wine-quality-prediction

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1 Predict wine quality using linear regression. Train a model, evaluate, and document insights for accurate predictions in this machine learning task.

2 Author: AHMED REKIK.

2.0.1 THE MACHINE LEARNING INTERNSHIP.

3 MODULES IMPORTATION

[69]:
```
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib.pyplot as plt
import statsmodels.api as sm
from sklearn.metrics import mean_squared_error
```

[ ]:
```
wine = pd.read_csv("/content/winequalityN.csv")
wine.head()
```

[ ]:
```
    type  fixed acidity  volatile acidity  citric acid  residual sugar  \
0  white            7.0              0.27         0.36            20.7
1  white            6.3              0.30         0.34             1.6
2  white            8.1              0.28         0.40             6.9
3  white            7.2              0.23         0.32             8.5
4  white            7.2              0.23         0.32             8.5

   chlorides  free sulfur dioxide  total sulfur dioxide  density    pH  \
0      0.045                 45.0                 170.0   1.0010  3.00
1      0.049                 14.0                 132.0   0.9940  3.30
2      0.050                 30.0                  97.0   0.9951  3.26
3      0.058                 47.0                 186.0   0.9956  3.19
4      0.058                 47.0                 186.0   0.9956  3.19

   sulphates  alcohol  quality
0       0.45      8.8        6
1       0.49      9.5        6
```

```
2        0.44      10.1          6
3        0.40       9.9          6
4        0.40       9.9          6
```

[ ]:
```
wine.describe()
```

[ ]:
```
       fixed acidity  volatile acidity  citric acid  residual sugar  \
count    6487.000000       6489.000000  6494.000000     6495.000000
mean        7.216579          0.339691     0.318722        5.444326
std         1.296750          0.164649     0.145265        4.758125
min         3.800000          0.080000     0.000000        0.600000
25%         6.400000          0.230000     0.250000        1.800000
50%         7.000000          0.290000     0.310000        3.000000
75%         7.700000          0.400000     0.390000        8.100000
max        15.900000          1.580000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide      density  \
count  6495.000000          6497.000000           6497.000000  6497.000000
mean      0.056042            30.525319            115.744574     0.994697
std       0.035036            17.749400             56.521855     0.002999
min       0.009000             1.000000              6.000000     0.987110
25%       0.038000            17.000000             77.000000     0.992340
50%       0.047000            29.000000            118.000000     0.994890
75%       0.065000            41.000000            156.000000     0.996990
max       0.611000           289.000000            440.000000     1.038980

                pH    sulphates      alcohol      quality
count  6488.000000  6493.000000  6497.000000  6497.000000
mean      3.218395     0.531215    10.491801     5.818378
std       0.160748     0.148814     1.192712     0.873255
min       2.720000     0.220000     8.000000     3.000000
25%       3.110000     0.430000     9.500000     5.000000
50%       3.210000     0.510000    10.300000     6.000000
75%       3.320000     0.600000    11.300000     6.000000
max       4.010000     2.000000    14.900000     9.000000
```

[6]:
```
wine.shape
```

[6]:
```
(6497, 13)
```

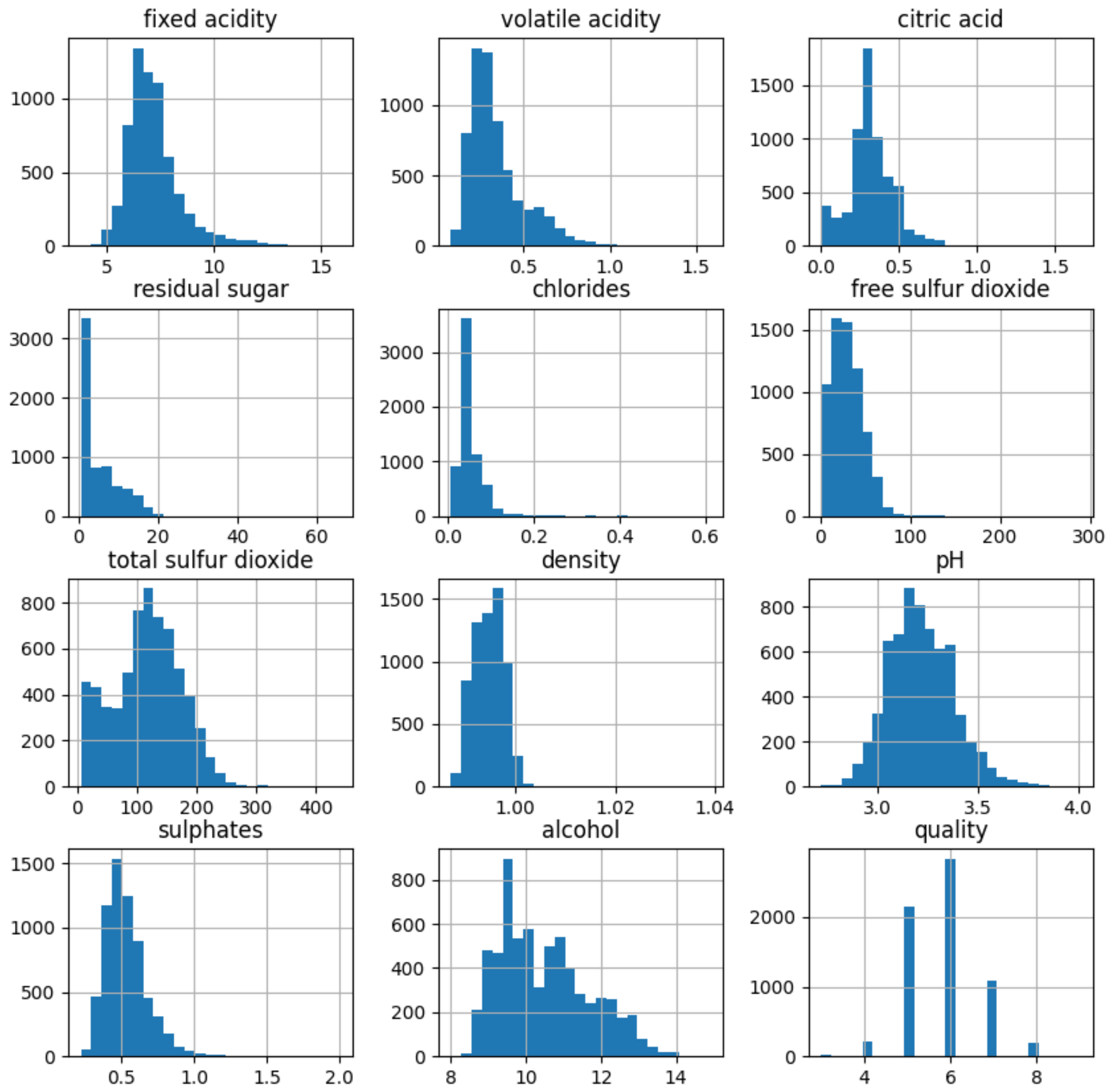
[10]:
```
wine.isnull().sum()
```

[10]:
```
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
```

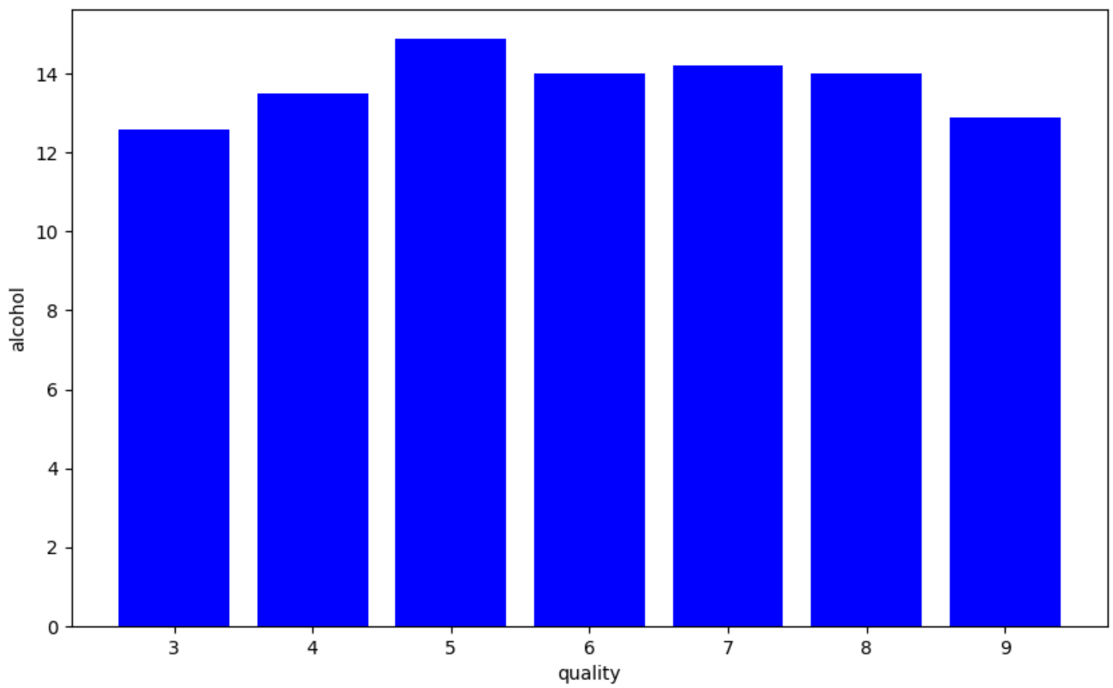
4 Visualization

[11]:
```python
wine.hist(bins=25,figsize=(10,10))
# display histogram
plt.show()
```



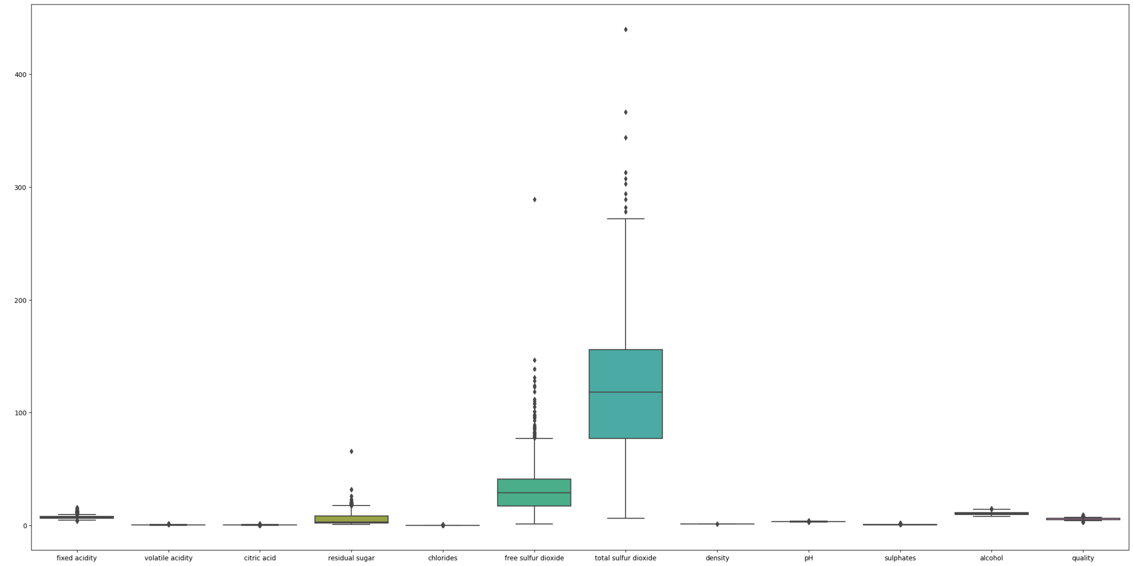
[12]:
```
plt.figure(figsize=[10,6])
# plot bar graph
plt.bar(wine['quality'],wine['alcohol'],color='blue')
# label x-axis
plt.xlabel('quality')
#label y-axis
plt.ylabel('alcohol')
```

[12]:
```
Text(0, 0.5, 'alcohol')
```



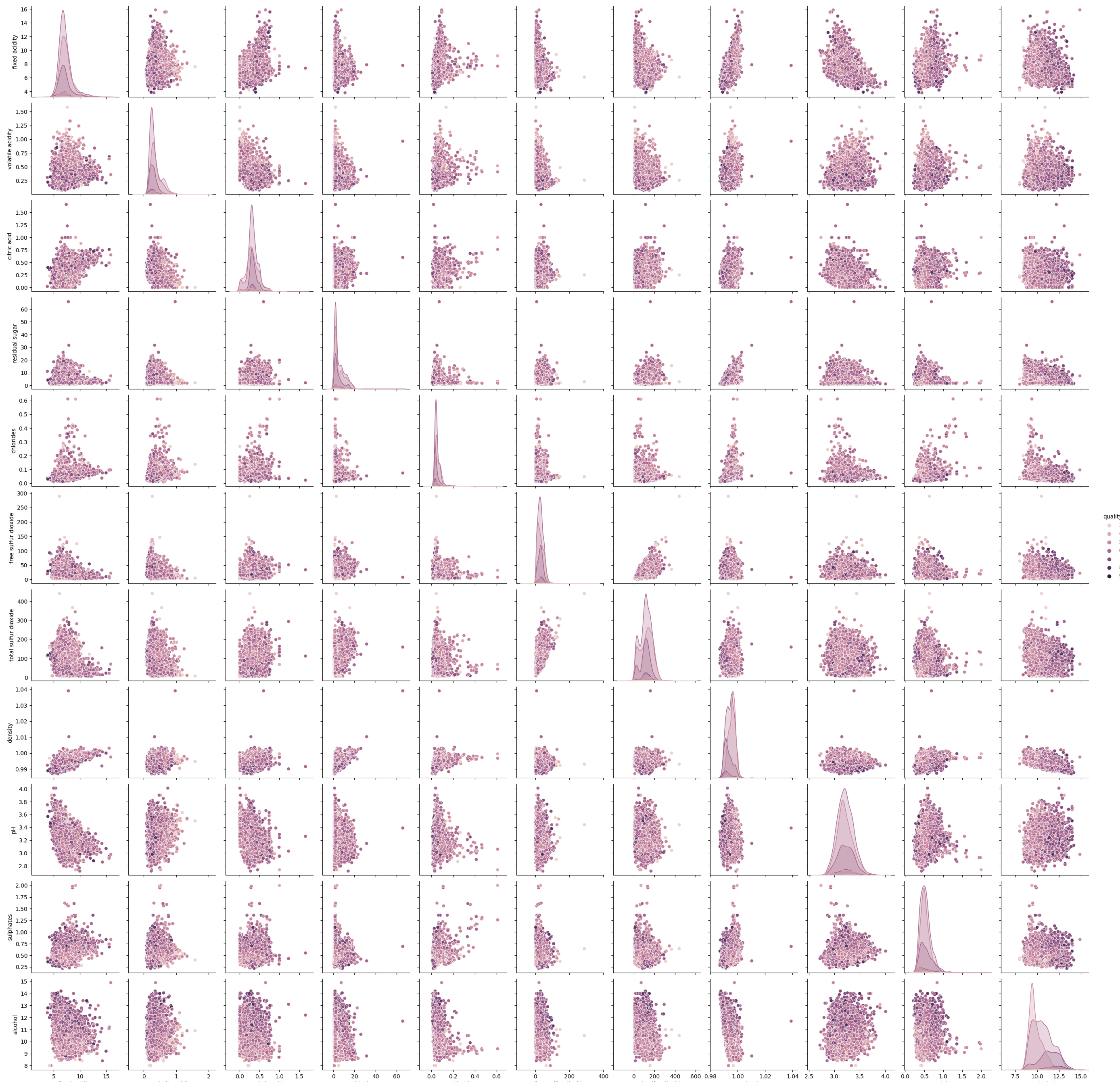
[53]:
```
plt.figure(figsize=(30,15))
sb.boxplot(data=wine)
```

[53]:
```
<Axes: >
```



[61]:
```
#Multivariate Analysis
plt.figure(figsize=(30, 15))
sb.pairplot(data=wine, hue='quality')
plt.show()
```

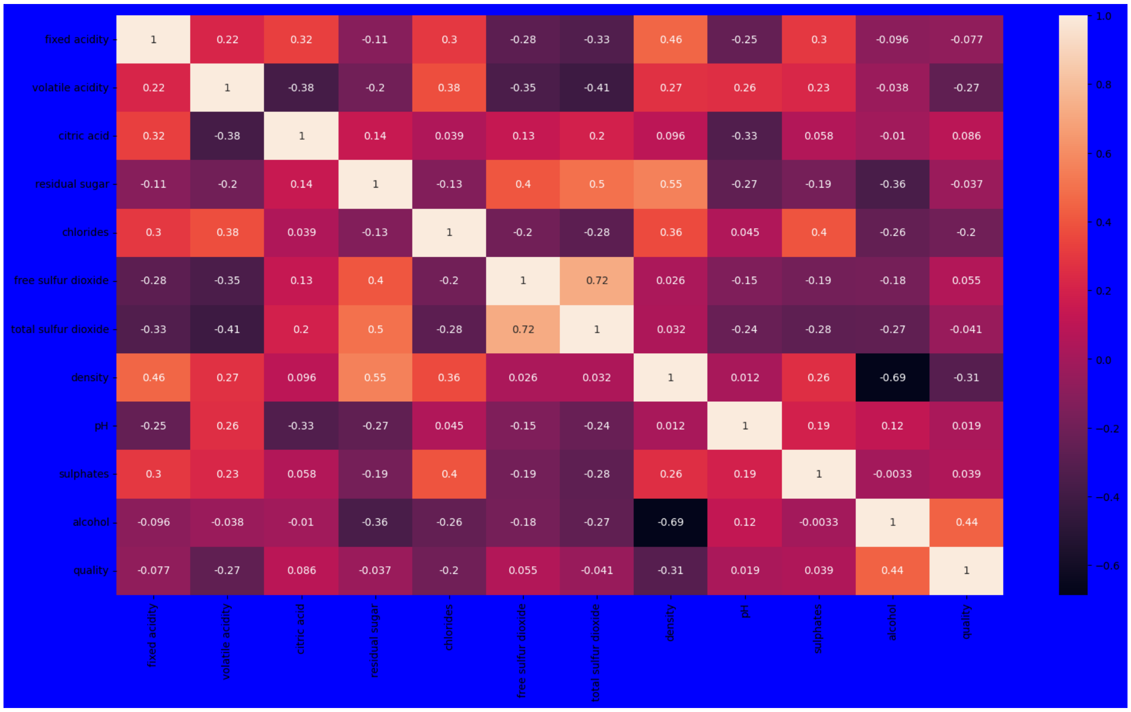
```
<Figure size 3000x1500 with 0 Axes>
```



[13]:
```
# ploting heatmap
plt.figure(figsize=[19,10],facecolor='blue')
sb.heatmap(wine.corr(),annot=True)
```

```
<ipython-input-13-b3c2b1f1d9bc>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sb.heatmap(wine.corr(),annot=True)
```

[13]:
```
<Axes: >
```



Now, we have to find those features that are fully correlated to each other by this we reduce the number of features from the data.

[14]:
```
for a in range(len(wine.corr().columns)):
    for b in range(a):
        if abs(wine.corr().iloc[a,b]) >0.7:
            name = wine.corr().columns[a]
            print(name)
```

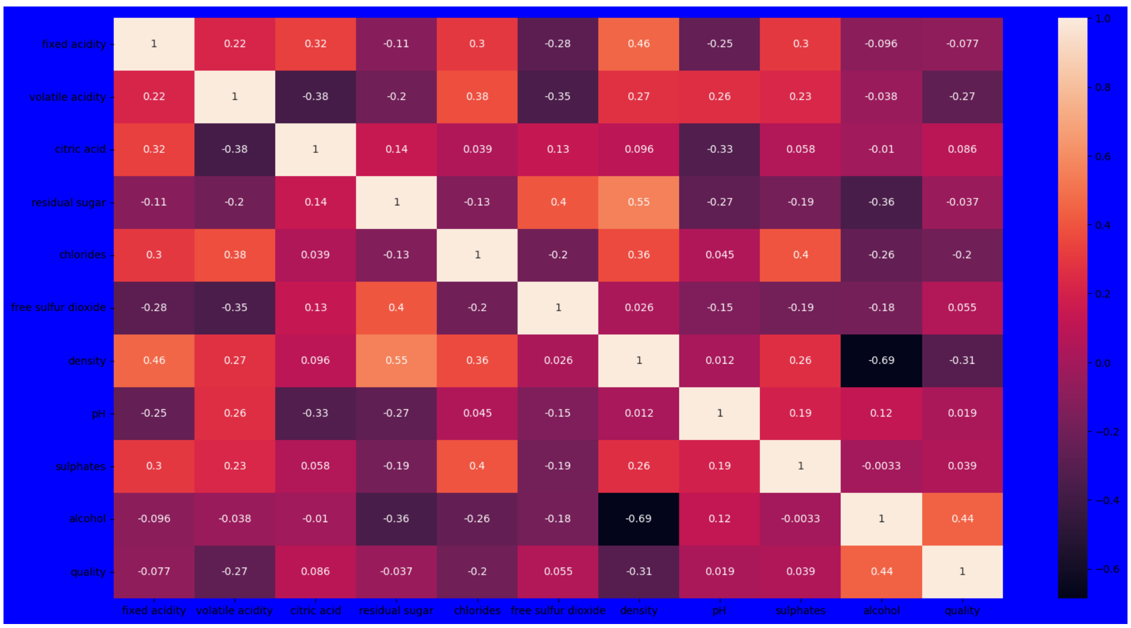
```
<ipython-input-14-b2e9a4146d97>:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  for a in range(len(wine.corr().columns)):
<ipython-input-14-b2e9a4146d97>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  if abs(wine.corr().iloc[a,b]) >0.7:
<ipython-input-14-b2e9a4146d97>:4: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  name = wine.corr().columns[a]

total sulfur dioxide
```

[16]:
```
new_wine=wine.drop('total sulfur dioxide',axis=1)
```

[18]:
```
# ploting heatmap
plt.figure(figsize=[19,10],facecolor='blue')
sb.heatmap(new_wine.corr(),annot=True)
```

```
<ipython-input-18-6d915c724d26>:3: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  sb.heatmap(new_wine.corr(),annot=True)
```

[18]:
```
<Axes: >
```



4.1 Handle null values

[20]:
```
new_wine.isnull().sum()
```

[20]:
```
type                    0
fixed acidity          10
volatile acidity        8
citric acid             3
residual sugar          2
chlorides               2
free sulfur dioxide     0
density                 0
pH                      9
```

```
sulphates               4
alcohol                 0
quality                 0
dtype: int64
```

[22]:
```python
new_wine.update(new_wine.fillna(new_wine.mean()))
```

```
<ipython-input-22-ae10a555ca56>:1: FutureWarning: The default value of
numeric_only in DataFrame.mean is deprecated. In a future version, it will
default to False. In addition, specifying 'numeric_only=None' is deprecated.
Select only valid columns or specify the value of numeric_only to silence this
warning.
  new_wine.update(new_wine.fillna(new_wine.mean()))
```

[23]:
```python
new_wine.isnull().sum()
```

[23]:
```
type                    0
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

[26]:
```python
# catogerical vars
next_wine = pd.get_dummies(new_wine,drop_first=True)
# display new dataframe
next_wine
```

[26]:
```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0               7.0             0.270         0.36            20.7      0.045
1               6.3             0.300         0.34             1.6      0.049
2               8.1             0.280         0.40             6.9      0.050
3               7.2             0.230         0.32             8.5      0.058
4               7.2             0.230         0.32             8.5      0.058
…                 …                 …            …               …        …
6492            6.2             0.600         0.08             2.0      0.090
6493            5.9             0.550         0.10             2.2      0.062
6494            6.3             0.510         0.13             2.3      0.076
6495            5.9             0.645         0.12             2.0      0.075
6496            6.0             0.310         0.47             3.6      0.067
```

```
      free sulfur dioxide  density    pH  sulphates  alcohol  quality  \
0                    45.0  1.00100  3.00   0.450000      8.8        6
1                    14.0  0.99400  3.30   0.490000      9.5        6
2                    30.0  0.99510  3.26   0.440000     10.1        6
3                    47.0  0.99560  3.19   0.400000      9.9        6
4                    47.0  0.99560  3.19   0.400000      9.9        6
…                     …       …     …        …          …       …
6492                 32.0  0.99490  3.45   0.580000     10.5        5
6493                 39.0  0.99512  3.52   0.531215     11.2        6
6494                 29.0  0.99574  3.42   0.750000     11.0        6
6495                 32.0  0.99547  3.57   0.710000     10.2        5
6496                 18.0  0.99549  3.39   0.660000     11.0        6

      type_white
0              1
1              1
2              1
3              1
4              1
…            …
6492           0
6493           0
6494           0
6495           0
6496           0

[6497 rows x 12 columns]
```

[31]:
```python
next_wine["best quality"] = [ 1 if x>=7 else 0 for x in wine.quality]
next_wine
```

[31]:
```
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0               7.0             0.270         0.36            20.7      0.045
1               6.3             0.300         0.34             1.6      0.049
2               8.1             0.280         0.40             6.9      0.050
3               7.2             0.230         0.32             8.5      0.058
4               7.2             0.230         0.32             8.5      0.058
…              …               …            …              …         …
6492            6.2             0.600         0.08             2.0      0.090
6493            5.9             0.550         0.10             2.2      0.062
6494            6.3             0.510         0.13             2.3      0.076
6495            5.9             0.645         0.12             2.0      0.075
6496            6.0             0.310         0.47             3.6      0.067

      free sulfur dioxide  density    pH  sulphates  alcohol  quality  \
0                    45.0  1.00100  3.00   0.450000      8.8        6
```

```
1                     14.0  0.99400  3.30   0.490000      9.5         6
2                     30.0  0.99510  3.26   0.440000     10.1         6
3                     47.0  0.99560  3.19   0.400000      9.9         6
4                     47.0  0.99560  3.19   0.400000      9.9         6
…                      …     …    …       …        …       …
6492                  32.0  0.99490  3.45   0.580000     10.5         5
6493                  39.0  0.99512  3.52   0.531215     11.2         6
6494                  29.0  0.99574  3.42   0.750000     11.0         6
6495                  32.0  0.99547  3.57   0.710000     10.2         5
6496                  18.0  0.99549  3.39   0.660000     11.0         6

      type_white  best quality
0              1             0
1              1             0
2              1             0
3              1             0
4              1             0
…          …            …
6492           0             0
6493           0             0
6494           0             0
6495           0             0
6496           0             0

[6497 rows x 13 columns]
```

4.1.1 in this dataset 'Type' feature contains two types Red and White, where Red consider as 0 and white considers as 1.

5 Splitting dataset

[62]:
```
column_train=["fixed acidity","volatile acidity","citric acid","residual␣
 ↪sugar","chlorides","free sulfur␣
 ↪dioxide","density","pH","sulphates","alcohol"]
x=next_wine[column_train]
y=next_wine["quality"]
```

[63]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test =train_test_split(x,y,test_size=0.
 ↪2,random_state=40)
```

6 Normalization

[64]:
```
#importing module
from sklearn.preprocessing import MinMaxScaler
# creating normalization object
norm = MinMaxScaler()
# fit data
norm_fit = norm.fit(x_train)
new_xtrain = norm_fit.transform(x_train)
new_xtest = norm_fit.transform(x_test)
# display values
print(new_xtrain)
```

```
[[0.34710744 0.1        0.22289157 … 0.46511628 0.14044944 0.26086957]
 [0.20661157 0.18       0.15662651 … 0.30232558 0.15168539 0.11594203]
 [0.24793388 0.06666667 0.18072289 … 0.21705426 0.16853933 0.14492754]
 …
 [0.33884298 0.38666667 0.         … 0.5503876  0.20224719 0.2173913 ]
 [0.24793388 0.34       0.06024096 … 0.53488372 0.25280899 0.24637681]
 [0.19008264 0.16666667 0.19277108 … 0.51937984 0.24157303 0.2173913 ]]
```

7 Applying Model

[65]:
```
from sklearn.linear_model import LinearRegression
Lrgr= LinearRegression()
Lrgr.fit(x_train,y_train)
```

[65]: LinearRegression()

[67]:
```
# Test prediction (Fixed Acidity, Volatile Acidity, Citric Acid, Residual␣
↪Sugar, Chlorides, Free Sulfur Dioxide, Total Sulfur Dioxide, Density, pH,␣
↪Sulphates, Alcohol)
print(Lrgr.predict([[15, 0.01, 0, 5, 0.001, 30, 0.95, 3, 0.9, 15]]))
```

```
[9.82662358]
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but LinearRegression was fitted with feature names
  warnings.warn(
```

8 Evaluation

[70]:
```
# Ordinary Least Square (OLS) Principle
x = sm.add_constant(x_train)
model = sm.OLS(y_train, x).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                quality   R-squared:                       0.285
Model:                            OLS   Adj. R-squared:                  0.284
Method:                 Least Squares   F-statistic:                     206.7
Date:                Thu, 12 Oct 2023   Prob (F-statistic):               0.00
Time:                        22:43:11   Log-Likelihood:                -5779.1
No. Observations:                5197   AIC:                         1.158e+04
Df Residuals:                    5186   BIC:                         1.165e+04
Df Model:                          10
Covariance Type:            nonrobust
================================================================================
=======
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-------
const                  34.2280     12.837      2.666      0.008       9.063
59.393
fixed acidity           0.0532      0.017      3.096      0.002       0.020
0.087
volatile acidity       -1.3115      0.087    -15.128      0.000      -1.481
-1.142
citric acid            -0.2576      0.086     -2.986      0.003      -0.427
-0.088
residual sugar          0.0315      0.006      5.715      0.000       0.021
0.042
chlorides              -0.2110      0.361     -0.585      0.558      -0.918
0.496
free sulfur dioxide     0.0024      0.001      3.450      0.001       0.001
0.004
density               -33.6139     13.115     -2.563      0.010     -59.324
-7.904
pH                      0.4065      0.100      4.085      0.000       0.211
0.602
sulphates               0.8277      0.085      9.782      0.000       0.662
0.994
alcohol                 0.3036      0.018     17.086      0.000       0.269
0.338
==============================================================================
Omnibus:                      101.971   Durbin-Watson:                   2.014
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              216.163
Skew:                           0.009   Prob(JB):                     1.15e-47
Kurtosis:                       3.999   Cond. No.                     6.78e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
```

```
specified.
[2] The condition number is large, 6.78e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[72]:
```python
# Evaluate our model using MSE criterion
y_pred = Lrgr.predict(x_test)
print("Mean Squared Error (MSE): ", mean_squared_error(y_test, y_pred))
```

```
Mean Squared Error (MSE):  0.5694187989872577
```

[73]:
```python
# Check quality value from dataset that is listed
print(next_wine['quality'].unique())
```

```
[6 5 7 8 4 3 9]
```

[74]:
```python
# MAPE
def mape(actual, pred):
  actual, pred = np.array(actual), np.array(pred)
  return np.mean(np.abs((actual - pred) / actual)) * 100
```

[75]:
```python
mape(y_test, y_pred)
# Error of our model is approximately 8-9% (Excellent)
# MAPE result Notes :
# 1. Below 10% = Excellent
# 2. 10% - 20% = Good
# 3. 21% - 50% = Reasonable
# 4. Above 50% = Inaccurate
```

[75]:
```
10.36550299232918
```

8.0.1 So the conclusion that we got, our MAPE result is 10.36550299232918 which is approximately 10% (Excellent)

9 THANKS.