# **Red Wine Quality Prediction Project**

### **Project Description**

The dataset is related to red and white variants of the Portuguese "Vinho Verde" wine. Due to privacy and logistic issues, only physicochemical (inputs) and sensory (the output) variables are available (e.g. there is no data about grape types, wine brand, wine selling price, etc.).

This dataset can be viewed as classification task. The classes are ordered and not balanced (e.g. there are many more normal wines than excellent or poor ones). Also, we are not sure if all input variables are relevant. So it could be interesting to test feature selection methods.

### **Attribute Information**

Input variables (based on physicochemical tests): 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)

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_m.
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import SVC
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.preprocessing import MinMaxScaler
import warnings
warnings.filterwarnings("ignore", category=FutureWarning)
```

```
In [3]: df = pd.read_csv('winequality-red (1).csv')
```

In [4]: df.head()

Out[4]:

	fixed acidity	volatile acidity	citric acid	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
4											•

In [5]: df.shape

Out[5]: (1599, 12)

In [6]: 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	рН	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]: # checking for missing vlaues
        df.isnull().sum()
Out[7]: fixed acidity
                                 0
        volatile acidity
                                 0
        citric acid
                                 0
        residual sugar
                                 0
        chlorides
        free sulfur dioxide
        total sulfur dioxide
        density
        рΗ
                                 0
        sulphates
                                 0
        alcohol
                                 0
        quality
        dtype: int64
```

There are no missing values.

```
In [8]: df['quality'].value_counts()

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

```
In [9]: df.describe()
```

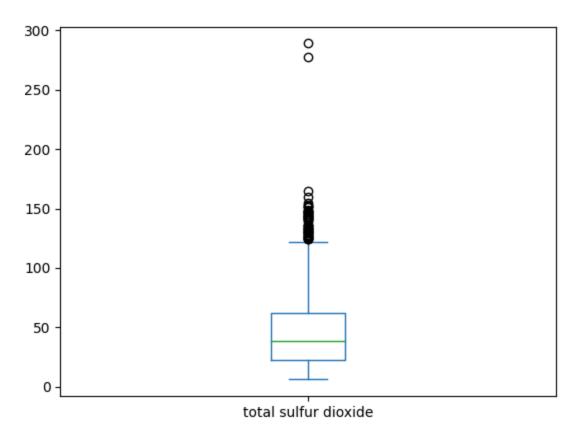
#### Out[9]:

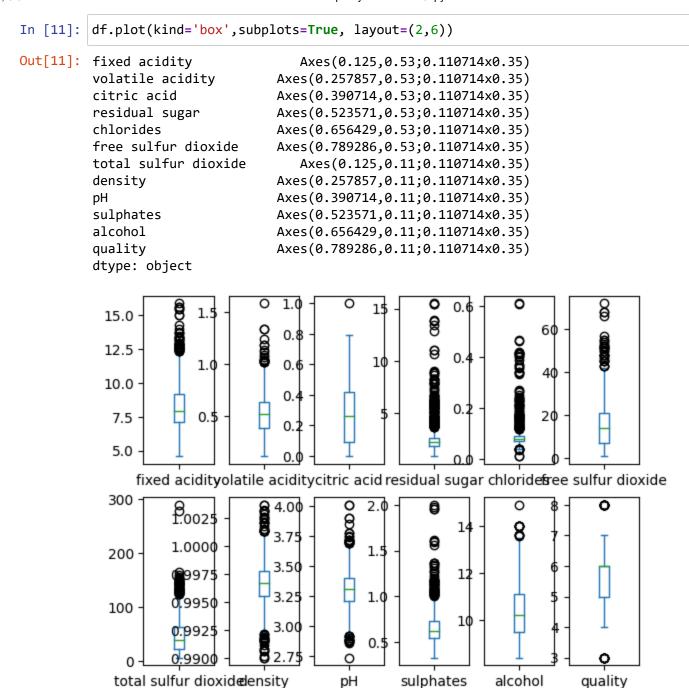
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulf dioxic
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.00000
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.46779
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.89532
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.00000
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.00000
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.00000
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.00000
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.00000
4							<b>•</b>

# Visualization and plots

In [10]: df['total sulfur dioxide'].plot.box()

Out[10]: <Axes: >





pН

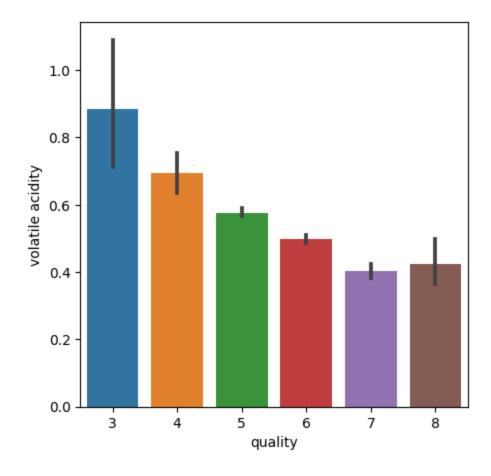
alcohol

quality

There is no Outlier in data.

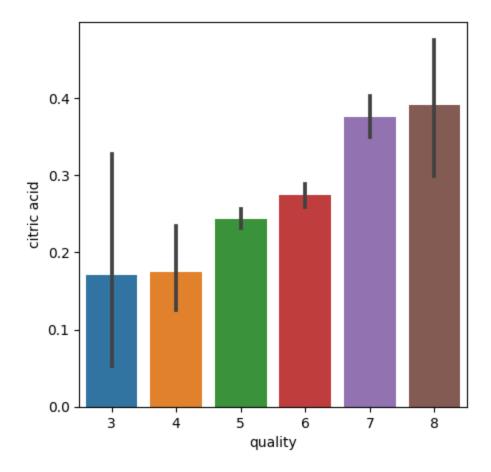
```
In [12]: fig=plt.figure(figsize=(5,5))
sns.barplot(x='quality',y='volatile acidity',data=df)
```

Out[12]: <Axes: xlabel='quality', ylabel='volatile acidity'>



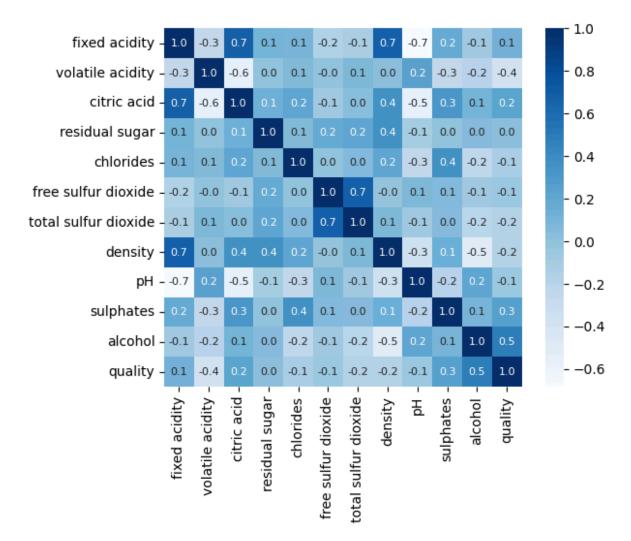
```
In [13]: fig=plt.figure(figsize=(5,5))
sns.barplot(x='quality',y='citric acid',data=df)
```

Out[13]: <Axes: xlabel='quality', ylabel='citric acid'>



```
In [14]: correlation=df.corr()
    sns.heatmap(correlation, cbar=True, square=True, fmt = '.1f', annot = True, an
```

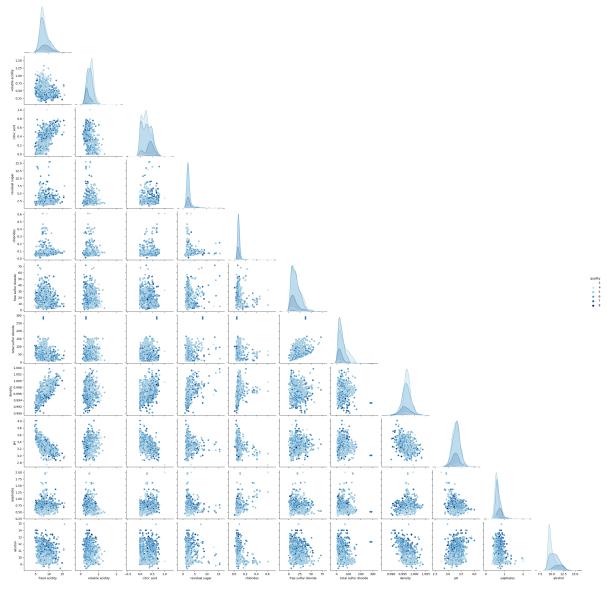
Out[14]: <Axes: >



Best Correlations are between : citeic\_acid & flex\_acidity ---> 0.7 density & flex\_acidity ---> 0.7 total sulfor dioxide & free sulfor dioxide ---> 0.7

```
In [23]: sns.pairplot(df, hue='quality', corner = True, palette='Blues')
```

Out[23]: <seaborn.axisgrid.PairGrid at 0x1e09c0f6510>



```
In [28]: X=df.drop("quality",axis=1)
Y=df['quality'].apply(lambda x:1 if x>=7 else 0)
```

X\_train, X\_test, Y\_train, Y\_test = train\_test\_split(X, Y, test\_size=0.2, random\_state=42)

```
In [29]: Y.value_counts()
```

Out[29]: 0 1382 1 217

Name: quality, dtype: int64

## **Normalization**

```
In [30]: scaler = MinMaxScaler(feature_range=(0, 1)).fit_transform(X)
X = pd.DataFrame(scaler, columns=X.columns)
```

### In [31]: print(X)

	fixed acidity v	olatile acidity	citric acid	residual sugar	chlorides
\					
0	0.247788	0.397260	0.00	0.068493	0.106845
1	0.283186	0.520548	0.00	0.116438	0.143573
2	0.283186	0.438356	0.04	0.095890	0.133556
3	0.584071	0.109589	0.56	0.068493	0.105175
4	0.247788	0.397260	0.00	0.068493	0.106845
	•••	• • •	• • •	•••	
1594	0.141593	0.328767	0.08	0.075342	0.130217
1595	0.115044	0.294521	0.10	0.089041	0.083472
1596	0.150442	0.267123	0.13	0.095890	0.106845
1597	0.115044	0.359589	0.12	0.075342	0.105175
1598	0.123894	0.130137	0.47	0.184932	0.091820
	free sulfur diox	ide total sulfu	r dioxide d	ensity pH	\
0	0.140			567548 0.606299	•
1	0.110			404136 0.363305	

	free sulfur dioxide	total sulfur dioxide	density	рН
0	0.140845	0.098940	0.567548	0.606299
1	0.338028	0.215548	0.494126	0.362205
2	0.197183	0.169611	0.508811	0.409449
3	0.225352	0.190813	0.582232	0.330709
4	0.140845	0.098940	0.567548	0.606299
• • •	• • •	• • •	• • •	• • •
1594	0.436620	0.134276	0.354626	0.559055
1595	0.535211	0.159011	0.370778	0.614173
1596	0.394366	0.120141	0.416300	0.535433
1597	0.436620	0.134276	0.396476	0.653543
1598	0.239437	0.127208	0.397944	0.511811

	sulphates	alcohol
0	0.137725	0.153846
1	0.209581	0.215385
2	0.191617	0.215385
3	0.149701	0.215385
4	0.137725	0.153846
1594	0.149701	0.323077
1595	0.257485	0.430769
1596	0.251497	0.400000
1597	0.227545	0.276923
1598	0.197605	0.400000

[1599 rows x 11 columns]

```
In [32]: X.describe()
```

#### Out[32]:

total sulf dioxic	free sulfur dioxide	chlorides	residual sugar	citric acid	volatile acidity	fixed acidity	
1599.00000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	count
0.1429	0.209506	0.125988	0.112247	0.270976	0.279329	0.329171	mean
0.11620	0.147326	0.078573	0.096570	0.194801	0.122644	0.154079	std
0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	min
0.05650	0.084507	0.096828	0.068493	0.090000	0.184932	0.221239	25%
0.11307	0.183099	0.111853	0.089041	0.260000	0.273973	0.292035	50%
0.19788	0.281690	0.130217	0.116438	0.420000	0.356164	0.407080	75%
1.00000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	max
							4

```
In [34]: # Splite Dataframe
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.25, random)
```

## RandomForestClassifier

Accuracy : 0.9225

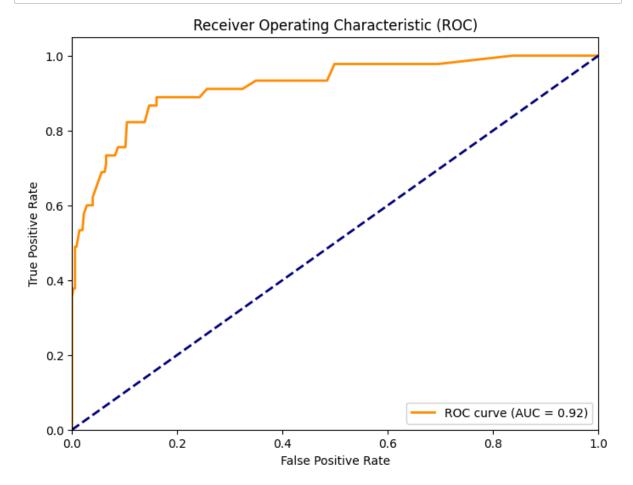
#### **Building a Predictive System**

```
In [44]: input_data = (7.5,0.5,0.36,6.1,0.071,17.0,102.0,0.9978,3.35,0.8,10.5)
         # changing the input data to a numpy array
         input_data_as_numpy_array = np.asarray(input_data)
         # reshape the data as we are predicting the label for only one instance
         input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)
         prediction = model.predict(input data reshaped)
         print(prediction)
         if (prediction[0]==1):
           print('Good Quality Wine')
           print('Bad Quality Wine')
         [0]
         Bad Quality Wine
         C:\Users\99Minds-1\AppData\Local\Programs\Python\Python311\Lib\site-packages
         \sklearn\base.py:439: UserWarning: X does not have valid feature names, but R
         andomForestClassifier was fitted with feature names
           warnings.warn(
In [46]: | confuion_matrix = confusion_matrix(y_test, X_test_prediction)
In [48]: confuion matrix
Out[48]: array([[342,
                       13],
                       27]], dtype=int64)
                [ 18,
In [50]:
          classification_report(y_test, X_test_prediction)
Out[50]:
                                      recall f1-score
                                                         support\n\n
                                                                                0
                        precision
         0.95
                   0.96
                              0.96
                                         355\n
                                                         1
                                                                 0.68
                                                                            0.60
                                                                                      0.
         64
                   45\n\n
                                                                 0.92
                                                                             400\n
                              accuracy
                                                                                     mac
         ro avg
                       0.81
                                 0.78
                                           0.80
                                                      400\nweighted avg
                                                                               0.92
                               400\n'
         0.92
                   0.92
```

### **ROC** and **AUC** value

```
In [55]: # Calculate ROC curve and AUC score
fpr, tpr, _ = roc_curve(y_test, model.predict_proba(X_test)[:, 1])
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc="lower right")
plt.show()
```



**Grid Search** 

```
In [56]: from sklearn.model_selection import GridSearchCV
# Define a grid of hyperparameters to search
param_grid = {
     'n_estimators': [50, 100, 150, 200],
     'max_depth': [None, 10, 20, 30]
}

# Create a GridSearchCV object
grid_search = GridSearchCV(estimator=rf, param_grid=param_grid, cv=5, scoring=grid_search.fit(X_train, y_train))

# Print the best parameters and the corresponding accuracy
print("Best Parameters:", grid_search.best_params_)
print("Best Accuracy:", grid_search.best_score_)
Best Parameters: {'max_depth': 20, 'n_estimators': 50}
Best Accuracy: 0.902433751743375
```

# **Thankyou**

```
In [ ]:
```