

Elisetty Naga Jyothi

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```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df = pd.read_csv('/content/winequality-red.csv')
df.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	\
0	7.4	0.70	0.00	1.9	0.076	
1	7.8	0.88	0.00	2.6	0.098	
2	7.8	0.76	0.04	2.3	0.092	
3	11.2	0.28	0.56	1.9	0.075	
4	7.4	0.70	0.00	1.9	0.076	

	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	\
0	11.0	34.0	0.9978	3.51	0.56	
1	25.0	67.0	0.9968	3.20	0.68	
2	15.0	54.0	0.9970	3.26	0.65	
3	17.0	60.0	0.9980	3.16	0.58	
4	11.0	34.0	0.9978	3.51	0.56	

	alcohol	quality
0	9.4	5
1	9.8	5
2	9.8	5
3	9.8	6
4	9.4	5

```
df.shape
```

```
(1599, 12)
```

```
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
```

```
df.quality.value_counts()
```

```

5    681
6    638
7    199
4     53
8     18
3     10

```

```
Name: quality, dtype: int64
```

```
df.isnull().any()
```

```

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

```

```
dtype: bool
```

```
df.describe()
```

```

      fixed acidity  volatile acidity  citric acid  residual sugar \
count      1599.000000      1599.000000  1599.000000      1599.000000
mean         8.319637         0.527821    0.270976         2.538806
std         1.741096         0.179060    0.194801         1.409928
min         4.600000         0.120000    0.000000         0.900000
25%         7.100000         0.390000    0.090000         1.900000
50%         7.900000         0.520000    0.260000         2.200000
75%         9.200000         0.640000    0.420000         2.600000
max        15.900000         1.580000    1.000000        15.500000

```

```

      chlorides  free sulfur dioxide  total sulfur dioxide      density \

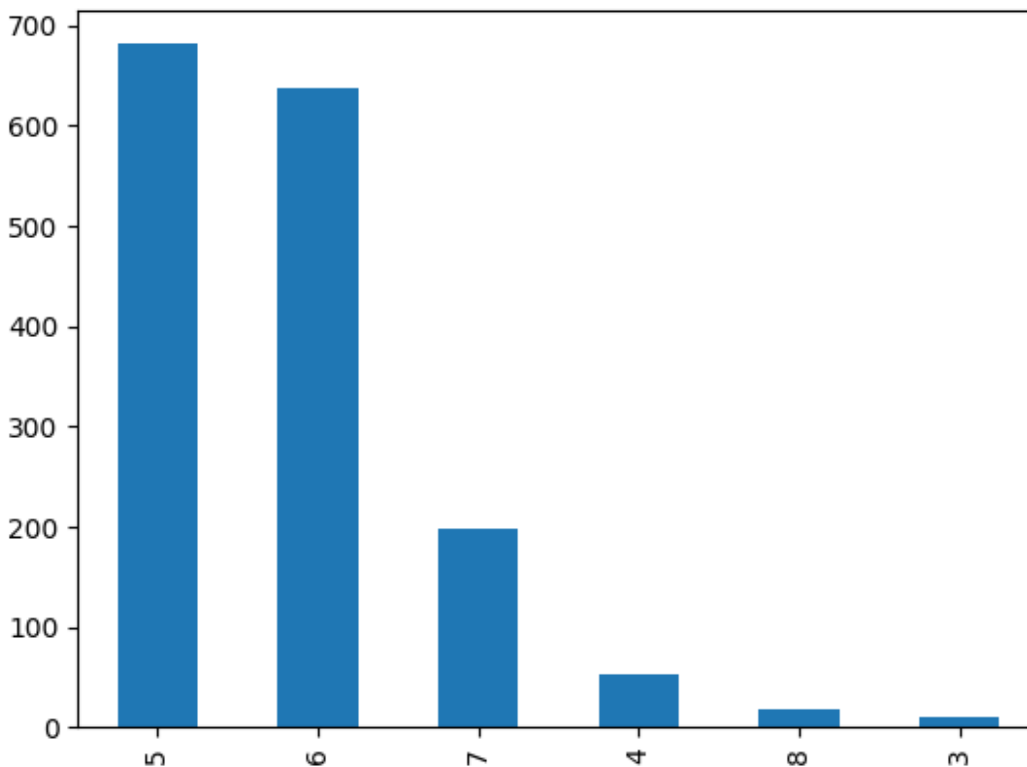
```

count	1599.000000	1599.000000	1599.000000	1599.000000
mean	0.087467	15.874922	46.467792	0.996747
std	0.047065	10.460157	32.895324	0.001887
min	0.012000	1.000000	6.000000	0.990070
25%	0.070000	7.000000	22.000000	0.995600
50%	0.079000	14.000000	38.000000	0.996750
75%	0.090000	21.000000	62.000000	0.997835
max	0.611000	72.000000	289.000000	1.003690

	pH	sulphates	alcohol	quality
count	1599.000000	1599.000000	1599.000000	1599.000000
mean	3.311113	0.658149	10.422983	5.636023
std	0.154386	0.169507	1.065668	0.807569
min	2.740000	0.330000	8.400000	3.000000
25%	3.210000	0.550000	9.500000	5.000000
50%	3.310000	0.620000	10.200000	6.000000
75%	3.400000	0.730000	11.100000	6.000000
max	4.010000	2.000000	14.900000	8.000000

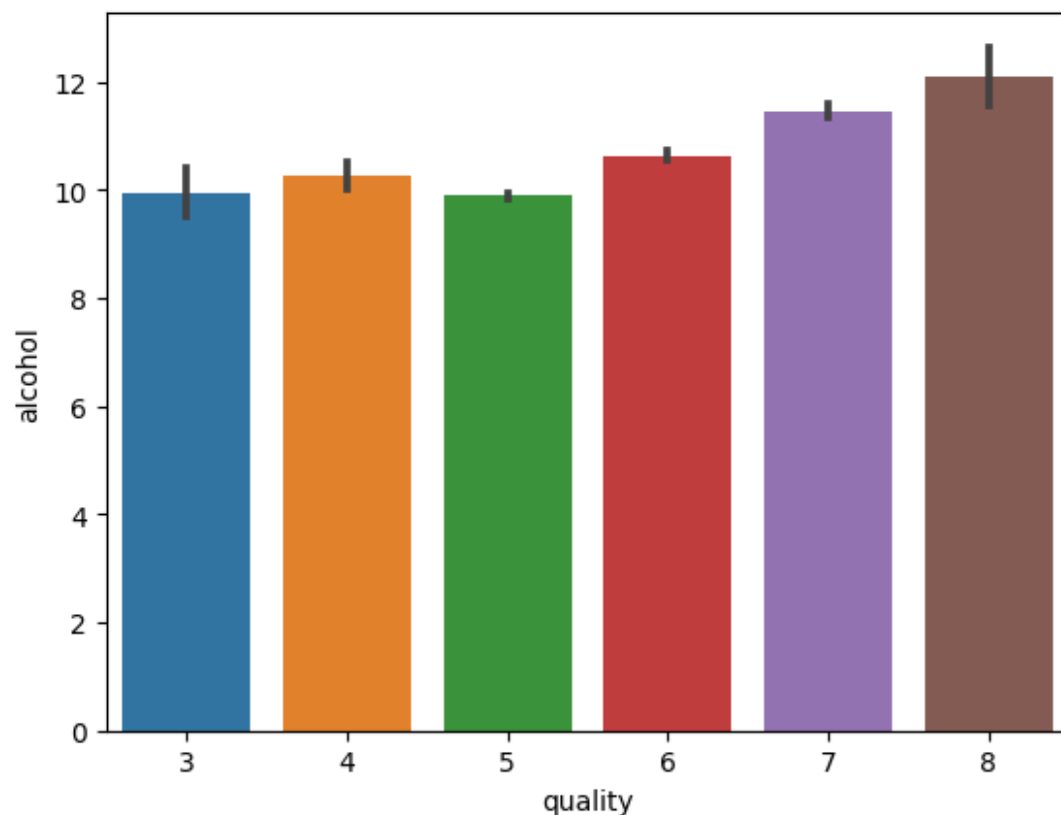
```
df["quality"].value_counts().plot(kind='bar')
```

<Axes: >



```
sns.barplot(x=df["quality"],y=df["alcohol"])
```

<Axes: xlabel='quality', ylabel='alcohol'>



df.corr()

	fixed acidity	volatile acidity	citric acid \
fixed acidity	1.000000	-0.256131	0.671703
volatile acidity	-0.256131	1.000000	-0.552496
citric acid	0.671703	-0.552496	1.000000
residual sugar	0.114777	0.001918	0.143577
chlorides	0.093705	0.061298	0.203823
free sulfur dioxide	-0.153794	-0.010504	-0.060978
total sulfur dioxide	-0.113181	0.076470	0.035533
density	0.668047	0.022026	0.364947
pH	-0.682978	0.234937	-0.541904
sulphates	0.183006	-0.260987	0.312770
alcohol	-0.061668	-0.202288	0.109903
quality	0.124052	-0.390558	0.226373

	residual sugar	chlorides	free sulfur dioxide \
fixed acidity	0.114777	0.093705	-0.153794
volatile acidity	0.001918	0.061298	-0.010504
citric acid	0.143577	0.203823	-0.060978
residual sugar	1.000000	0.055610	0.187049
chlorides	0.055610	1.000000	0.005562
free sulfur dioxide	0.187049	0.005562	1.000000
total sulfur dioxide	0.203028	0.047400	0.667666
density	0.355283	0.200632	-0.021946

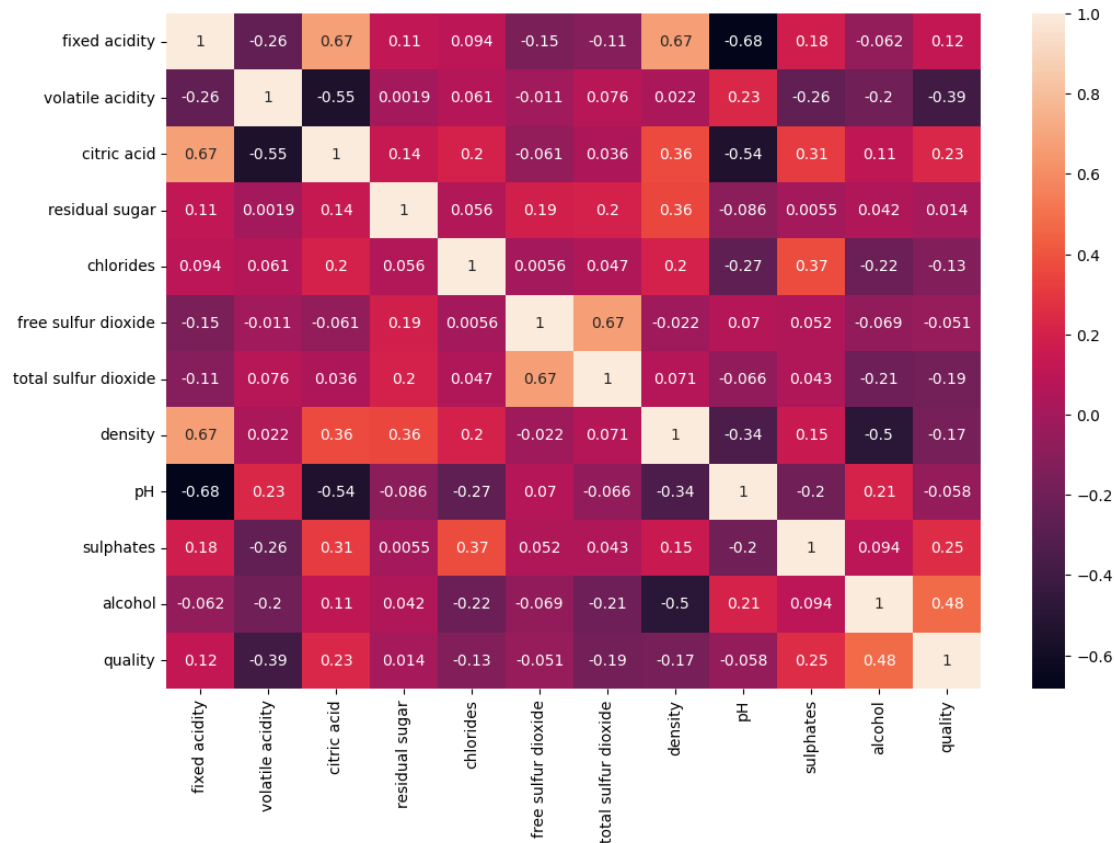
pH	-0.085652	-0.265026	0.070377
sulphates	0.005527	0.371260	0.051658
alcohol	0.042075	-0.221141	-0.069408
quality	0.013732	-0.128907	-0.050656

	total sulfur dioxide	density	pH	sulphates \
fixed acidity	-0.113181	0.668047	-0.682978	0.183006
volatile acidity	0.076470	0.022026	0.234937	-0.260987
citric acid	0.035533	0.364947	-0.541904	0.312770
residual sugar	0.203028	0.355283	-0.085652	0.005527
chlorides	0.047400	0.200632	-0.265026	0.371260
free sulfur dioxide	0.667666	-0.021946	0.070377	0.051658
total sulfur dioxide	1.000000	0.071269	-0.066495	0.042947
density	0.071269	1.000000	-0.341699	0.148506
pH	-0.066495	-0.341699	1.000000	-0.196648
sulphates	0.042947	0.148506	-0.196648	1.000000
alcohol	-0.205654	-0.496180	0.205633	0.093595
quality	-0.185100	-0.174919	-0.057731	0.251397

	alcohol	quality
fixed acidity	-0.061668	0.124052
volatile acidity	-0.202288	-0.390558
citric acid	0.109903	0.226373
residual sugar	0.042075	0.013732
chlorides	-0.221141	-0.128907
free sulfur dioxide	-0.069408	-0.050656
total sulfur dioxide	-0.205654	-0.185100
density	-0.496180	-0.174919
pH	0.205633	-0.057731
sulphates	0.093595	0.251397
alcohol	1.000000	0.476166
quality	0.476166	1.000000

```
plt.figure(figsize=(12, 8))
cor=df.corr()
sns.heatmap(cor,annot=True)
```

<Axes: >



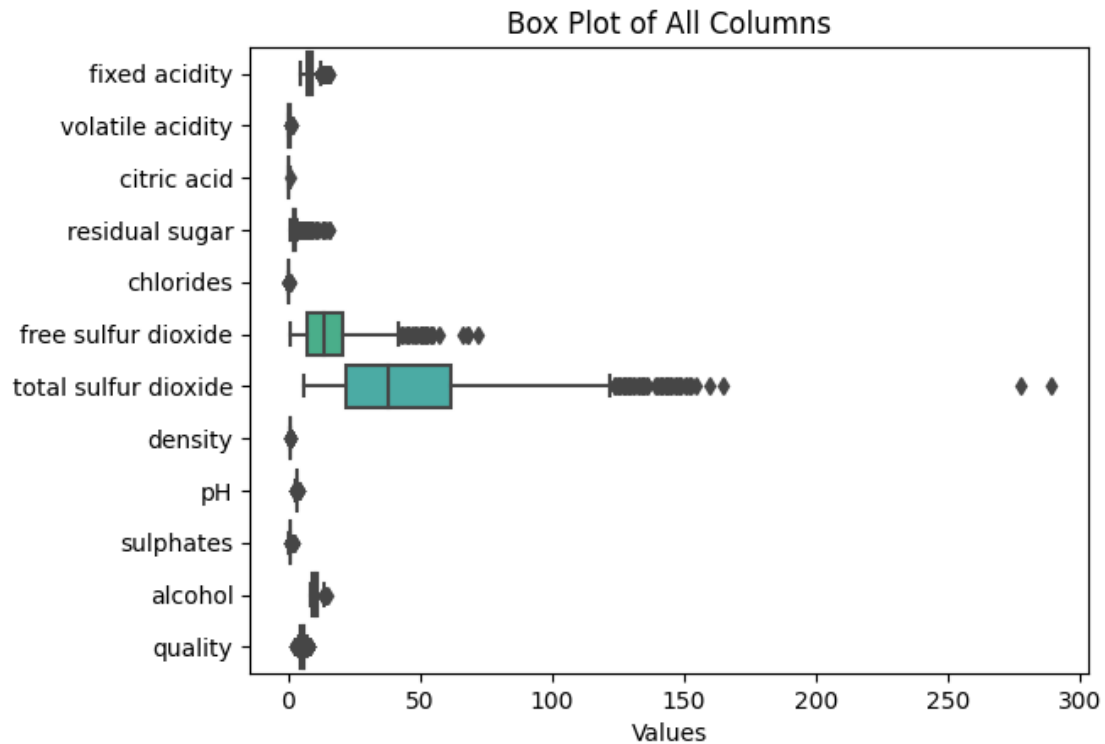
```
df.corr().quality.sort_values(ascending=False)
```

```
quality          1.000000
alcohol          0.476166
sulphates        0.251397
citric acid      0.226373
fixed acidity    0.124052
residual sugar   0.013732
free sulfur dioxide -0.050656
pH              -0.057731
chlorides        -0.128907
density          -0.174919
total sulfur dioxide -0.185100
volatile acidity -0.390558
Name: quality, dtype: float64
```

```
sns.boxplot(data=df,orient='h')
```

```
plt.xlabel('Values')
plt.title('Box Plot of All Columns')
```

```
Text(0.5, 1.0, 'Box Plot of All Columns')
```



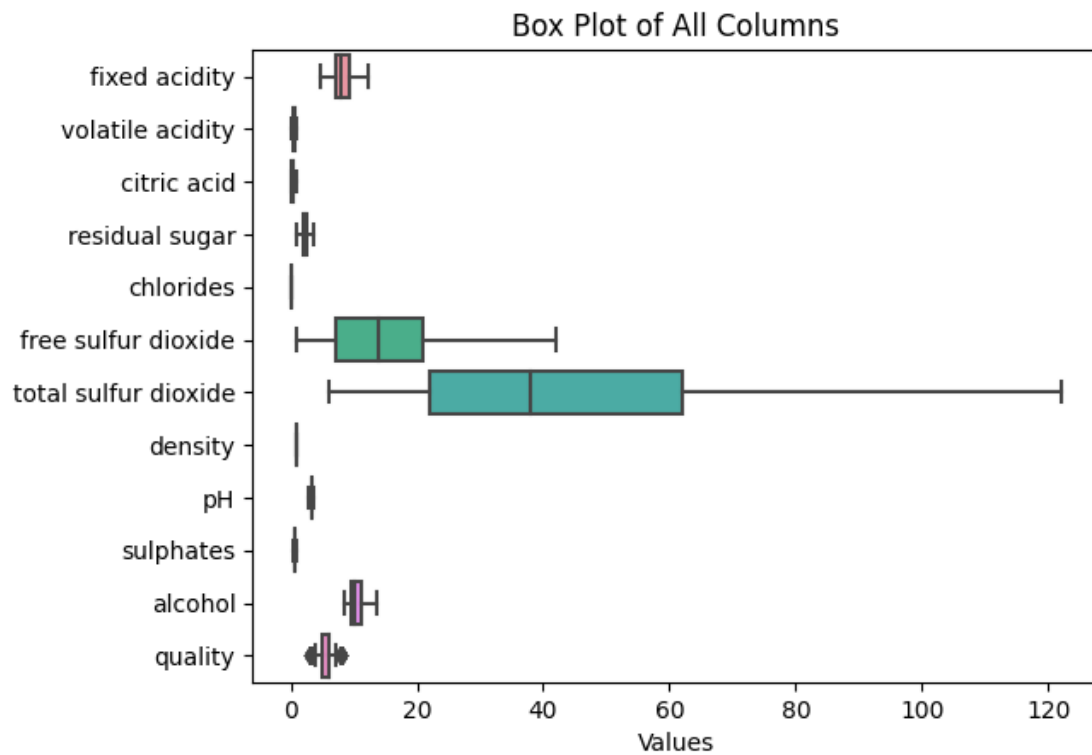
```
l=["fixed acidity","volatile acidity","citric acid","residual
sugar","chlorides","free sulfur dioxide","total sulfur
dioxide","density","pH","sulphates","alcohol"]

for i in l:
    q1=df[i].quantile(0.25)
    q3=df[i].quantile(0.75)
    iqr=q3-q1
    upperL=q3+1.5*iqr
    lowerL=q1-1.5*iqr
    df[i]=np.where(df[i]>upperL,upperL,np.where(df[i]<lowerL,lowerL,df[i]))

sns.boxplot(data=df, orient='h')

plt.xlabel('Values')
plt.title('Box Plot of All Columns')

Text(0.5, 1.0, 'Box Plot of All Columns')
```



```
x =df.drop(columns =['quality'],axis =1)
```

```
x.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	\
0	7.4	0.70	0.00	1.9	0.076	
1	7.8	0.88	0.00	2.6	0.098	
2	7.8	0.76	0.04	2.3	0.092	
3	11.2	0.28	0.56	1.9	0.075	
4	7.4	0.70	0.00	1.9	0.076	

	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	\
0	11.0	34.0	0.9978	3.51	0.56	
1	25.0	67.0	0.9968	3.20	0.68	
2	15.0	54.0	0.9970	3.26	0.65	
3	17.0	60.0	0.9980	3.16	0.58	
4	11.0	34.0	0.9978	3.51	0.56	

	alcohol
0	9.4
1	9.8
2	9.8
3	9.8
4	9.4



```
y =df.quality
y.head()
```

```
0    5
1    5
2    5
3    6
4    5
```

```
Name: quality, dtype: int64
```

```
from sklearn.preprocessing import MinMaxScaler
scale =MinMaxScaler()
```

```
scaled_x = pd.DataFrame(scale.fit_transform(X),columns =X.columns)
scaled_x.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides \
0	0.361290	0.648045	0.000000	0.363636	0.4500
1	0.412903	0.849162	0.000000	0.618182	0.7250
2	0.412903	0.715084	0.043716	0.509091	0.6500
3	0.851613	0.178771	0.612022	0.363636	0.4375
4	0.361290	0.648045	0.000000	0.363636	0.4500

	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates
0	0.243902	0.241379	0.621085	0.769737	0.343284
1	0.585366	0.525862	0.509228	0.361842	0.522388
2	0.341463	0.413793	0.531600	0.440789	0.477612
3	0.390244	0.465517	0.643456	0.309211	0.373134
4	0.243902	0.241379	0.621085	0.769737	0.343284

	alcohol
0	0.196078
1	0.274510
2	0.274510
3	0.274510
4	0.196078

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(scaled_x,y,test_size =
0.2,random_state = 0)
```

```
x_train.shape
```

```
(1279, 11)
```

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
```

```

model.fit(x_train, y_train)
y_pred = model.predict(x_test)

/usr/local/lib/python3.10/dist-
packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs
failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

Please also refer to the documentation for alternative solver options:

[https://scikit-learn.org/stable/modules/linear\\_model.html#logistic-regression](https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)

```
n_iter_i = _check_optimize_result(
```

```

from sklearn.metrics import accuracy_score,
confusion_matrix, classification_report, roc_auc_score, roc_curve

```

```
accuracy_score(y_test, y_pred)
```

```
0.61875
```

```
confusion_matrix(y_test, y_pred)
```

```

array([[ 0,  0,  2,  0,  0,  0],
       [ 0,  0,  7,  4,  0,  0],
       [ 0,  0, 102, 33,  0,  0],
       [ 0,  0, 40, 88, 14,  0],
       [ 0,  0,  2, 17,  8,  0],
       [ 0,  0,  0,  1,  2,  0]])

```

```
pd.crosstab(y_test, y_pred)
```

```

col_0    5    6    7
quality
3         2    0    0
4         7    4    0
5        102   33    0
6         40   88   14
7          2   17    8
8          0    1    2

```

```
print(classification_report(y_test, y_pred))
```

	precision	recall	f1-score	support
3	0.00	0.00	0.00	2
4	0.00	0.00	0.00	11
5	0.67	0.76	0.71	135
6	0.62	0.62	0.62	142
7	0.33	0.30	0.31	27

	8	0.00	0.00	0.00	3
accuracy				0.62	320
macro avg	0.27	0.28	0.27		320
weighted avg	0.58	0.62	0.60		320

```
/usr/local/lib/python3.10/dist-
packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
/usr/local/lib/python3.10/dist-
packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
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_warn_prf(average, modifier, msg_start, len(result))
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```
/usr/local/lib/python3.10/dist-
packages/sklearn/metrics/_classification.py:1344: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
```

```
_warn_prf(average, modifier, msg_start, len(result))
```

```
sample_check=[[6.5, 0.6, 0.5, 2.2, 0.07, 15.0, 80.0, 0.996, 3.4, 0.7, 9.5],
               [8.0, 0.4, 0.9, 4.8, 0.945, 75.0, 55.0, 0.998, 7.2, 0.95, 15.2]]
```

```
for i in sample_check:
    x=model.predict([i])
    if(x>=6):
        print(x, "--> Good" )
    elif(x<6):
        print(x, "--> Not Good")
```

```
[5] --> Not Good
```

```
[5] --> Not Good
```

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

```
warnings.warn(
```

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

```
warnings.warn(
```