bivariate Exploaration

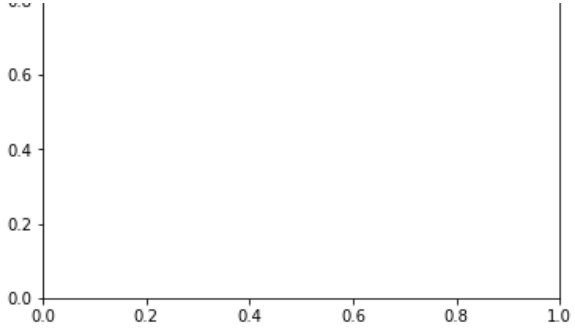
Analysing the features with respect to quality

In [12]:
```
x = df.drop(columns="quality")
fig, axs = plt.subplots(4,3, figsize=(20,20))
fig.patch.set_facecolor('white')
attributes = x.columns
att = 0
for i in range(4):
    for j in range(3):
        try:
            sns.barplot(x="quality", y=attributes[att], data=df, estimator=np.mean, ax=axs[i][j])
        except: #to handle index value 11
            print()
        att += 1
```


fixed acidity
volatile acidity
citric acid
residual sugar
chlorides
free sulfur dioxide
total sulfur dioxide
density
pH
quality







Observations:

- volatile acidity and chlorides shows downward trend hence inversely proportional to quality.
- Citric Acid, sulfate, and alcohol shows upward trend and are directly proportional to quality.
- Density, Residual sugar, and pH have no or little impact on quality
- free sulfur and total sulfur have similar kinds of impact

Correlation coefficient

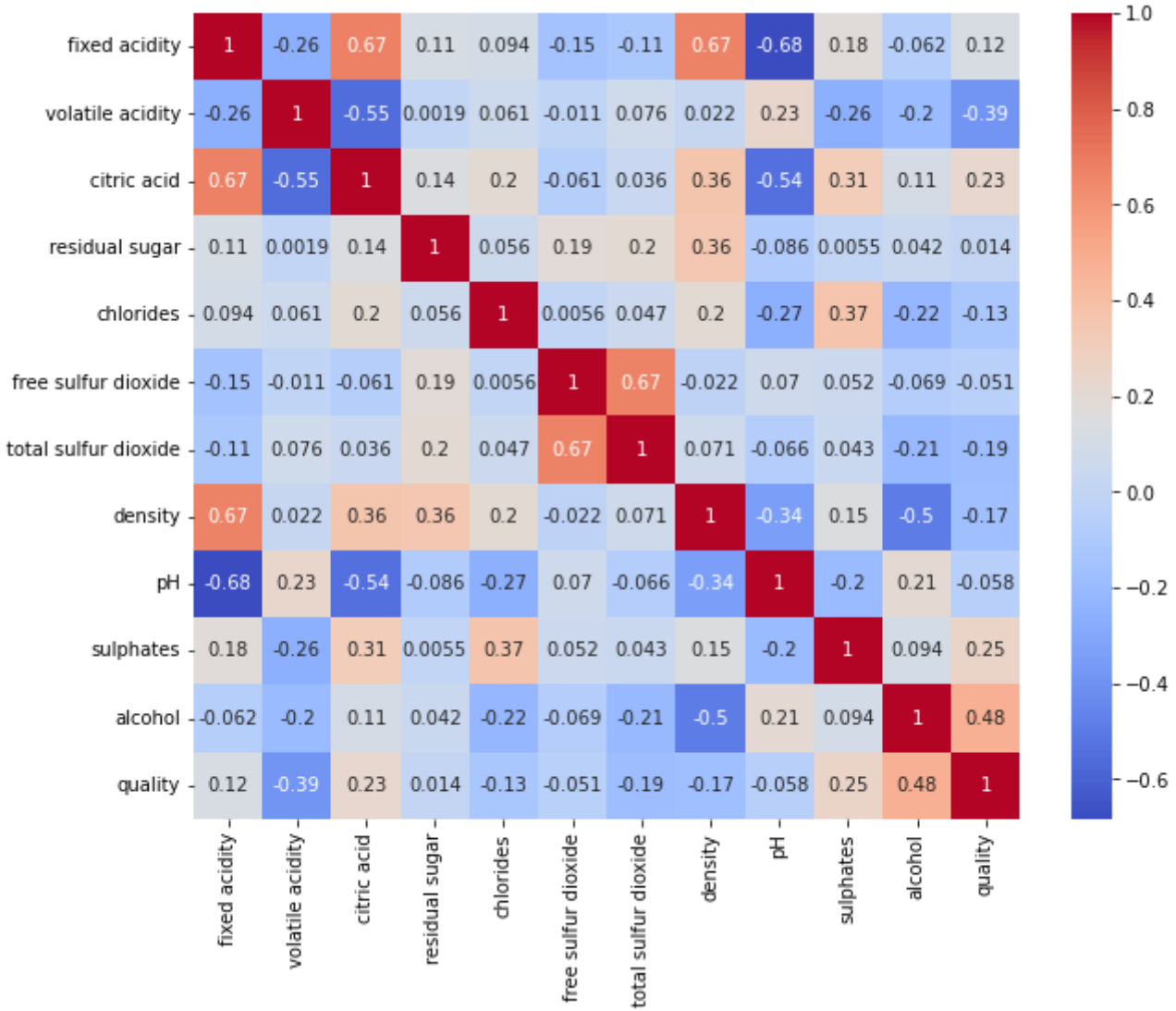
In [13]:
```
c = df.corr()
c
```

Out[13]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-0.682978	0.183006	-0.061668	0.124052
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026	0.234937	-0.260987	-0.202288	-0.390558
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947	-0.541904	0.312770	0.109903	0.226373
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-0.085652	0.005527	0.042075	0.013732
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-0.265026	0.371260	-0.221141	-0.128907
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946	0.070377	0.051658	-0.069408	-0.050656
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269	-0.066495	0.042947	-0.205654	-0.185100
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000	-0.341699	0.148506	-0.496180	-0.174919
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699	1.000000	-0.196648	0.205633	-0.057731
sulphates	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.148506	-0.196648	1.000000	0.093595	0.251397
alcohol	-0.061668	-0.202288	0.109903	0.042075	-0.221141	-0.069408	-0.205654	-0.496180	0.205633	0.093595	1.000000	0.476166
quality	0.124052	-0.390558	0.226373	0.013732	-0.128907	-0.050656	-0.185100	-0.174919	-0.057731	0.251397	0.476166	1.000000

In [14]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(c, cmap = 'coolwarm', annot = True)
```

Out[14]:
```
<AxesSubplot:>
```



Observations:

- There is no strong correlation between quality and the other features. Notables are alcohol, sulfate, citric acid, and volatile acidity.
- Quality has a moderate positive correlation with alcohol and a weak positive correlation with fixed acidity, sulfate, and citric acid
- Quality has a moderate negative correlation with volatile acidity
- Free sulfur dioxide and total sulfur dioxide appear to be multicollinear we can drop one of them

6. Conclusion of EDA

- The dataset provided appears to be pretty clean, with no missing values observed.
- All independent variables are numeric and the target value is classification based so we can apply logistic regression algorithms
- To have a good quality, wine must contain a good portion of citric acid, sulfate, and alcohol. Volatile acidity and chlorides amount must be kept low.
- Free sulfur dioxide and total sulfur dioxide have an almost similar impact on quality hence are multicollinear thus one of them can be dropped during training and testing.
- Density, Residual Sugar and pH have no direct impact on quality but have correlations with other features so should be kept in the data as of now.

7. Preprocessing Data

In [15]:
```
#first copy the original dataset to maintain backup

dfML = df.copy()
dfML.head()
```

Out[15]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

Feature Encoding

Let's convert the target variable quality to the bivariate variable using feature encoding. This will help later to compare the confusion matrix for each applied model.

In [16]:
```
# encode quality into 2 classes, - ["Poor","Good"]
# here bins are the range, 0-6 and 6-10
bins = [0, 6, 10]
labels = ["Poor","Good"]
dfML['quality'] = pd.cut(dfML['quality'], bins=bins, labels=labels)
```

In [17]:
```
#Now lets assign a labels to our quality variable
label_quality = LabelEncoder()
dfML['quality'] = label_quality.fit_transform(dfML['quality'])
dfML['quality'].value_counts()
```

Out[17]:
```
1    1382
0     217
Name: quality, dtype: int64
```

Train Test data splitting

- Here the dataset will first need to be separated into X = independent variables and y = target variable.
- Then dataset will be split into train and test datasets. We will use 80 - 20 split
- random_state = 42 is used for reproduction
- Fun Fact: Number 42 is used as an inside joke in the scientific and sci-fi community and it is derived from 'Hitchhiker's Guide to the Galaxy. The number 42 also has a Wikipedia page for many pop culture references.

In [18]:
```
X = dfML.drop('quality', axis = 1)
y = dfML['quality']
```

In [19]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 42)
```

Feature Scaling

Applying Standard scaling to get optimized result

In [20]:
```
sc = StandardScaler()
```

In [21]:
```
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

8. Applying ML models

Creating a function to do common tasks performed while applying the model so that we can reduce code repetition.

In [22]:
```
# First initialize the list variables to store different outputs
# We will use this later to compare all the different ML alorithms
lst_model = []
lst_accuracy  = []
lst_accuracy_train = []
lst_accuracy_test = []
lst_cv_score = []
lst_TP = []
lst_TN = []
lst_FP = []
lst_FN = []

# fuction : accepts input model which is nothing but object instantiated of an algos
def applyMLmodel(model):
    # train the model
    model.fit(X_train, y_train)
    accuracy = model.score(X_test, y_test) * 100
    lst_accuracy.append(accuracy)
    print("Accuracy :", accuracy)

    # cross-validation , y_train.ravel() is similar to y_train.reshape(-1)
    cv = cross_val_score(estimator = model, X = X_train, y = y_train.ravel(), cv = 10)
    lst_cv_score.append(cv.mean())
    print("CV Score :", cv.mean())

    # predicting accuracy for training data set
    y_pred_train = model.predict(X_train)
    accuracy_train = accuracy_score(y_train, y_pred_train)
    lst_accuracy_train.append(accuracy_train)
    print("Accuracy(Training) :", accuracy_train)

    # predicting accuracy for test data set
    y_pred_test = model.predict(X_test)
    accuracy_test = accuracy_score(y_test, y_pred_test)
    lst_accuracy_test.append(accuracy_test)
    print("Accuracy(Test) :", accuracy_test)
```

```
    # confusion matrix
    cm = confusion_matrix(y_test, y_pred_test)
    print("Confusion Matrix :")
    print(cm)

    # storing TN,TP,FN and FP as a part of list
    lst_TN.append(cm[0,0])
    lst_FP.append(cm[0,1])
    lst_FN.append(cm[1,0])
    lst_TP.append(cm[1,1])
```

LogisticRegression

In [23]:
```
model = LogisticRegression()
applyMLmodel(model)
lst_model.append("LogisticRegression")
```

```
Accuracy : 87.5
CV Score : 0.885857529527559
Accuracy(Training) : 0.8858483189992181
Accuracy(Test) : 0.875
Confusion Matrix :
[[ 12  35]
 [  5 268]]
```

DecisionTreeClassifier

In [24]:
```
model = DecisionTreeClassifier()
applyMLmodel(model)
lst_model.append("DecisionTreeClassifier")
```

```
Accuracy : 84.375
CV Score : 0.8694697342519685
Accuracy(Training) : 1.0
Accuracy(Test) : 0.84375
Confusion Matrix :
[[ 22  25]
 [ 25 248]]
```

RandomForestClassifier

In [25]:
```
model = RandomForestClassifier()
applyMLmodel(model)
lst_model.append("RandomForestClassifier")
```

```
Accuracy : 88.75
CV Score : 0.9101070374015748
Accuracy(Training) : 1.0
Accuracy(Test) : 0.8875
Confusion Matrix :
[[ 20  27]
 [  9 264]]
```

KNearest

In [26]:
```
model =KNeighborsClassifier()
applyMLmodel(model)
lst_model.append("KNeighborsClassifier")
```

```
Accuracy : 87.5
CV Score : 0.8725701279527559
Accuracy(Training) : 0.9124315871774824
Accuracy(Test) : 0.875
Confusion Matrix :
[[ 19  28]
 [ 12 261]]
```

GaussianNB - Naive Bayes

In [27]:
```
model = GaussianNB()
applyMLmodel(model)
lst_model.append("GaussianNB")
```

```
Accuracy : 85.3125
CV Score : 0.8373462106299213
Accuracy(Training) : 0.8389366692728695
Accuracy(Test) : 0.853125
Confusion Matrix :
[[ 35  12]
 [ 35 238]]
```

9. Comparing the results of ML algorithms

We will first convert all the list of outputs into dataframe which will be easy to compare and visuallize

In [28]:
```
predictiondf = pd.DataFrame({'Model': np.array(lst_model),
                             'Accuracy': np.array(lst_accuracy),
                             'Accuracy(Training)' : np.array(lst_accuracy_train),
                             'Accuracy(Test)' : np.array(lst_accuracy_test),
                             'CV Score' : np.array(lst_cv_score),
                             'True Positive' : np.array(lst_TP),
                             'True Negative' : np.array(lst_TN),
                             'False Positive' : np.array(lst_FP),
                             'False Negative' : np.array(lst_FN)
                            })
predictiondf
```

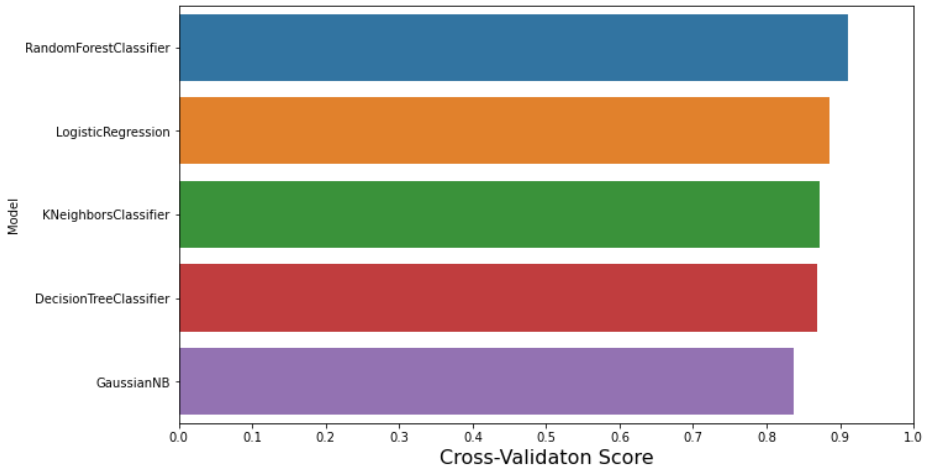
Out[28]:

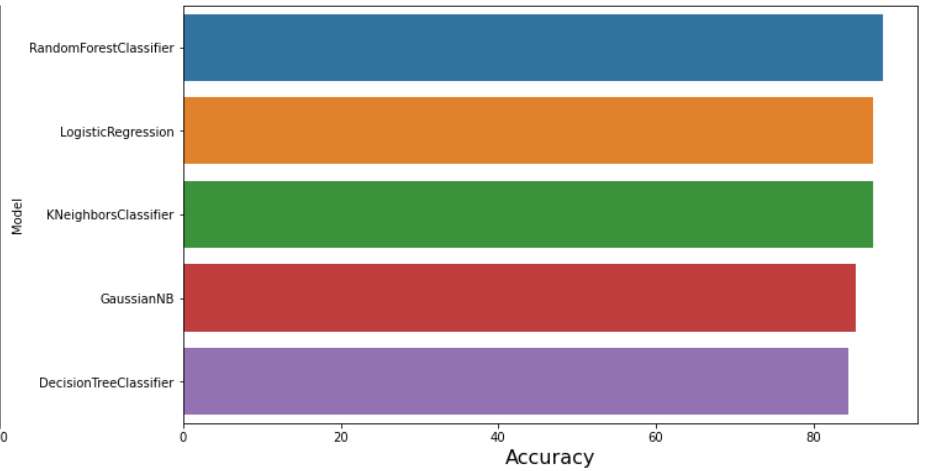
	Model	Accuracy	Accuracy(Training)	Accuracy(Test)	CV Score	True Positive	True Negative	False Positive	False Negative
0	LogisticRegression	87.5000	0.885848	0.875000	0.885858	268	12	35	5
1	DecisionTreeClassifier	84.3750	1.000000	0.843750	0.869470	248	22	25	25
2	RandomForestClassifier	88.7500	1.000000	0.887500	0.910107	264	20	27	9
3	KNeighborsClassifier	87.5000	0.912432	0.875000	0.872570	261	19	28	12
4	GaussianNB	85.3125	0.838937	0.853125	0.837346	238	35	12	35

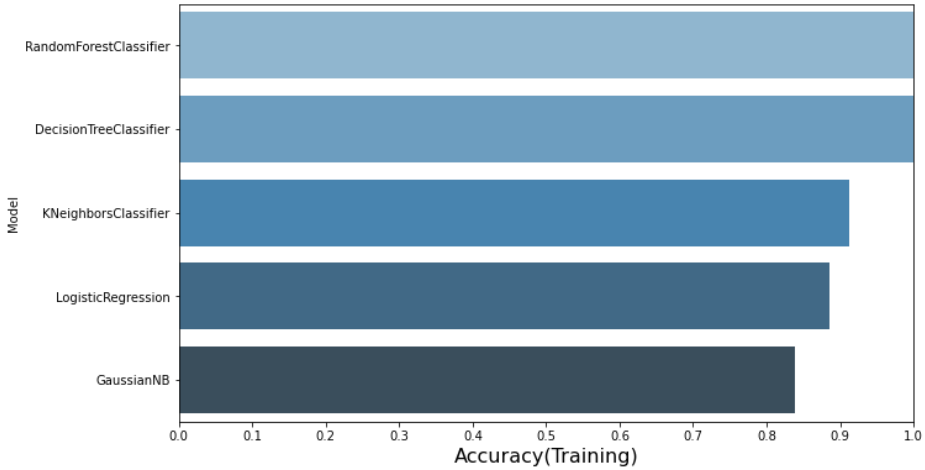
Comparing the outputs using visalization

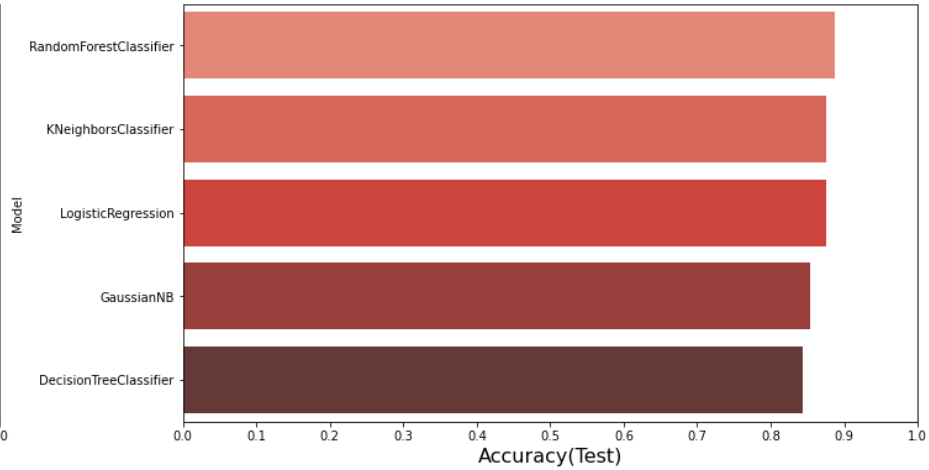
In [29]:
```
fig, ax = plt.subplots(2,2, figsize=(24,14))
plt.subplots_adjust(wspace = .25, hspace = .25)
#comparing CV score
predictiondf.sort_values(by=['CV Score'], ascending=False, inplace=True)

sns.barplot(x='CV Score', y='Model', data = predictiondf, ax = ax[0][0])
ax[0][0].set_xlabel('Cross-Validaton Score', size=16)
ax[0][0].set_ylabel('Model')
ax[0][0].set_xlim(0,1.0)
ax[0][0].set_xticks(np.arange(0, 1.1, 0.1))
```

```
#comparing accuracy
predictiondf.sort_values(by=['Accuracy'], ascending=False, inplace=True)

sns.barplot(x='Accuracy', y='Model', data = predictiondf, ax = ax[0][1])
ax[0][1].set_xlabel('Accuracy', size=16)
ax[0][1].set_ylabel('Model')

#comparing accuracy(training)
predictiondf.sort_values(by=['Accuracy(Training)'], ascending=False, inplace=True)

sns.barplot(x='Accuracy(Training)', y='Model', data = predictiondf, palette='Blues_d', ax = ax[1][0])
ax[1][0].set_xlabel('Accuracy(Training)', size=16)
ax[1][0].set_ylabel('Model')
ax[1][0].set_xlim(0,1.0)
ax[1][0].set_xticks(np.arange(0, 1.1, 0.1))

#comparing accuracy(testing)
predictiondf.sort_values(by=['Accuracy(Test)'], ascending=False, inplace=True)

sns.barplot(x='Accuracy(Test)', y='Model', data = predictiondf, palette='Reds_d', ax = ax[1][1])
ax[1][1].set_xlabel('Accuracy(Test)', size=16)
ax[1][1].set_ylabel('Model')
ax[1][1].set_xlim(0,1.0)
ax[1][1].set_xticks(np.arange(0, 1.1, 0.1))

plt.show()
```

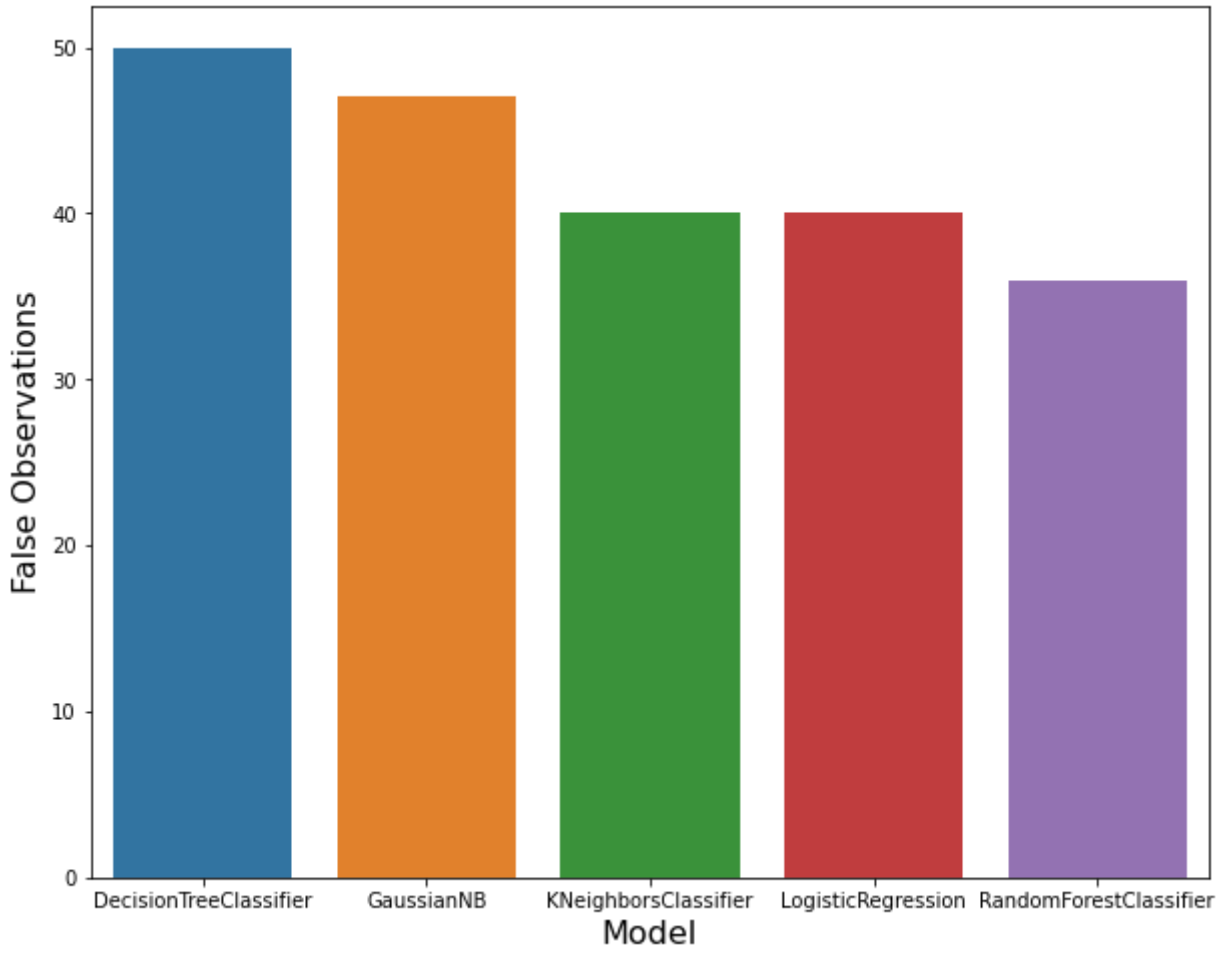








In [30]:
```
# Comparing how many false prediction made by each model
predictiondf.sort_values(by=(['Accuracy(Test)']), ascending=True, inplace=True)

f, axe = plt.subplots(1,1, figsize=(10,8))
sns.barplot(x = predictiondf['Model'], y=predictiondf['False Positive'] + predictiondf['False Negative'], ax = axe)
axe.set_xlabel('Model', size=16)
axe.set_ylabel('False Observations', size=16)

plt.show()
```



Observation :

- The random Forest algorithm gives the highest CV score and highest accuracy
- K-Neighbor performs consistently across the accuracy but has scored a little low on CV score than other algos.
- GaussianNB model is poor performing on every aspect when compared to other algos.
- The Decision Tree predicts a higher percentage of false predictions, and logistic regression has the least number of false predictions.
- All of the model has accuracy in the range of 84-88, so pretty accurate.