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

In [2]:
```python
red_wine = pd.read_csv('winequality-red.csv', sep=';')
white_wine = pd.read_csv('winequality-white.csv', sep=';')
```

Main objective of the analysis is to predict the quality of wine good or Bad.

two datasets were created, using red and white wine samples. The inputs include objective tests (e.g. PH values) and the output is based on sensory data (median of at least 3 evaluations made by wine experts). Each expert graded the wine quality between 0 (very bad) and 10 (very excellent).

Two datasets one for red wine and one for white wine

Number of Instances: red wine - 1599; white wine - 4898.

Number of Attributes: 11 + output attribute

- 1 - fixed acidity
- 2 - volatile acidity
- 3 - citric acid
- 4 - residual sugar
- 5 - chlorides
- 6 - free sulfur dioxide
- 7 - total sulfur dioxide
- 8 - density
- 9 - pH
- 10 - sulphates
- 11 - alcohol

- Output variable (based on sensory data):

- 12 - quality (score between 0 and 10)

In [3]:
```python
red_wine.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
```

In [4]:
```python
red_wine.head()
```

Out[4]:

	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

In [5]:
```python
white_wine.head()
```

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
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	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49	9.5	6
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44	10.1	6
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6

check null values and data types

In [6]:
```python
red_wine.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
```

In [7]:
```python
white_wine.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4898 entries, 0 to 4897
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         4898 non-null   float64
 1   volatile acidity      4898 non-null   float64
 2   citric acid           4898 non-null   float64
 3   residual sugar        4898 non-null   float64
 4   chlorides             4898 non-null   float64
 5   free sulfur dioxide   4898 non-null   float64
 6   total sulfur dioxide  4898 non-null   float64
 7   density               4898 non-null   float64
 8   pH                    4898 non-null   float64
 9   sulphates             4898 non-null   float64
 10  alcohol               4898 non-null   float64
 11  quality               4898 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 459.3 KB
```

combine datasets in wine_df

add a new feature or column to each data set to indicate whether the wine is red or white.

In [8]:
```python
red_wine['color'] = 'red'
red_wine.head()
```

Out[8]:

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

In [9]:
```python
white_wine['color'] = 'white'
white_wine.head()
```

Out[9]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality	color
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.0010	3.00	0.45	8.8	6	white
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.9940	3.30	0.49	9.5	6	white
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.9951	3.26	0.44	10.1	6	white
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6	white
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.9956	3.19	0.40	9.9	6	white

In [10]:
```python
# append dataframes
wine_df = red_wine.append(white_wine, sort=False)

# view dataframe to check for success
wine_df.head()
```

Out[10]:

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

In [11]:
```python
wine_df.columns
```

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

In [12]:
```python
wine_df.to_csv('winequality_edited.csv', sep=';')
```

In [13]:
```python
wine_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6497 entries, 0 to 4897
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         6497 non-null   float64
 1   volatile acidity      6497 non-null   float64
 2   citric acid           6497 non-null   float64
 3   residual sugar        6497 non-null   float64
 4   chlorides             6497 non-null   float64
 5   free sulfur dioxide   6497 non-null   float64
 6   total sulfur dioxide  6497 non-null   float64
 7   density               6497 non-null   float64
 8   pH                    6497 non-null   float64
 9   sulphates             6497 non-null   float64
 10  alcohol               6497 non-null   float64
 11  quality               6497 non-null   int64  
 12  color                 6497 non-null   object 
dtypes: float64(11), int64(1), object(1)
memory usage: 710.6+ KB
```

In [14]:
```python
wine_df['quality'].unique()
```

Out[14]:
```
array([5, 6, 7, 4, 8, 3, 9])
```

In [ ]:

in this part i check the data quality, assess any issues in the data and fix it:

- null values in each column
- each column has the proper data type
- duplicate rows
- outliers
- distribution for each column (skewness)

check for nulls

In [15]:
```python
wine_df.isna().sum()
```

Out[15]:
```
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
color                   0
dtype: int64
```

check columns datatypes

In [16]:
```python
wine_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6497 entries, 0 to 4897
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         6497 non-null   float64
 1   volatile acidity      6497 non-null   float64
 2   citric acid           6497 non-null   float64
 3   residual sugar        6497 non-null   float64
 4   chlorides             6497 non-null   float64
 5   free sulfur dioxide   6497 non-null   float64
 6   total sulfur dioxide  6497 non-null   float64
 7   density               6497 non-null   float64
 8   pH                    6497 non-null   float64
 9   sulphates             6497 non-null   float64
 10  alcohol               6497 non-null   float64
 11  quality               6497 non-null   int64  
 12  color                 6497 non-null   object 
dtypes: float64(11), int64(1), object(1)
memory usage: 710.6+ KB
```

check duplicates and remove

In [17]:
```python
sum(wine_df.duplicated())
```

Out[17]:
```
1177
```

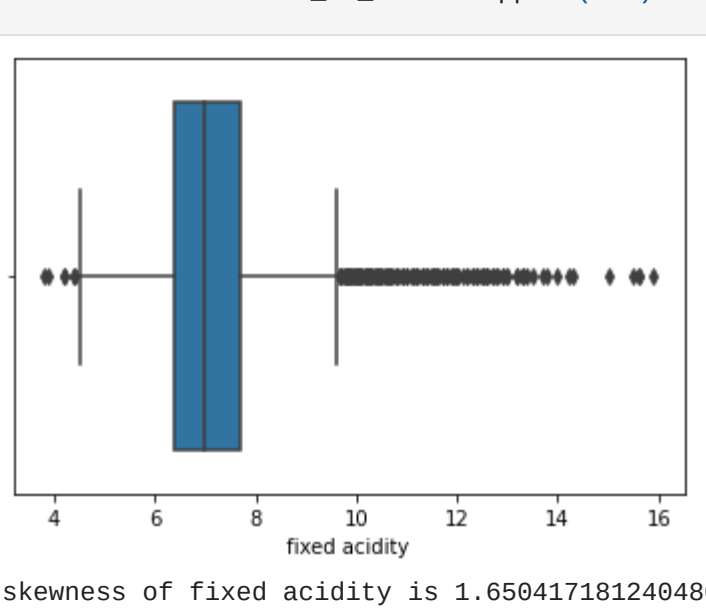
In [18]:
```python
wine_df.drop_duplicates(inplace =True)
```

In [19]:
```python
sum(wine_df.duplicated())
```

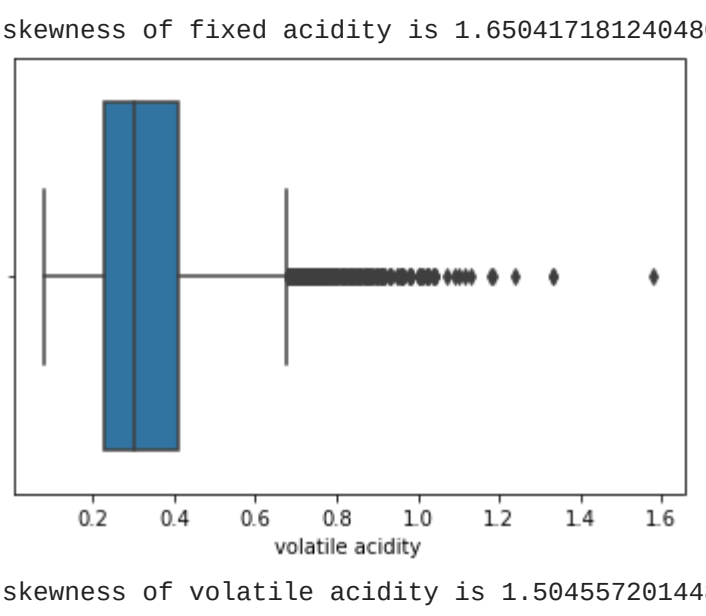
Out[19]:
```
0
```

check for outliers and skewness

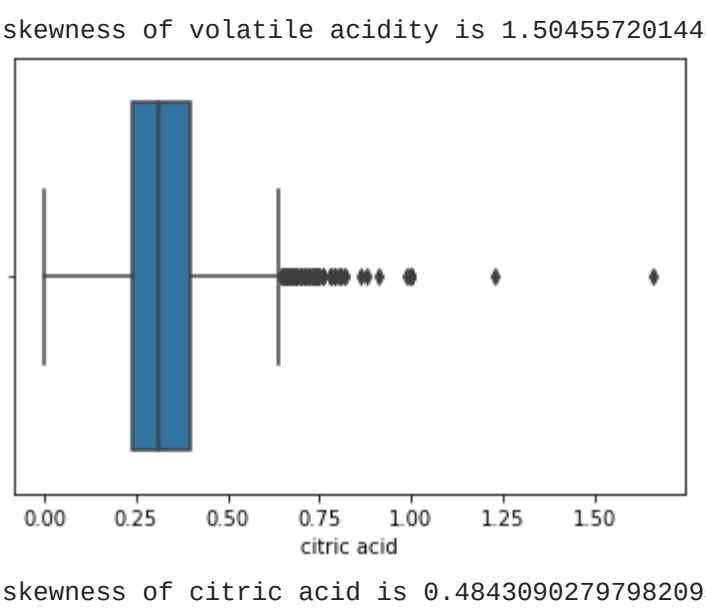
In [20]:
```python
columns_to_unskew = []
for col in wine_df.columns:
    if col != 'color':
        sns.boxplot(x = wine_df[col])
        plt.show()

        skew = wine_df[col].skew()
        print("skewness of {} is {}".format(col, skew))
        if skew > 1 or skew <- 1:
            columns_to_unskew.append(col)
```



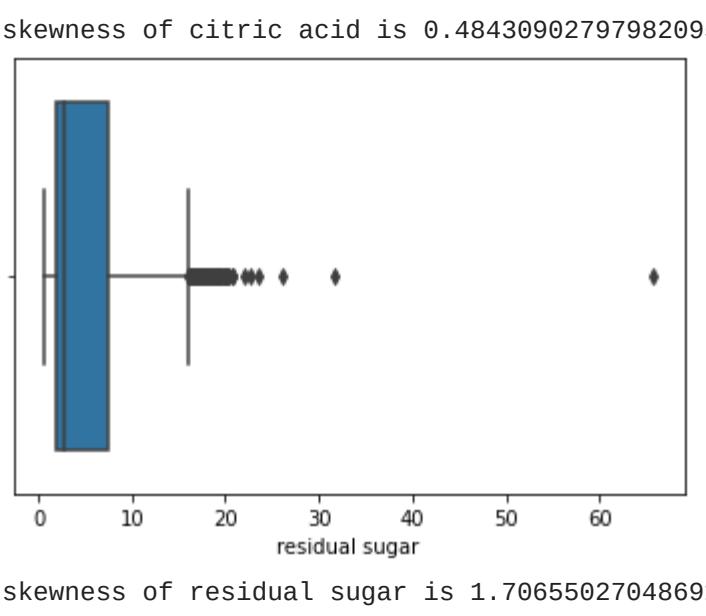
skewness of fixed acidity is 1.6504171812404804



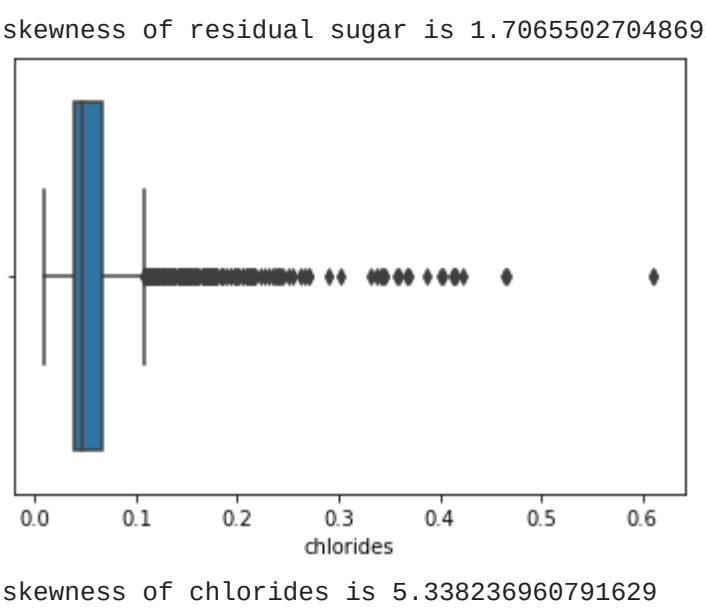
skewness of volatile acidity is 1.5045572014481647



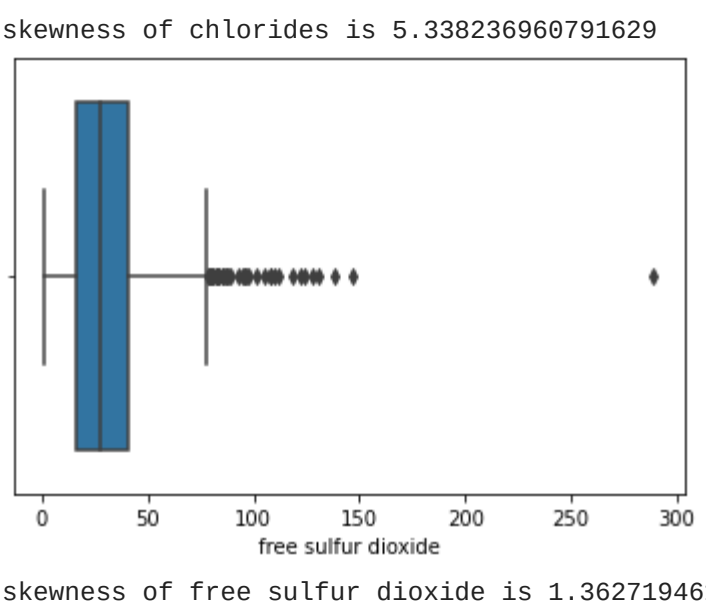
skewness of citric acid is 0.48430902797982095



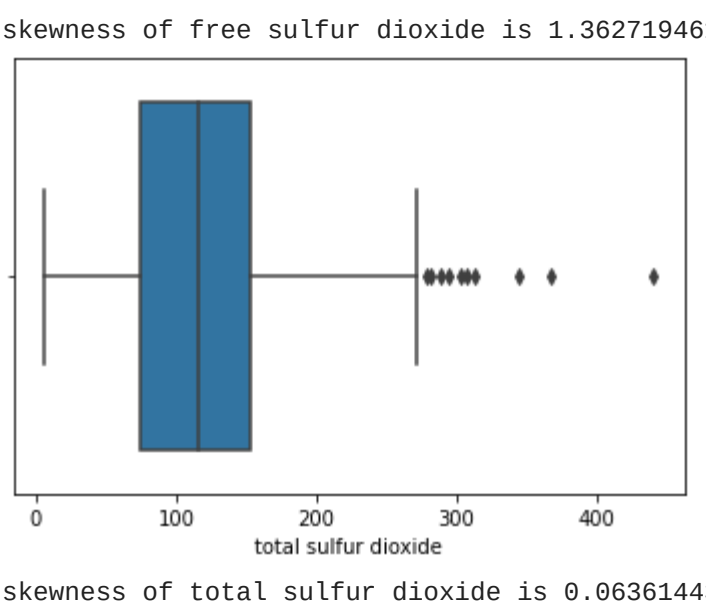
skewness of residual sugar is 1.7065502704869113



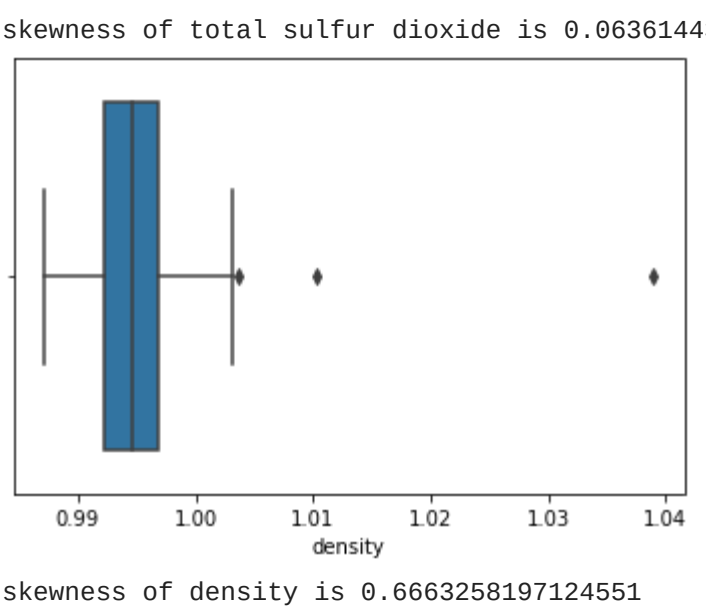
skewness of chlorides is 5.338236960791629



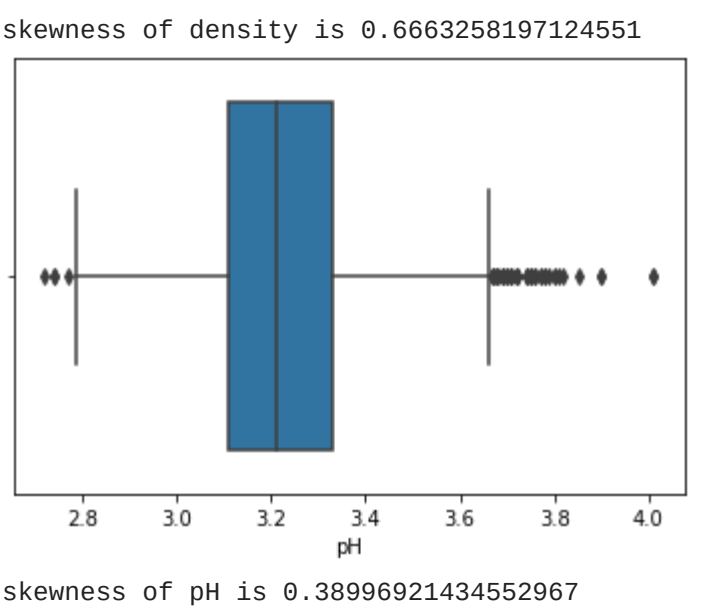
skewness of free sulfur dioxide is 1.3627194619464467



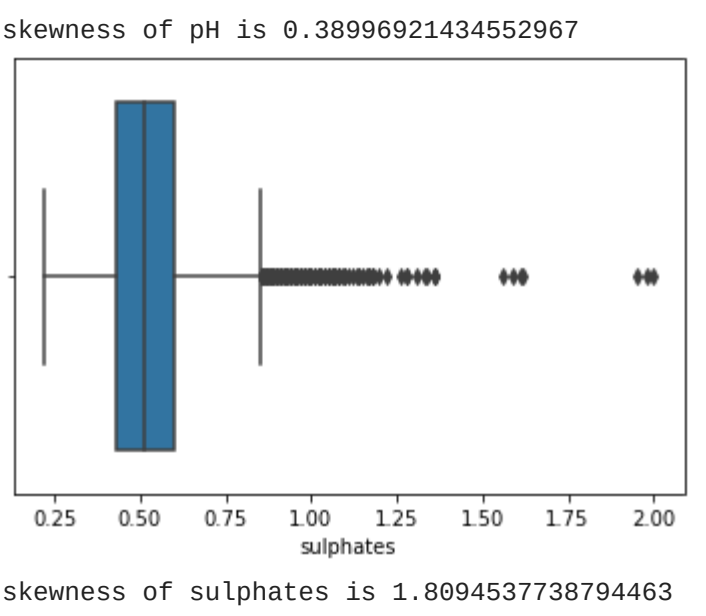
skewness of total sulfur dioxide is 0.06361443392014983



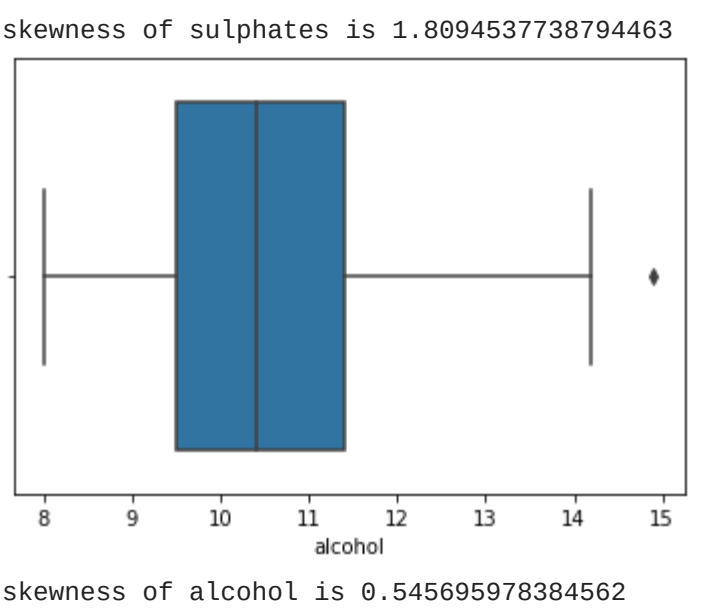
skewness of density is 0.6663258197124551



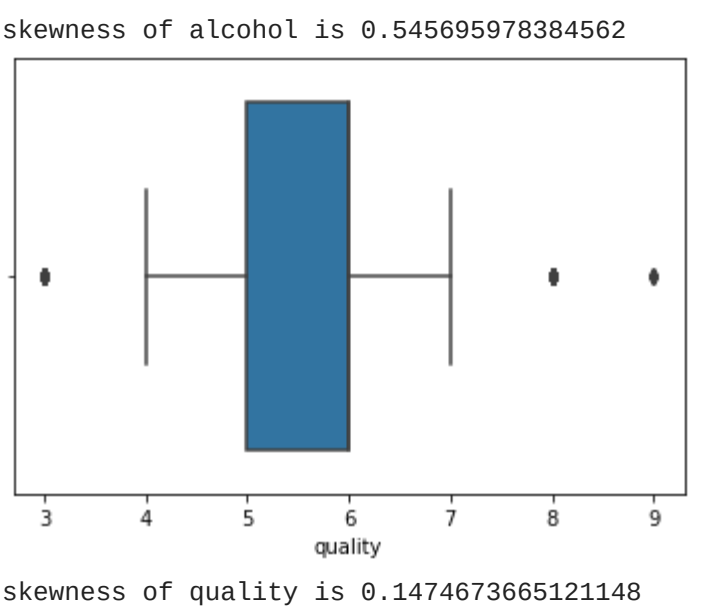
skewness of pH is 0.38996921434552967



skewness of sulphates is 1.8094537738794463



skewness of alcohol is 0.545695978384562



skewness of quality is 0.1474673665121148

most of the features are skewed and have lots of outliers so we can't remove them

outliers could be wine with very high quality or very low quality

log transformation

In [21]:
```python
for col in columns_to_unskew:
    wine_df[col] = np.log(wine_df[col])
    print("skewness of {} is {}".format(col, wine_df[col].skew()))
```

```
skewness of fixed acidity is 0.8431187613658074
skewness of volatile acidity is 0.3304079923552218
skewness of residual sugar is 0.32647404052053697
skewness of chlorides is 0.9066531061816026
skewness of free sulfur dioxide is -0.7893362805953683
skewness of sulphates is 0.39395419995852554
```

encode color column

In [22]:
```python
wine_df['color']= pd.get_dummies(wine_df['color'], drop_first=True)
```

In [23]:
```python
wine_df
```

Out[23]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality	color
0	2.001480	-0.356675	0.00	0.641854	-2.577022	2.397895	34.0	0.99780	3.51	-0.579818	9.4	5	0
1	2.054124	-0.127833	0.00	0.955511	-2.322788	3.218876	67.0	0.99680	3.20	-0.385662	9.8	5	0
2	2.054124	-0.274437	0.04	0.832909	-2.385967	2.708050	54.0	0.99700	3.26	-0.430783	9.8	5	0
3	2.415914	-1.272966	0.56	0.641854	-2.590267	2.833213	60.0	0.99800	3.16	-0.544727	9.8	6	0
5	2.001480	-0.415515	0.00	0.587787	-2.590267	2.564949	40.0	0.99780	3.51	-0.579818	9.4	5	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
4893	1.824549	-1.560648	0.29	0.470004	-3.244194	3.178054	92.0	0.99114	3.27	-0.693147	11.2	6	1
4894	1.887070	-1.139434	0.36	2.079442	-3.057608	4.043051	168.0	0.99490	3.15	-0.776529	9.6	5	1
4895	1.871802	-1.427116	0.19	0.182322	-3.194183	3.401197	111.0	0.99254	2.99	-0.776529	9.4	6	1
4896	1.704748	-1.237874	0.30	0.095310	-3.816713	2.995732	110.0	0.98869	3.34	-0.967584	12.8	7	1
4897	1.791759	-1.560648	0.38	-0.223144	-3.912023	3.091042	98.0	0.98941	3.26	-1.139434	11.8	6	1

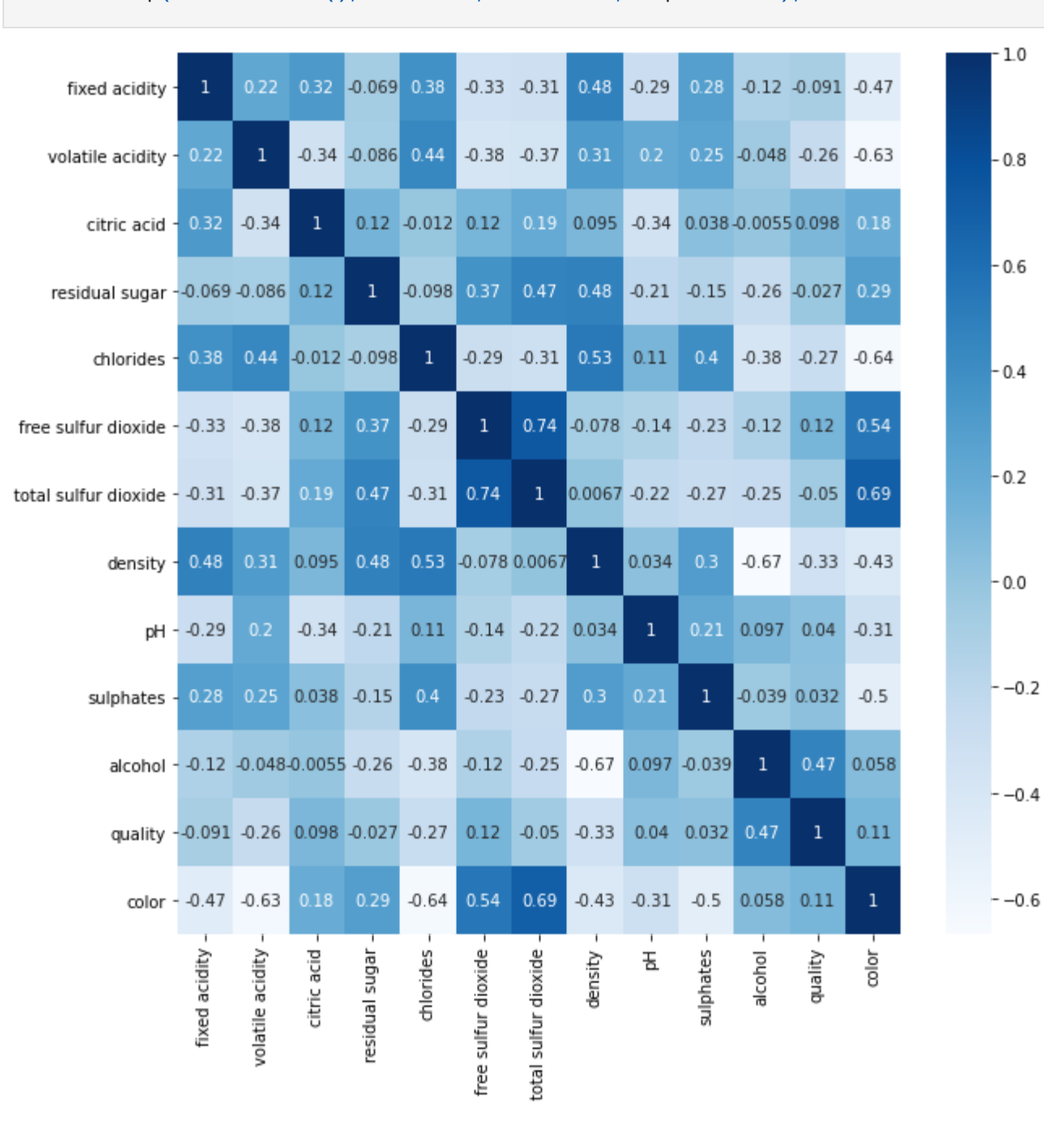
5320 rows × 13 columns

In [24]:
```python
wine_df.corr()
```

Out[24]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
fixed acidity	1.000000	0.220109	0.320073	-0.068722	0.376426	-0.326154	-0.307004	0.483131	-0.291425	0.281534	-0.123079	-0.091052
volatile acidity	0.220109	1.000000	-0.340334	-0.086402	0.443129	-0.380876	-0.365291	0.307104	0.201273	0.245456	-0.048363	-0.257036
citric acid	0.320073	-0.340334	1.000000	0.123839	-0.012140	0.116065	0.194835	0.094758	-0.344735	0.037581	-0.005496	0.097954
residual sugar	-0.068722	-0.086402	0.123839	1.000000	-0.097723	0.365977	0.469693	0.480986	-0.214883	-0.154597	-0.258628	-0.027043
chlorides	0.376426	0.443129	-0.012140	-0.097723	1.000000	-0.286262	-0.310019	0.533019	0.109704	0.395847	-0.382938	-0.272067
free sulfur dioxide	-0.326154	-0.380876	0.116065	0.365977	-0.286262	1.000000	0.740785	-0.077548	-0.139170	-0.229993	-0.124016	0.115441
total sulfur dioxide	-0.307004	-0.365291	0.194835	0.469693	-0.310019	0.740785	1.000000	0.006711	-0.222956	-0.265684	-0.249004	-0.050296
density	0.483131	0.307104	0.094758	0.480986	0.533019	-0.077548	0.006711	1.000000	0.034273	0.302393	-0.667811	-0.326434
pH	-0.291425	0.201273	-0.344735	-0.214883	0.109704	-0.139170	-0.222956	0.034273	1.000000	0.209510	0.097314	0.039733
sulphates	0.281534	0.245456	0.037581	-0.154597	0.395847	-0.229993	-0.265684	0.302393	0.209510	1.000000	-0.038807	0.031693
alcohol	-0.123079	-0.048363	-0.005496	-0.258628	-0.382938	-0.124016	-0.249004	-0.667811	0.097314	-0.038807	1.000000	0.469422
quality	-0.091052	-0.257036	0.097954	-0.027043	-0.272067	0.115441	-0.050296	-0.326434	0.039733	0.031693	0.469422	1.000000
color	-0.473887	-0.625216	0.183759	0.287201	-0.639336	0.540016	0.694229	-0.429377	-0.310919	-0.496562	0.057756	0.114809

In [25]:
```python
plt.figure(figsize=(10,10))
sns.heatmap(wine_df.corr(),cbar=True,annot=True,cmap='Blues');
```



remove feature with correlation more than 0.7

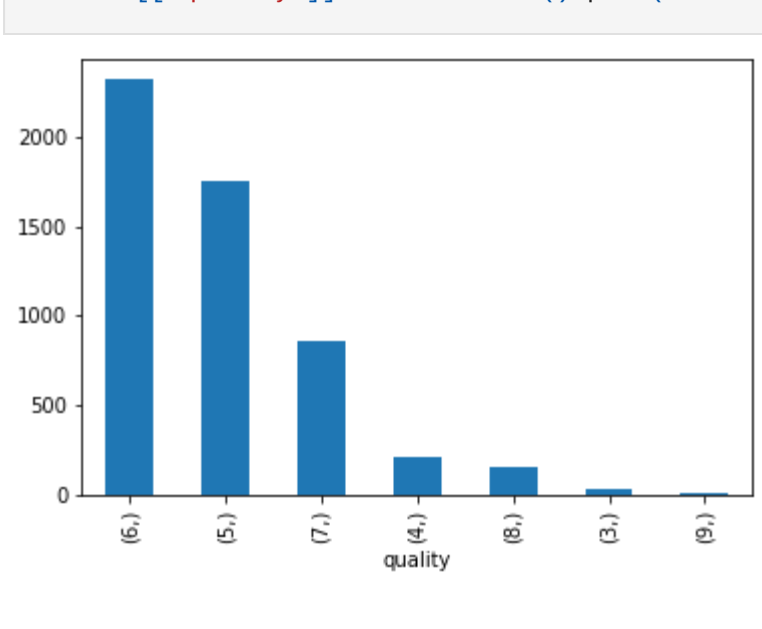
In [26]:
```python
for a in range(len(wine_df.corr().columns)):
    for b in range(a):
        if abs(wine_df.corr().iloc[a,b]) >0.7:
            name = wine_df.corr().columns[a]
            print(name, a, b)
```

```
total sulfur dioxide 6 5
```

In [27]:
```python
wine_df= wine_df.drop('total sulfur dioxide',axis=1)
```

check categories

In [28]:
```python
wine_df[['quality']].value_counts().plot(kind='bar');
```



The data is very unbalanced

In [29]:
```python
wine_df.shape
```

Out[29]:
```
(5320, 12)
```

In [30]:
```python
wine_df['quality'].unique()
```

Out[30]:
```
array([5, 6, 7, 4, 8, 3, 9])
```

In [31]:
```python
wine_df['quality'].value_counts()
```

Out[31]:
```
6    2323
5    1752
7     856
4     206
8     148
3      30
9       5
Name: quality, dtype: int64
```

wine with quality > 5 is considered good

wine with quality <= 5 is considered bad

In [32]:
```python
wine_df.loc[wine_df['quality'] <=5, 'quality'] = 0
wine_df.loc[wine_df['quality'] > 5, 'quality'] = 1
wine_df['quality'].value_counts()
```

Out[32]:
```
1    3332
0    1988
Name: quality, dtype: int64
```

features and labels

In [33]:
```python
X = wine_df.drop(columns='quality')
print(X.shape)
```

```
(5320, 11)
```

In [34]:
```python
y = wine_df['quality']
print(y.shape)
```

```
(5320,)
```

In [ ]:

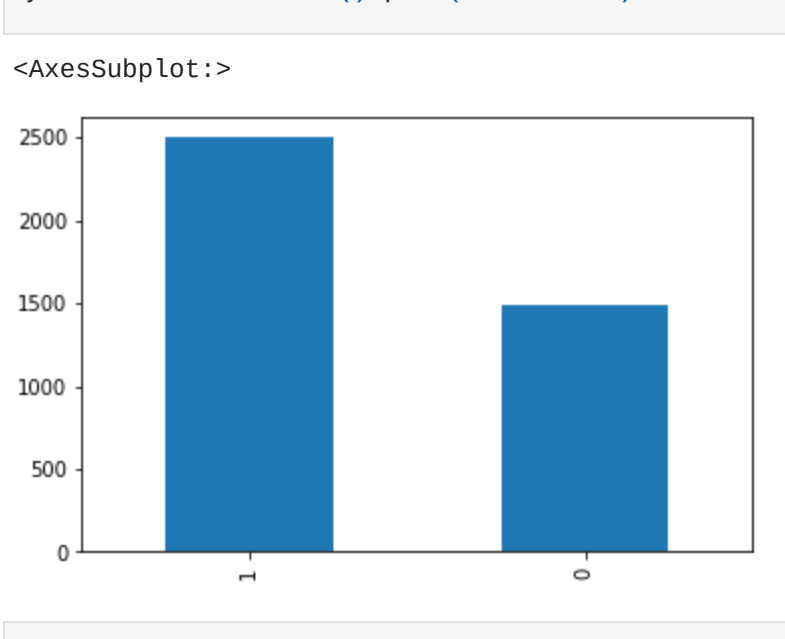
In [ ]:

Train Test split

In [35]:
```python
from sklearn.model_selection import StratifiedShuffleSplit

sss=StratifiedShuffleSplit(n_splits=1,test_size=0.25,random_state=0)

for train_index, test_index in sss.split(X, y):
    X_train = X.iloc[train_index]
    y_train = y.iloc[train_index]

    X_test = X.iloc[test_index]
    y_test = y.iloc[test_index]
```

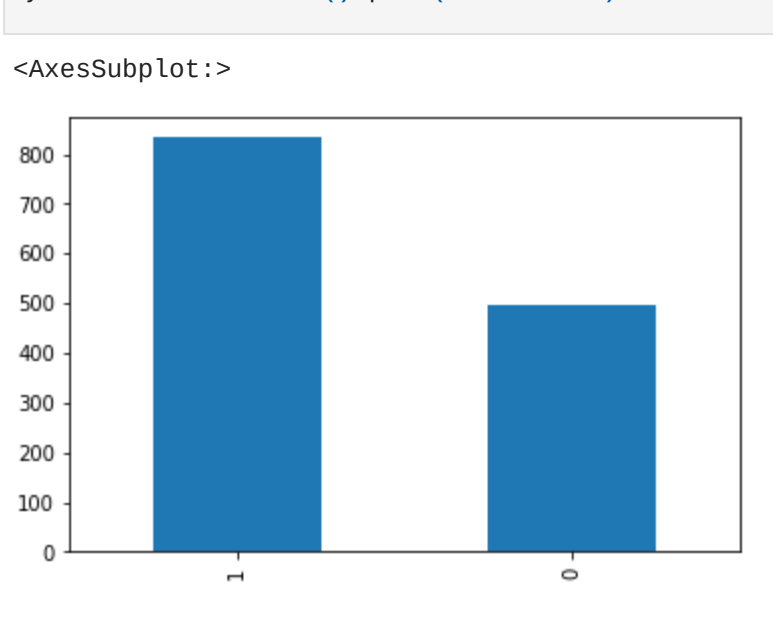
In [36]:
```python
y_train.value_counts().plot(kind='bar')
```

Out[36]:
```
<AxesSubplot:>
```



In [37]:
```python
y_test.value_counts().plot(kind='bar')
```

Out[37]:
```
<AxesSubplot:>
```



Models

In [38]:
```python
scores_dict = {}
```

logistic regression

In [39]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
model1 = LogisticRegression(max_iter= 1000,  class_weight='balanced')
model1.fit(X_train_scaled, y_train)
print("Train score: ", model1.score(X_train_scaled, y_train))
y_pred = model1.predict(X_test_scaled)
```

```
Train score:  0.7343358395989975
```

In [40]:
```python
cr_lr = classification_report(y_test, y_pred, output_dict=True)
cr_lr
```

Out[40]:
```
{'0': {'precision': 0.6378466557911908,
  'recall': 0.7867203219315896,
  'f1-score': 0.7045045045045045,
  'support': 497},
 '1': {'precision': 0.8521617852161785,
  'recall': 0.7334933973589436,
  'f1-score': 0.7883870967741935,
  'support': 833},
 'accuracy': 0.7533834586466165,
 'macro avg': {'precision': 0.7450042205036846,
  'recall': 0.7601068596452666,
  'f1-score': 0.7464458006393491,
  'support': 1330},
 'weighted avg': {'precision': 0.7720756052731567,
  'recall': 0.7533834586466165,
  'f1-score': 0.7570414965049939,
  'support': 1330}}
```

In [41]:
```python
scores_dict['logistic_regression'] = cr_lr['macro avg']['f1-score']
```

In [42]:
```
scores_dict
```

Out[42]:
```
{'logistic_regression': 0.7464458006393491}
```

SVM

In [43]:
```
from sklearn.svm import SVC
from sklearn.pipeline import Pipeline
from sklearn.model_selection import GridSearchCV

pipe = Pipeline([('scaler', StandardScaler()), ('svc', SVC())])
parameters = { 'svc__gamma':['auto'],
             'svc__C':[ 0.1, 1, 10, 100],
             'svc__kernel':['linear', 'rbf'] }

grid_svc = GridSearchCV(pipe, parameters, cv=3)
grid_svc.fit(X_train, y_train)
```

Out[43]:
```
GridSearchCV(cv=3,
             estimator=Pipeline(steps=[('scaler', StandardScaler()),
                                       ('svc', SVC())]),
             param_grid={'svc__C': [0.1, 1, 10, 100], 'svc__gamma': ['auto'],
                         'svc__kernel': ['linear', 'rbf']})
```

In [44]:
```
grid_svc.best_params_
```

Out[44]:
```
{'svc__C': 1, 'svc__gamma': 'auto', 'svc__kernel': 'rbf'}
```

In [45]:
```
print("Train score: ", grid_svc.score(X_train, y_train))
```

```
Train score:  0.7884711779448621
```

In [46]:
```
y_pred = grid_svc.predict(X_test)
svc_test = classification_report(y_test, y_pred, output_dict=True)
scores_dict['svc'] = svc_test['macro avg']['f1-score']
```

In [47]:
```
scores_dict
```

Out[47]:
```
{'logistic_regression': 0.7464458006393491, 'svc': 0.7550895140664962}
```

ensemble

random forest

In [48]:
```
from sklearn.ensemble import RandomForestClassifier

parameters = {'max_depth':[2,3,4,5,6,7,8,9,10]}
grid_rf = GridSearchCV( RandomForestClassifier(), parameters, cv=3)
grid_rf.fit(X_train, y_train)
```

Out[48]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(),
             param_grid={'max_depth': [2, 3, 4, 5, 6, 7, 8, 9, 10]})
```

In [49]:
```
grid_rf.best_params_
```

Out[49]:
```
{'max_depth': 10}
```

In [50]:
```
print("Train score: ", grid_rf.score(X_train, y_train))
```

```
Train score:  0.9090225563909774
```

In [51]:
```
y_pred = grid_rf.predict(X_test)
rf_test = classification_report(y_test, y_pred, output_dict=True)
scores_dict['Random forest'] = rf_test['macro avg']['f1-score']
```

In [52]:
```
scores_dict
```

Out[52]:
```
{'logistic_regression': 0.7464458006393491,
 'svc': 0.7550895140664962,
 'Random forest': 0.7583768017838656}
```

bagging

In [53]:
```
from sklearn.ensemble import BaggingClassifier

clf = BaggingClassifier(base_estimator=SVC(),
                        n_estimators=50).fit(X_train, y_train)

score_train = clf.score(X_train, y_train)
print("train score of bagging with svc: ", score_train)
y_pred = clf.predict(X_test)
bag_test = classification_report(y_test, y_pred, output_dict=True)
scores_dict['Bagging_svc'] = bag_test['macro avg']['f1-score']
```

```
train score of bagging with svc:  0.7358395989974937
```

In [54]:
```
scores_dict
```

Out[54]:
```
{'logistic_regression': 0.7464458006393491,
 'svc': 0.7550895140664962,
 'Random forest': 0.7583768017838656,
 'Bagging_svc': 0.7254033945594048}
```

In [ ]:

In [ ]:

In [ ]:

opservation and flaws

1- several of the attributes are correlated

2- Data had lot's of outliers

3- unbalanced classes

Best model

the best score on the testset was acheived by Random forest with an avg f1-score of 0.758

future steps

1- Outlier detection algorithms could be used to detect the few excellent or poor wines.

upsampling or downsampling techniques

In [ ]:

In [ ]:

In [ ]: