Dmpm Lab -9

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Topic: Wine type (red/white) prediction using logistic regression and wine quality dataset

Importing the libraries

In [1]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

from sklearn.metrics import accuracy_score,auc,confusion_matrix,precision_score,recall_score,roc_curve,classi
fication_report
import matplotlib.pyplot as plt
import seaborn as sns
```

Preprocessing

In [ ]:
```
df = pd.read_csv("D:\TY sem6\DMPM LAB\winequalityN.csv")
```

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

Out[3]:

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

In [4]:
```
df["quality"].value_counts()
```

Out[4]:
```
6    2836
5    2138
7    1079
4     216
8     193
3      30
9       5
Name: quality, dtype: int64
```

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6497 entries, 0 to 6496
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   type                  6497 non-null   object 
 1   fixed acidity         6487 non-null   float64
 2   volatile acidity      6489 non-null   float64
 3   citric acid           6494 non-null   float64
 4   residual sugar        6495 non-null   float64
 5   chlorides             6495 non-null   float64
 6   free sulfur dioxide   6497 non-null   float64
 7   total sulfur dioxide  6497 non-null   float64
 8   density               6497 non-null   float64
 9   pH                    6488 non-null   float64
 10  sulphates             6493 non-null   float64
 11  alcohol               6497 non-null   float64
 12  quality               6497 non-null   int64  
dtypes: float64(11), int64(1), object(1)
memory usage: 660.0+ KB
```

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
type                     0
fixed acidity           10
volatile acidity         8
citric acid              3
residual sugar           2
chlorides                2
free sulfur dioxide      0
total sulfur dioxide     0
density                  0
pH                       9
sulphates                4
alcohol                  0
quality                  0
dtype: int64
```

In [7]:
```
df.dropna(inplace = True)
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
type                    0
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
```

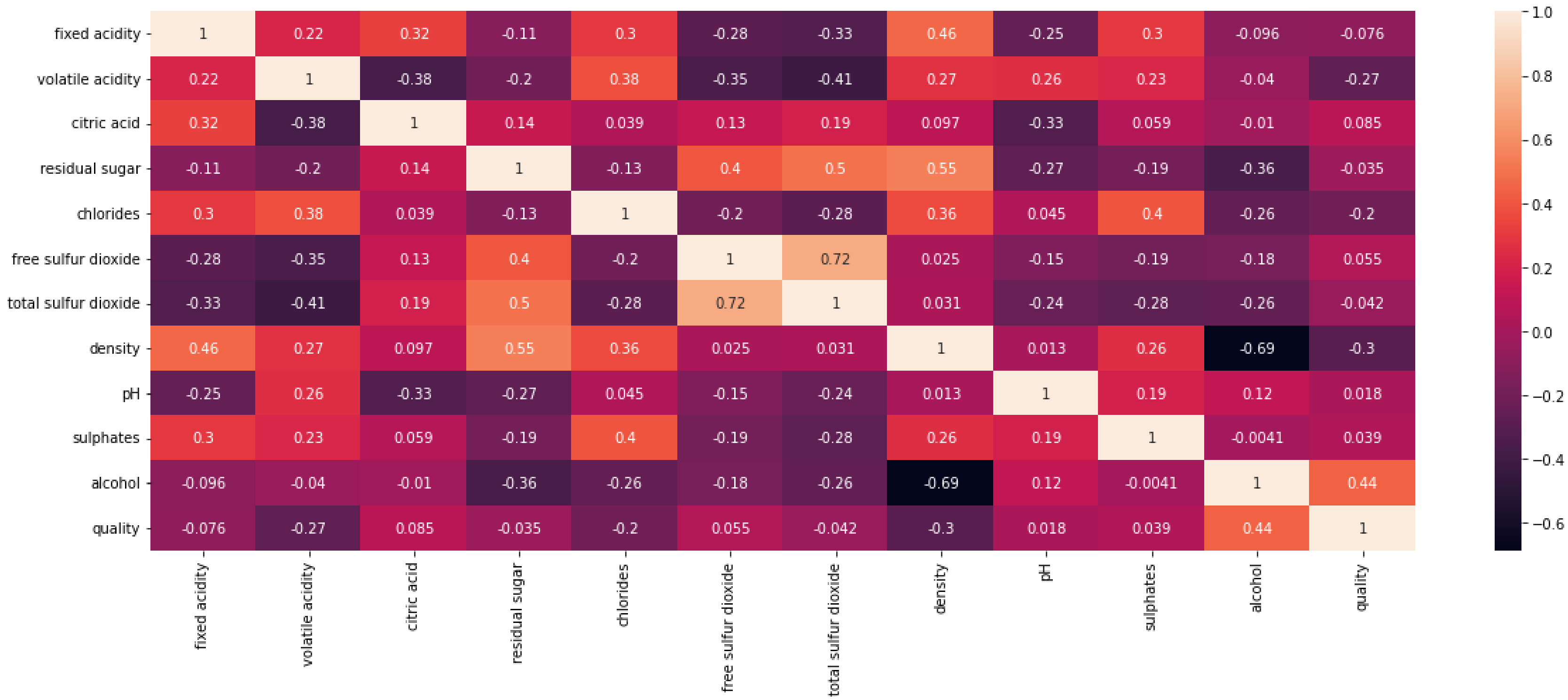
In [9]:
```
corr = df.corr()
corr
```

Out[9]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	qu
fixed acidity	1.000000	0.221066	0.323744	-0.113442	0.299104	-0.283485	-0.330543	0.459713	-0.251121	0.301263	-0.096190	-0.07
volatile acidity	0.221066	1.000000	-0.377512	-0.196677	0.377995	-0.353402	-0.414729	0.272101	0.260134	0.225656	-0.039528	-0.26
citric acid	0.323744	-0.377512	1.000000	0.142324	0.039412	0.132271	0.194398	0.097068	-0.327860	0.059070	-0.010056	0.08
residual sugar	-0.113442	-0.196677	0.142324	1.000000	-0.128814	0.403449	0.495684	0.551494	-0.266481	-0.185616	-0.359132	-0.03
chlorides	0.299104	0.377995	0.039412	-0.128814	1.000000	-0.195428	-0.279602	0.363108	0.044653	0.396240	-0.257664	-0.20
free sulfur dioxide	-0.283485	-0.353402	0.132271	0.403449	-0.195428	1.000000	0.721476	0.025113	-0.145164	-0.188947	-0.179477	0.05
total sulfur dioxide	-0.330543	-0.414729	0.194398	0.495684	-0.279602	0.721476	1.000000	0.031419	-0.237204	-0.275878	-0.264385	-0.04
density	0.459713	0.272101	0.097068	0.551494	0.363108	0.025113	0.031419	1.000000	0.012525	0.260019	-0.687432	-0.30
pH	-0.251121	0.260134	-0.327860	-0.266481	0.044653	-0.145164	-0.237204	0.012525	1.000000	0.190864	0.120473	0.01
sulphates	0.301263	0.225656	0.059070	-0.185616	0.396240	-0.188947	-0.275878	0.260019	0.190864	1.000000	-0.004116	0.03
alcohol	-0.096190	-0.039528	-0.010056	-0.359132	-0.257664	-0.179477	-0.264385	-0.687432	0.120473	-0.004116	1.000000	0.44
quality	-0.076174	-0.266677	0.084926	-0.034654	-0.200553	0.054924	-0.041598	-0.304447	0.018403	0.039054	0.444637	1.00

In [10]:
```
plt.figure(1,(20,7))
sns.heatmap(df.corr(), annot=True)
```

Out[10]: <AxesSubplot:>



Encoding and scaling categorical and numerical variables

In [16]:
```
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
```

In [17]:
```
from sklearn.preprocessing import StandardScaler

from sklearn.compose import ColumnTransformer
```

In [23]:
```
X_unscaled = df.drop("type",axis=1)
X_unscaled.columns
```

Out[23]:
```
Index(['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
       'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density',
       'pH', 'sulphates', 'alcohol', 'quality'],
      dtype='object')
```

In [24]:
```
sc = StandardScaler()
sc.fit(X_unscaled)
scaled_values=sc.transform(X_unscaled)
X_scaled = pd.DataFrame(scaled_values)
X_scaled.columns = ["fixed acidity","volatile acidity","citric acid","residual sugar","chlorides","free sulfu
r dioxide","total sulfur dioxide","density","pH","sulphates","alcohol","quality"]
X_scaled.drop("quality",axis=1,inplace=True)
X_scaled.head()
```

Out[24]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
0	-0.167786	-0.422710	0.283959	3.207420	-0.315228	0.815609	0.960779	2.099926	-1.359160	-0.544987	-1.418922
1	-0.707155	-0.240479	0.146257	-0.808151	-0.201180	-0.930138	0.288479	-0.232465	0.508399	-0.276354	-0.832184
2	0.679794	-0.361966	0.559363	0.306117	-0.172668	-0.029107	-0.330745	0.134053	0.259391	-0.612146	-0.329265
3	-0.013681	-0.665684	0.008554	0.642500	0.055427	0.928238	1.243853	0.300653	-0.176373	-0.880779	-0.496905
4	-0.013681	-0.665684	0.008554	0.642500	0.055427	0.928238	1.243853	0.300653	-0.176373	-0.880779	-0.496905

In [26]:
```
num_attribs = list(X_scaled)
print(num_attribs)
cat_attribs = ["quality"]
print(cat_attribs)
```

```
['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar', 'chlorides', 'free sulfur dioxide', 't
otal sulfur dioxide', 'density', 'pH', 'sulphates', 'alcohol']
['quality']
```

In [27]:
```
num_pipeline = Pipeline([
('std_scaler', StandardScaler()),
])
```

Pipeline for Transforming the data

In [28]:
```
full_pipeline = ColumnTransformer([
("num", num_pipeline, num_attribs),
("cat", OneHotEncoder(), cat_attribs),
])
winedf = full_pipeline.fit_transform(X_unscaled)
```

In [30]:
```
winedf=pd.DataFrame(winedf)
```

In [31]:
```
winedf.head()
```

Out[31]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	-0.167786	-0.422710	0.283959	3.207420	-0.315228	0.815609	0.960779	2.099926	-1.359160	-0.544987	-1.418922	0.0	0.0	0.0
1	-0.707155	-0.240479	0.146257	-0.808151	-0.201180	-0.930138	0.288479	-0.232465	0.508399	-0.276354	-0.832184	0.0	0.0	0.0
2	0.679794	-0.361966	0.559363	0.306117	-0.172668	-0.029107	-0.330745	0.134053	0.259391	-0.612146	-0.329265	0.0	0.0	0.0
3	-0.013681	-0.665684	0.008554	0.642500	0.055427	0.928238	1.243853	0.300653	-0.176373	-0.880779	-0.496905	0.0	0.0	0.0
4	-0.013681	-0.665684	0.008554	0.642500	0.055427	0.928238	1.243853	0.300653	-0.176373	-0.880779	-0.496905	0.0	0.0	0.0

In [32]:
```
winedf.columns = ["fixed acidity","volatile acidity","citric acid","residual sugar","chlorides","free sulfur dioxide","total sulfur dioxide","density","pH","sulphates","alcohol","3","4","5","6","7","8","9"]
winedf.head()
```

Out[32]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	3	4	5
0	-0.167786	-0.422710	0.283959	3.207420	-0.315228	0.815609	0.960779	2.099926	-1.359160	-0.544987	-1.418922	0.0	0.0	0.0
1	-0.707155	-0.240479	0.146257	-0.808151	-0.201180	-0.930138	0.288479	-0.232465	0.508399	-0.276354	-0.832184	0.0	0.0	0.0
2	0.679794	-0.361966	0.559363	0.306117	-0.172668	-0.029107	-0.330745	0.134053	0.259391	-0.612146	-0.329265	0.0	0.0	0.0
3	-0.013681	-0.665684	0.008554	0.642500	0.055427	0.928238	1.243853	0.300653	-0.176373	-0.880779	-0.496905	0.0	0.0	0.0
4	-0.013681	-0.665684	0.008554	0.642500	0.055427	0.928238	1.243853	0.300653	-0.176373	-0.880779	-0.496905	0.0	0.0	0.0

In [35]:
```
y=df["type"]
```

Splitting the dataset (80:20)

In [36]:
```
X_train,X_test,y_train,y_test = train_test_split(winedf,y,test_size=0.2,random_state=10,stratify=y)
```

In [37]:
```
X_train.shape,y_train.shape,X_test.shape,y_test.shape
```

Out[37]: ((5170, 18), (5170,), (1293, 18), (1293,))

First logistic model

In [ ]:
```
model = LogisticRegression()
```

In [39]:
```
model.fit(X_train,y_train)
```

Out[39]: LogisticRegression()

In [40]:
```
model.score(X_train,y_train)
```

Out[40]:
```
0.9945841392649903
```

In [56]:
```
y_pred_train1 = model.predict(X_train)

summary=classification_report(y_train,y_pred_train1)
print(summary)
```

```
              precision    recall  f1-score   support

         red       0.99      0.99      0.99      1274
       white       1.00      1.00      1.00      3896

    accuracy                           0.99      5170
   macro avg       0.99      0.99      0.99      5170
weighted avg       0.99      0.99      0.99      5170
```

Check for overfitting and ranking the features accordingly

In [42]:
```
from mlxtend.feature_selection import SequentialFeatureSelector
from sklearn.feature_selection import RFE
```

In [43]:
```
model2 = LogisticRegression()
```

In [45]:
```
rfe = RFE(estimator=model, step=1,verbose=2)
rfe.fit(X_train,y_train)
```

```
Fitting estimator with 18 features.
Fitting estimator with 17 features.
Fitting estimator with 16 features.
Fitting estimator with 15 features.
Fitting estimator with 14 features.
Fitting estimator with 13 features.
Fitting estimator with 12 features.
Fitting estimator with 11 features.
Fitting estimator with 10 features.
```

Out[45]:
```
RFE(estimator=LogisticRegression(), verbose=2)
```

In [46]:
```
selected_rfe_features=pd.DataFrame({"Features":list(X_train),"Ranking":rfe.ranking_})
selected_rfe_features.sort_values(by="Ranking")
```

Out[46]:

	Features	Ranking
1	volatile acidity	1
3	residual sugar	1
4	chlorides	1
5	free sulfur dioxide	1
6	total sulfur dioxide	1
7	density	1
9	sulphates	1
10	alcohol	1
12	4	1
13	5	2
14	6	3
2	citric acid	4
0	fixed acidity	5
8	pH	6
15	7	7
11	3	8
16	8	9
17	9	10

In [47]:
```
X_train_rfe = rfe.transform(X_train)

X_train_rfe.shape
```

Out[47]: (5170, 9)

In [49]:
```
model2.fit(X_train_rfe, y_train)
```

Out[49]:
```
LogisticRegression()
```

In [50]:
```
r2_rfe = model2.score(X_train_rfe, y_train)
r2_rfe
```

Out[50]:
```
0.995164410058027
```

In [52]:
```
y_pred_train = model2.predict(X_train_rfe)
```

In [53]:
```
confusion_matrix(y_train,y_pred_train)
```

Out[53]:
```
array([[1259,   15],
       [  10, 3886]], dtype=int64)
```

Final report of the final model

In [54]:
```
summary=classification_report(y_train,y_pred_train)
print(summary)
```

```
              precision    recall  f1-score   support

         red       0.99      0.99      0.99      1274
       white       1.00      1.00      1.00      3896

    accuracy                           1.00      5170
   macro avg       0.99      0.99      0.99      5170
weighted avg       1.00      1.00      1.00      5170
```