Scikit learn

```
In [3]:
             import pandas as pd
           2 import seaborn as sns
           3 import matplotlib.pyplot as plt
           4 from sklearn.ensemble import RandomForestClassifier
           5 from sklearn.svm import SVC
           6 from sklearn import svm
           7 | from sklearn.neural_network import MLPClassifier
           8 from sklearn.linear_model import SGDClassifier
           9 from sklearn.metrics import confusion_matrix,classification_report
          10 | from sklearn.preprocessing import StandardScaler,LabelEncoder
          11 from sklearn.model selection import train test split
          12 %matplotlib inline
In [69]:
           1 df=pd.read csv(r"C:\Users\user\Downloads\winequality-red.csv")
In [70]:
           1 df.head(10)
```

Out[70]:

	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
5	7.4	0.66	0.00	1.8	0.075	13.0	40.0	0.9978	3.51	0.56	9.4
6	7.9	0.60	0.06	1.6	0.069	15.0	59.0	0.9964	3.30	0.46	9.4
7	7.3	0.65	0.00	1.2	0.065	15.0	21.0	0.9946	3.39	0.47	10.0
8	7.8	0.58	0.02	2.0	0.073	9.0	18.0	0.9968	3.36	0.57	9.5
9	7.5	0.50	0.36	6.1	0.071	17.0	102.0	0.9978	3.35	0.80	10.5
4											

```
1 df.info()
In [71]:
```

<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 [72]:
           1 df.isnull().sum()
```

Out[72]: fixed acidity 0 volatile acidity 0 citric acid 0 residual sugar 0 chlorides 0 free sulfur dioxide 0 total sulfur dioxide 0 density 0 0 рΗ sulphates 0 alcohol 0 quality 0 dtype: int64

In [73]:

1 df.head()

Out[73]:

	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 [86]:
                 #preprocessing data
              2
                 bins=(2,6.5,8)
              3
                 group_names=["good","bad"]
                 df["quality"]=pd.cut(df["quality"],bins=bins,labels=group names)
                 df["quality"].unique()
Out[86]: [NaN, 'good']
           Categories (2, object): ['good' < 'bad']</pre>
In [87]:
                 label_quality=LabelEncoder()
In [88]:
                 df["quality"]=label_quality.fit_transform(df["quality"])
In [89]:
                 df.head(10)
Out[89]:
                                                               free
                                                                       total
                        volatile
                                 citric
                 fixed
                                       residual
                                                 chlorides
                                                             sulfur
                                                                      sulfur
                                                                              density
                                                                                        pH sulphates
                                                                                                       alcohol
                acidity
                        acidity
                                 acid
                                         sugar
                                                            dioxide
                                                                     dioxide
                                                                                      3.51
            0
                   7.4
                           0.70
                                 0.00
                                            1.9
                                                     0.076
                                                               11.0
                                                                        34.0
                                                                              0.9978
                                                                                                  0.56
                                                                                                            9.4
                   7.8
                                 0.00
                                            2.6
                                                     0.098
                                                               25.0
                                                                        67.0
                                                                              0.9968 3.20
                                                                                                  0.68
            1
                           0.88
                                                                                                            9.8
                                                     0.092
            2
                   7.8
                           0.76
                                 0.04
                                            2.3
                                                               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
                                                     0.076
            4
                   7.4
                           0.70
                                 0.00
                                            1.9
                                                               11.0
                                                                        34.0
                                                                              0.9978 3.51
                                                                                                  0.56
                                                                                                            9.4
            5
                   7.4
                           0.66
                                 0.00
                                            1.8
                                                     0.075
                                                               13.0
                                                                        40.0
                                                                              0.9978
                                                                                      3.51
                                                                                                  0.56
                                                                                                            9.4
            6
                   7.9
                           0.60
                                 0.06
                                            1.6
                                                     0.069
                                                               15.0
                                                                        59.0
                                                                              0.9964
                                                                                      3.30
                                                                                                  0.46
                                                                                                            9.4
                                 0.00
                                                     0.065
            7
                   7.3
                           0.65
                                            1.2
                                                               15.0
                                                                        21.0
                                                                              0.9946 3.39
                                                                                                  0.47
                                                                                                           10.0
                                            2.0
            8
                   7.8
                           0.58
                                 0.02
                                                     0.073
                                                                9.0
                                                                        18.0
                                                                               0.9968
                                                                                      3.36
                                                                                                  0.57
                                                                                                            9.5
                                                                              0.9978 3.35
            9
                   7.5
                           0.50
                                 0.36
                                            6.1
                                                     0.071
                                                               17.0
                                                                       102.0
                                                                                                  0.80
                                                                                                           10.5
```

In [90]: 1 df["quality"].value_counts()

Out[90]: 0 855 1 744

Namas avaldus dusmas

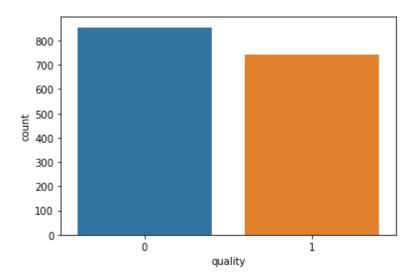
Name: quality, dtype: int64

In [91]: 1 sns.countplot(df["quality"])

C:\Users\user\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarn ing: Pass the following variable as a keyword arg: x. From version 0.12, the on ly valid positional argument will be `data`, and passing other arguments withou t an explicit keyword will result in an error or misinterpretation.

warnings.warn(

Out[91]: <AxesSubplot:xlabel='quality', ylabel='count'>



```
In [106]:
           1 x train[:10]
Out[106]: array([[ 0.21833164,
                               0.88971201,
                                            0.19209222,
                                                         0.30972563, -0.04964208,
                   0.69100692,
                               1.04293362, 1.84669643, 1.09349989, 0.45822284,
                   1.12317723],
                 [-1.29016623, -1.78878251, 0.65275338, -0.80507963, -0.45521361,
                   2.38847304, 3.59387025, -3.00449133, -0.40043872, -0.40119696,
                   1.40827174],
                 [ 1.49475291, -0.78434707, 1.01104539, -0.52637831, 0.59927236,
                  -0.95796016, -0.99174203, 0.76865471, -0.07566946, 0.51551749,
                  -0.58738978],
                 [0.27635078, 0.86181102, -0.06383064, -0.66572897, -0.00908493,
                   0.01202048, -0.71842739, 0.08948842, 0.05423824, -1.08873281,
                  -0.96751578],
                 [ 0.04427419, 2.81487994, -0.62686095, 2.39998549, -0.31326357,
                  -0.47296984,
                               0.2229897 , 1.1998714 , 0.37900751, -0.9741435 ,
                  -0.49235828],
                 [-0.07176411, -0.78434707, 1.11341454, -0.17800167, 0.21397941,
                   3.01896045, 2.62208486, 0.60694845, 0.44396136, 1.89058918,
                  -0.58738978],
                 [-1.17412793, 0.10848444, -0.62686095, -0.52637831, -0.23214927,
                   0.98200112, -0.35400787, -1.95879086, 0.05423824, 0.91658007,
                   1.12317723],
                 [-0.1878024, -0.17052541, 0.60156881, 0.03102432, -0.13075639,
                  -0.37597178, -0.01995665, 0.93036097, 0.76873063, -0.229313
                   0.26789373],
                               0.61070216, -0.01264607, -0.38702766, 0.13286511,
                 [-0.07176411,
                  -1.05495822, 0.92146044, 0.37516948, -1.17988496, -0.229313 ,
                  -1.25261029],
                 [ 1.8428678 , -1.95618842, 1.21578369, 1.00647892, 0.31537229,
                  -1.15195628, -0.71842739, 1.52328391, -0.20557717, 1.77599987,
                  -0.30229528]])
```

Random forest classifier

```
In [116]:
            1 #model performing
               print(classification_report(y_test,pred_rfc))
                         precision
                                       recall f1-score
                                                           support
                      0
                              0.81
                                         0.81
                                                   0.81
                                                               179
                              0.76
                                         0.76
                                                   0.76
                      1
                                                               141
                                                   0.79
                                                               320
               accuracy
                                                               320
              macro avg
                              0.78
                                         0.78
                                                   0.78
          weighted avg
                              0.79
                                         0.79
                                                   0.79
                                                               320
```

Sym classifier

```
In [117]:
               clf=svm.SVC()
            2 clf.fit(x train,y train)
               pred_clf=clf.predict(x_test)
In [118]:
               print(classification report(y test,pred clf))
               print(confusion_matrix(y_test,pred_clf))
                         precision
                                       recall f1-score
                                                          support
                      0
                              0.81
                                         0.77
                                                   0.79
                                                               179
                      1
                              0.73
                                         0.77
                                                   0.75
                                                               141
                                                               320
               accuracy
                                                   0.77
                                                   0.77
                                                               320
                              0.77
                                         0.77
             macro avg
          weighted avg
                              0.77
                                         0.77
                                                   0.77
                                                               320
          [[138 41]
            [ 32 109]]
```

Neural network

C:\Users\user\anaconda3\lib\site-packages\sklearn\neural_network_multilayer_pe
rceptron.py:692: ConvergenceWarning: Stochastic Optimizer: Maximum iterations
(500) reached and the optimization hasn't converged yet.
 warnings.warn(

In [122]: 1 print(classification_report(y_test,pred_mlpc))
2 print(confusion_matrix(y_test,pred_mlpc))

precision recall f1-score support 0 0.78 0.78 0.78 179 0.72 0.72 0.72 1 141 320 0.75 accuracy 0.75 0.75 0.75 320 macro avg 0.75 320 weighted avg 0.75 0.75

[[139 40] [40 101]]

In [123]:

- 1 from sklearn.metrics import accuracy_score
- 2 cm=accuracy_score(y_test,pred_rfc)
- 3 cm

Out[123]: 0.7875

In [124]: 1 df.head()

Out[124]:

	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