wine-analysis

July 4, 2023

```
import pandas as pd
[1]:
[2]: from google.colab import files
     upload =files.upload()
    <IPython.core.display.HTML object>
    Saving 1788410-1767134-1729261-1613779-Red_wine__(1) (2).csv to
    1788410-1767134-1729261-1613779-Red_wine__(1) (2).csv
[3]: df = pd.read_csv('1788410-1767134-1729261-1613779-Red_wine__(1) (2).csv')
[4]:
     df.head(10)
[4]:
        fixed acidity volatile acidity citric acid residual sugar
                                                                          chlorides \
                                     0.70
                                                  0.00
                                                                    1.9
     0
                  7.4
                                                                              0.076
                  7.8
                                     0.88
                                                  0.00
                                                                    2.6
                                                                              0.098
     1
     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
                                                                    1.9
                                                  0.00
                                                                              0.076
     5
                  7.4
                                     0.66
                                                  0.00
                                                                    1.8
                                                                              0.075
     6
                  7.9
                                                                    1.6
                                     0.60
                                                  0.06
                                                                              0.069
     7
                  7.3
                                                  0.00
                                                                     1.2
                                     0.65
                                                                              0.065
     8
                  7.8
                                     0.58
                                                  0.02
                                                                    2.0
                                                                              0.073
     9
                  7.5
                                     0.50
                                                  0.36
                                                                    6.1
                                                                              0.071
        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
                                                                           0.65
                                                               3.26
     3
                        17.0
                                               60.0
                                                       0.9980
                                                               3.16
                                                                           0.58
     4
                        11.0
                                               34.0
                                                       0.9978
                                                                           0.56
                                                               3.51
                                               40.0
     5
                        13.0
                                                       0.9978
                                                               3.51
                                                                           0.56
     6
                        15.0
                                               59.0
                                                       0.9964
                                                               3.30
                                                                           0.46
     7
                        15.0
                                               21.0
                                                       0.9946
                                                               3.39
                                                                           0.47
     8
                         9.0
                                               18.0
                                                       0.9968
                                                               3.36
                                                                           0.57
     9
                        17.0
                                                NaN
                                                       0.9978
                                                              3.35
                                                                           0.80
```

```
alcohol quality
     0
            9.4
                      5.0
            9.8
                      5.0
     1
     2
            9.8
                      5.0
     3
            9.8
                     6.0
     4
            9.4
                     5.0
     5
            9.4
                     5.0
     6
            9.4
                     5.0
     7
           10.0
                     7.0
     8
            9.5
                     7.0
     9
           10.5
                     5.0
[5]: df.shape
[5]: (1599, 12)
[6]: df.info()
     df.isnull().sum()
    <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	1598 non-null	float64
7	density	1599 non-null	float64
8	рН	1598 non-null	float64
9	sulphates	1599 non-null	float64
10	alcohol	1599 non-null	float64
11	quality	1598 non-null	float64

dtypes: float64(12) memory usage: 150.0 KB

[6]: fixed acidity 0 volatile acidity 0 citric acid 0 residual sugar 0 chlorides 0 free sulfur dioxide 0 total sulfur dioxide 1 density 0

```
0
     sulphates
     alcohol
                               0
     quality
                               1
     dtype: int64
[7]: df.describe()
[7]:
            fixed acidity
                            volatile acidity
                                                              residual sugar
                                                citric acid
     count
               1599.000000
                                  1599.000000
                                                1599.000000
                                                                 1599.000000
                                     0.527821
                                                                    2.538806
     mean
                  8.319637
                                                   0.270976
     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%
                                                                    2.200000
                  7.900000
                                     0.520000
                                                   0.260000
     75%
                                                   0.420000
                  9.200000
                                     0.640000
                                                                    2.600000
                 15.900000
                                                   1.000000
                                     1.580000
                                                                   15.500000
     max
                          free sulfur dioxide
                                                 total sulfur dioxide
                                                                             density
              chlorides
                                                          1598.000000
                                                                         1599.000000
     count
            1599.000000
                                   1599.000000
                0.087467
                                     15.874922
                                                             46.433041
                                                                            0.996747
     mean
     std
                0.047065
                                     10.460157
                                                             32.876249
                                                                            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
                                                            289.000000
                                                                            1.003690
     max
                0.611000
                                     72.000000
                      рΗ
                            sulphates
                                             alcohol
                                                          quality
     count
            1598.000000
                          1599.000000
                                        1599.000000
                                                      1598.000000
     mean
                             0.658149
                                          10.422983
                                                         5.636421
                3.498586
     std
                0.080346
                             0.169507
                                            1.065668
                                                         0.807665
     min
                                            8.400000
                2.740000
                             0.330000
                                                         3.000000
     25%
                3.520000
                             0.550000
                                            9.500000
                                                         5.000000
     50%
                3.520000
                             0.620000
                                          10.200000
                                                         6.000000
     75%
                3.520000
                             0.730000
                                          11.100000
                                                         6.000000
                3.900000
                             2.000000
                                          14.900000
     max
                                                         8.000000
[8]: import matplotlib.pyplot as plt
     import seaborn as sb
     import numpy as np
     %matplotlib inline
[9]: df['quality'].unique()
[9]: array([5., 6., 7., 4., nan, 8.,
                                             3.])
```

рΗ

1

```
[10]: df['quality'].value_counts()
[10]: 5.0
             680
      6.0
             638
      7.0
             199
      4.0
              53
      8.0
              18
      3.0
              10
      Name: quality, dtype: int64
[54]: df['quality'].count()
[54]: 1599
[56]: sb.countplot(x='quality', data=df)
[56]: <Axes: xlabel='quality', ylabel='count'>
               700
               600
               500
               400
            count
               300
              200
               100
                 0
                                 i
                                          ż
                                                                      5
                       0
                                                   3
                                                             4
                                                 quality
```

```
[13]: df1 = df.select_dtypes([np.int,np.float])
for i, col in enumerate(df1.columns):
```

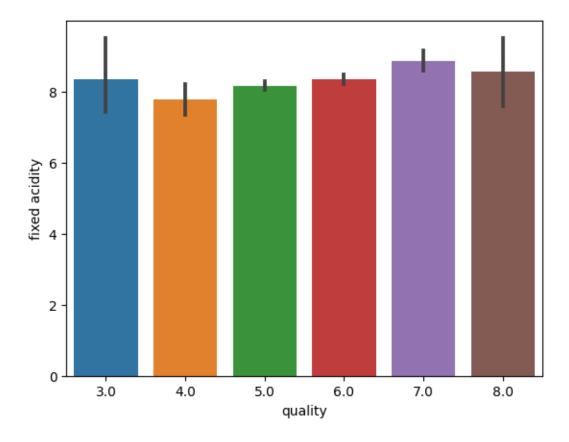
```
plt.figure(i)
sb.barplot(x='quality', y =col , data=df1)
```

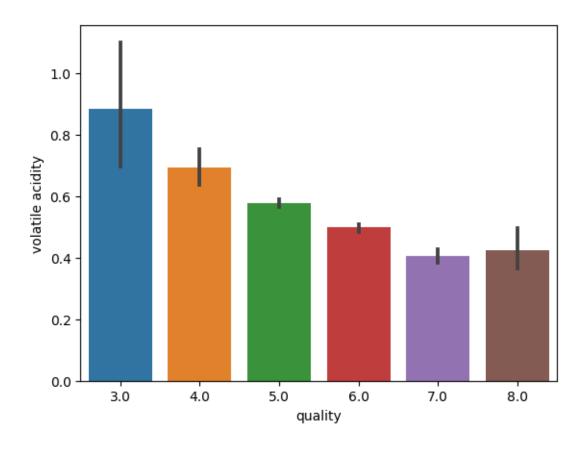
<ipython-input-13-2b9e59579017>:1: DeprecationWarning: `np.int` is a deprecated
alias for the builtin `int`. To silence this warning, use `int` by itself. Doing
this will not modify any behavior and is safe. When replacing `np.int`, you may
wish to use e.g. `np.int64` or `np.int32` to specify the precision. If you wish
to review your current use, check the release note link for additional
information.

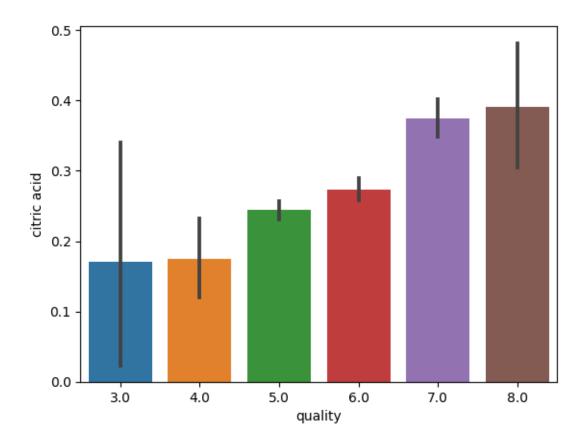
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
 df1 = df.select_dtypes([np.int,np.float])
<ipython-input-13-2b9e59579017>:1: DeprecationWarning: `np.float` is a

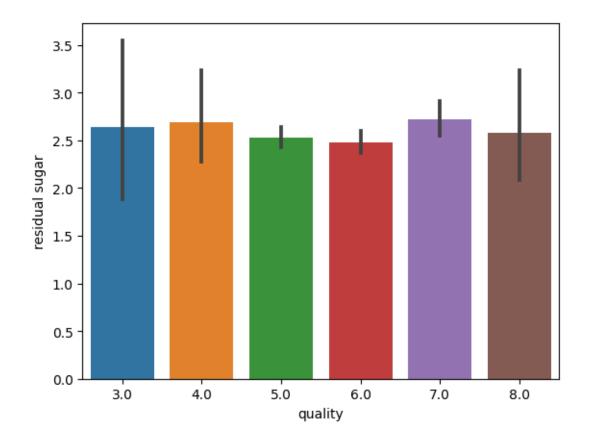
<ipython-input-13-2b9e59579017>:1: DeprecationWarning: `np.float` is a
deprecated alias for the builtin `float`. To silence this warning, use `float`
by itself. Doing this will not modify any behavior and is safe. If you
specifically wanted the numpy scalar type, use `np.float64` here.
Deprecated in NumPy 1.20; for more details and guidance:

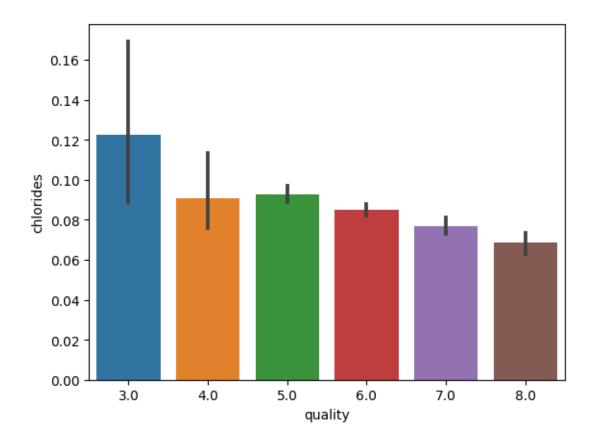
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
df1 = df.select_dtypes([np.int,np.float])

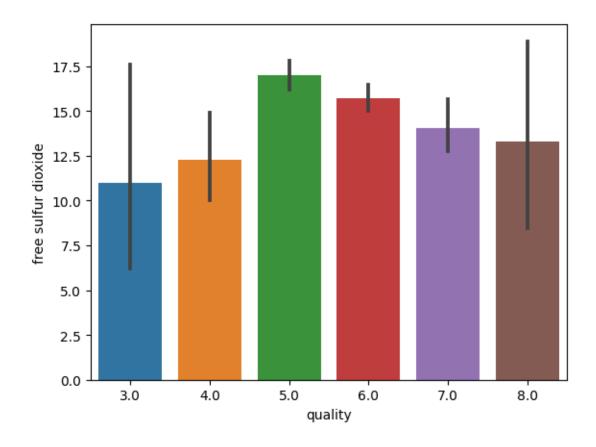


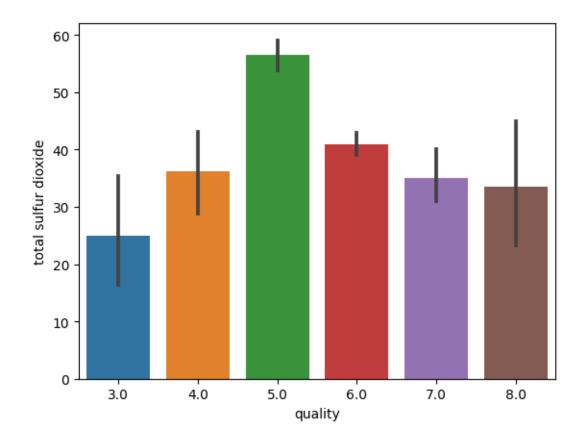


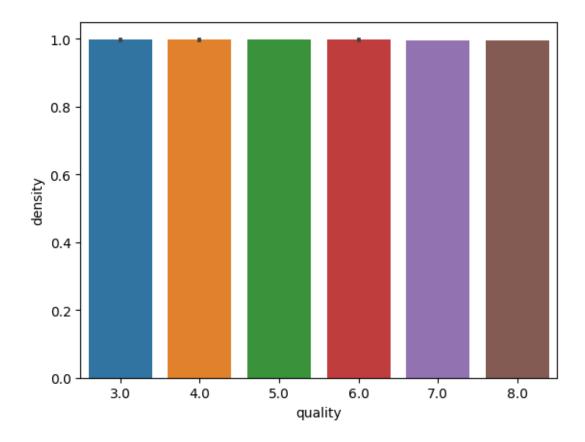


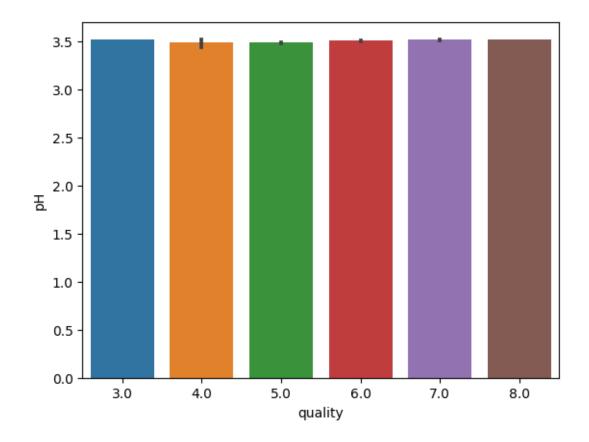


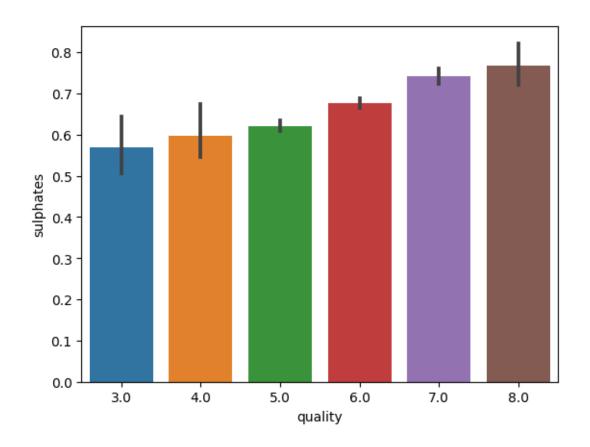


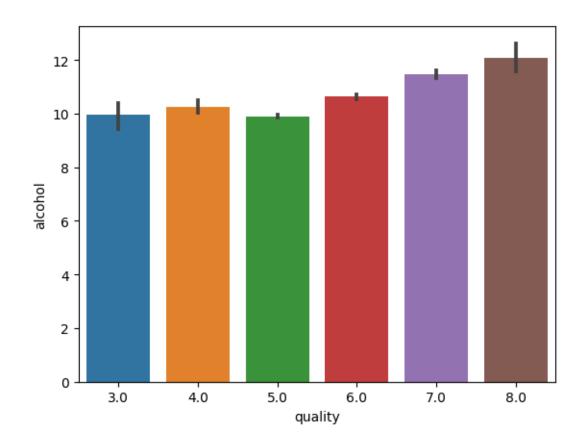


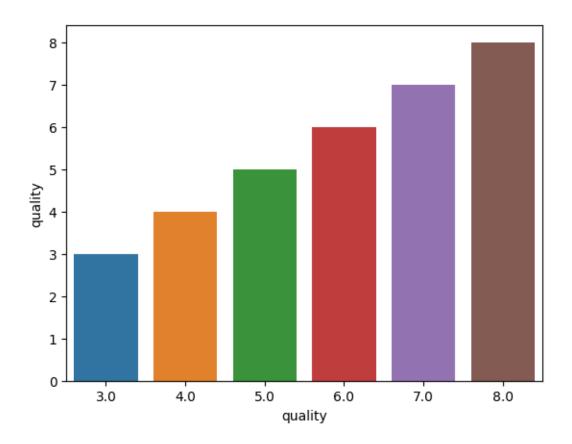




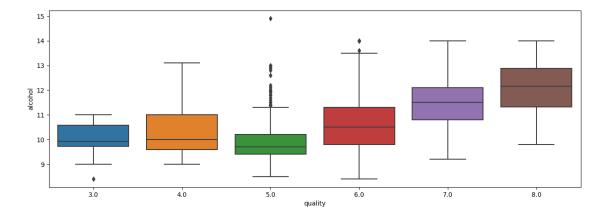






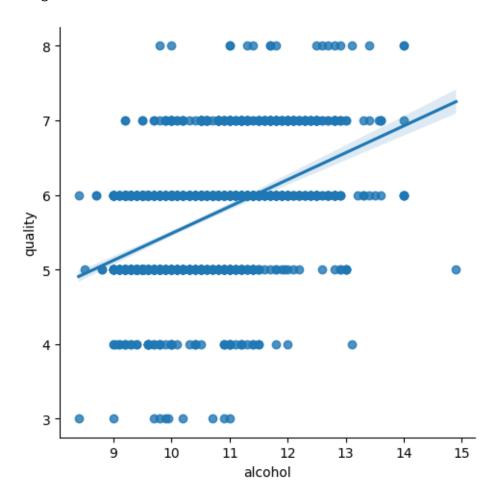


[16]: <Axes: xlabel='quality', ylabel='alcohol'>



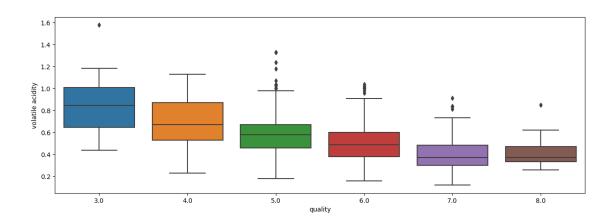
```
[17]: sns.lmplot(x="alcohol", y="quality", data=df)
```

[17]: <seaborn.axisgrid.FacetGrid at 0x7f62a1c50280>



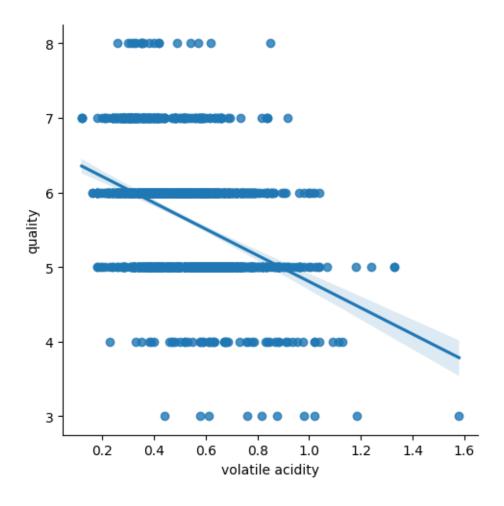
```
[19]: plt.figure(figsize=(15,5))
sns.boxplot(x="quality", y="volatile acidity", data=df)
```

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



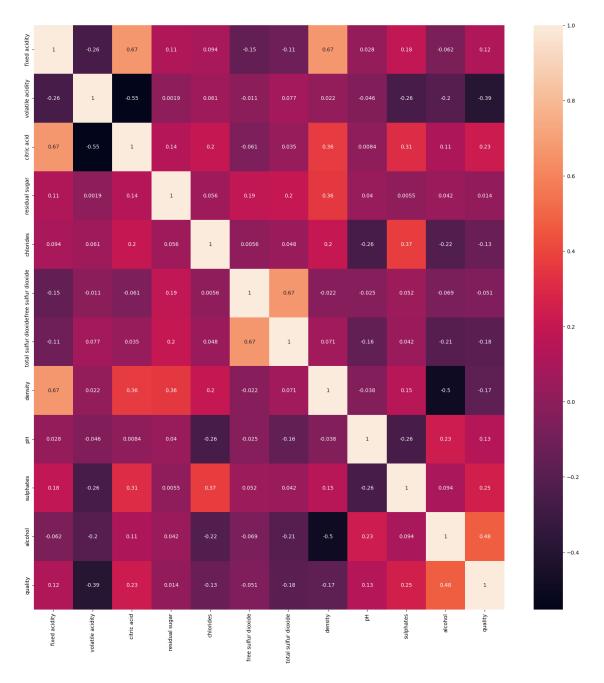
[18]: sns.lmplot(x="volatile acidity", y="quality", data=df)

[18]: <seaborn.axisgrid.FacetGrid at 0x7f62a1c538b0>



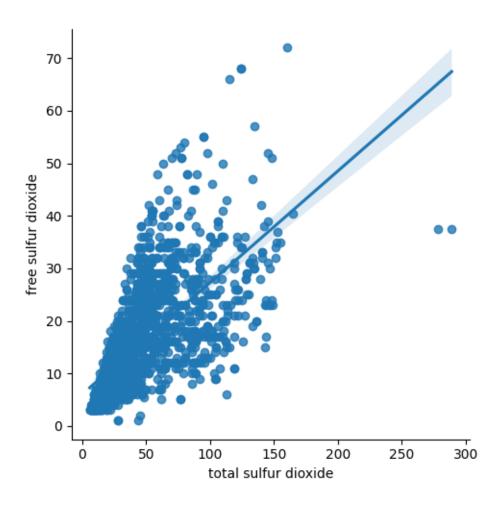
```
[20]: plt.figure(figsize=(20,20))
sns.heatmap(df.corr(),color ="k", annot=True)
```

[20]: <Axes: >



```
[21]: sns.lmplot(X="total sulfur dioxide", Y="free sulfur dioxide", data=df)
```

[21]: <seaborn.axisgrid.FacetGrid at 0x7f62a230f370>



```
[]: bins = (2,6.5,8)
      group_names = ['bad','good']
      df['quality'] = pd.cut(df['quality'], bins = bins , labels = group_names)
[26]: from sklearn.ensemble import RandomForestClassifier,GradientBoostingClassifier
      from sklearn.svm import SVC,LinearSVC
      from sklearn.linear_model import SGDClassifier
      from sklearn.metrics import confusion_matrix,classification_report
      from sklearn.preprocessing import StandardScaler,LabelEncoder
      from sklearn.model_selection import train_test_split, GridSearchCV,__
       ⇔cross_val_score
      from sklearn.linear_model import LogisticRegression
      from sklearn.neighbors import KNeighborsClassifier
      from sklearn.naive_bayes import GaussianNB
      from sklearn.metrics import accuracy_score
[27]: label_quality=LabelEncoder()
      df['quality']=label_quality.fit_transform(df['quality'])
```

```
[28]: df.head(10)
[28]:
         fixed acidity volatile acidity citric acid residual sugar
                                                                          chlorides \
      0
                   7.4
                                      0.70
                                                   0.00
                                                                     1.9
                                                                               0.076
                   7.8
                                      0.88
                                                   0.00
                                                                     2.6
      1
                                                                               0.098
                                                                     2.3
      2
                   7.8
                                      0.76
                                                   0.04
                                                                               0.092
      3
                   11.2
                                      0.28
                                                   0.56
                                                                     1.9
                                                                               0.075
      4
                   7.4
                                      0.70
                                                   0.00
                                                                     1.9
                                                                               0.076
      5
                   7.4
                                      0.66
                                                   0.00
                                                                     1.8
                                                                               0.075
                   7.9
                                                   0.06
                                                                     1.6
      6
                                      0.60
                                                                               0.069
      7
                   7.3
                                      0.65
                                                   0.00
                                                                     1.2
                                                                               0.065
      8
                   7.8
                                      0.58
                                                   0.02
                                                                     2.0
                                                                               0.073
                   7.5
      9
                                      0.50
                                                   0.36
                                                                     6.1
                                                                               0.071
         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
                                                       0.9980
      3
                         17.0
                                                60.0
                                                                3.16
                                                                           0.58
      4
                         11.0
                                                34.0
                                                       0.9978
                                                                3.51
                                                                           0.56
      5
                                                40.0
                         13.0
                                                       0.9978
                                                                3.51
                                                                           0.56
      6
                         15.0
                                                59.0
                                                       0.9964
                                                                3.30
                                                                           0.46
      7
                         15.0
                                                21.0
                                                       0.9946
                                                                3.39
                                                                           0.47
      8
                          9.0
                                                18.0
                                                       0.9968
                                                                3.36
                                                                           0.57
      9
                         17.0
                                                 {\tt NaN}
                                                       0.9978 3.35
                                                                           0.80
         alcohol quality
             9.4
      0
                         2
             9.8
                         2
      1
      2
             9.8
                         2
             9.8
                         3
      3
      4
             9.4
                         2
             9.4
                         2
      5
      6
             9.4
                         2
      7
            10.0
                         4
             9.5
                         4
      8
                         2
      9
            10.5
[41]: Y=df.quality
      X=df.drop('quality',axis=1)
[42]: X_train, X_test, Y_train, Y_test=train_test_split(X,Y,test_size=0.2,random_state=0)
[43]: sc=StandardScaler()
      X_train=sc.fit_transform(X_train)
      X_test=sc.transform(X_test)
```

```
[44]: def models(X_train,Y_train):
          from sklearn.linear_model import LogisticRegression
          log=LogisticRegression(random_state=0)
          log.fit(X_train,Y_train)
          from sklearn.neighbors import kNeighborsClassifier
          knn=KNeighborsClassifier(n_neighbors=5,metric='minkowski',p=2)
          knn.fit(X_train,Y_train)
          from sklearn.svm import SVC
          svc_lin =SVC(kernel='linear',random_state=0)
          svc_lin.fit(X_train,Y_train)
          from sklearn.svm import SVC
          svc_rbf =SVC(kernel='rbf',random_state=0)
          svc_rbf.fit(X_train,Y_train)
          from sklearn.navie_bayes import GaussianNB
          gauss=GaussianNB()
          gauss.fit(X_train,Y_train)
          from sklearn.tree import DecisionTreeClassifier
          tree=DecisionTreeClassifier(criterion='entropy',random_state=0)
          tree.fit(X_train,Y_train)
          from sklearn.ensemble import RandomForestClassifier
       →forest=RandomForestClassifier(n_estimators=10,criterion='entropy',random_state=0)
          forest.fit(X_train,Y_train)
          print('[0]Logistic Regression Training Accuracy:',log.
       ⇒score(X_train,Y_train))
          print('[1]k Nearest Neighbor Training Accurac:',knn.score(X train,Y train))
          print('[2]Support Vector Machine (Linear Classifier) Training Accuracy:

¬',svc_lin.score(X_train,Y_train))
          print('[3]Support Vector Machine (RBF Classifier) Training Accuracy:
       , svc_rbf.score(X_train,Y_train))
          print('[4]Gaussian Naive Bayes Training Accuracy:',gauss.
       ⇔score(X_train,Y_train))
          print('[5]DecisionTreeClassifier Training Accuracy:',tree.
       ⇒score(X_train,Y_train))
          print('[6]Random forest Classifier Training Accuracy:',forest.

¬score(X_train,Y_train))
          return log,knn,svc_lin,svc_rbf,gauss,tree,forest
```