Data Analytics III

- 1. Implement Simple Naïve Bayes classification algorithm using Python/R on iris.csv dataset.
- 2. Compute Confusion matrix to find TP, FP, TN, FN, Accuracy, Error rate, Precision, Recall on the given dataset.

In [1]:

```
import pandas as pd
from matplotlib import pyplot as plt
%matplotlib inline
```

In [2]:

```
df = pd.read_csv("iris.csv")
df.head(10)
```

Out[2]:

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa
5	5.4	3.9	1.7	0.4	setosa
6	4.6	3.4	1.4	0.3	setosa
7	5.0	3.4	1.5	0.2	setosa
8	4.4	2.9	1.4	0.2	setosa
9	4.9	3.1	1.5	0.1	setosa

In [3]:

```
X=df.iloc[:,0:4]
y=df.iloc[:,-1]
y
```

Out[3]:

```
0
          setosa
1
          setosa
2
          setosa
3
          setosa
4
         setosa
145
       virginica
146
      virginica
      virginica
147
148
       virginica
149
       virginica
Name: species, Length: 150, dtype: object
```

In [4]:

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,train_size=0.8,random_state=1)
X_test

Out[4]:

14 5.8 4.0 1.2 0.2 98 5.1 2.5 3.0 1.1 75 6.6 3.0 4.4 1.4 16 5.4 3.9 1.3 0.4 131 7.9 3.8 6.4 2.0 56 6.3 3.3 4.7 1.6 141 6.9 3.1 5.1 2.3 44 5.1 3.8 1.9 0.4 29 4.7 3.2 1.6 0.2 120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6		sepal_length	sepal_width	petal_length	petal_width
75 6.6 3.0 4.4 1.4 16 5.4 3.9 1.3 0.4 131 7.9 3.8 6.4 2.0 56 6.3 3.3 4.7 1.6 141 6.9 3.1 5.1 2.3 44 5.1 3.8 1.9 0.4 29 4.7 3.2 1.6 0.2 120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4	14	5.8	4.0	1.2	0.2
16 5.4 3.9 1.3 0.4 131 7.9 3.8 6.4 2.0 56 6.3 3.3 4.7 1.6 141 6.9 3.1 5.1 2.3 44 5.1 3.8 1.9 0.4 29 4.7 3.2 1.6 0.2 120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 <th>98</th> <th>5.1</th> <th>2.5</th> <th>3.0</th> <th>1.1</th>	98	5.1	2.5	3.0	1.1
131 7.9 3.8 6.4 2.0 56 6.3 3.3 4.7 1.6 141 6.9 3.1 5.1 2.3 44 5.1 3.8 1.9 0.4 29 4.7 3.2 1.6 0.2 120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 <th>75</th> <th>6.6</th> <th>3.0</th> <th>4.4</th> <th>1.4</th>	75	6.6	3.0	4.4	1.4
56 6.3 3.3 4.7 1.6 141 6.9 3.1 5.1 2.3 44 5.1 3.8 1.9 0.4 29 4.7 3.2 1.6 0.2 120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 <th>16</th> <th>5.4</th> <th>3.9</th> <th>1.3</th> <th>0.4</th>	16	5.4	3.9	1.3	0.4
141 6.9 3.1 5.1 2.3 44 5.1 3.8 1.9 0.4 29 4.7 3.2 1.6 0.2 120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 96 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 <th>131</th> <th>7.9</th> <th>3.8</th> <th>6.4</th> <th>2.0</th>	131	7.9	3.8	6.4	2.0
44 5.1 3.8 1.9 0.4 29 4.7 3.2 1.6 0.2 120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 <th>56</th> <th>6.3</th> <th>3.3</th> <th>4.7</th> <th>1.6</th>	56	6.3	3.3	4.7	1.6
29 4.7 3.2 1.6 0.2 120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 <th>141</th> <th>6.9</th> <th>3.1</th> <th>5.1</th> <th>2.3</th>	141	6.9	3.1	5.1	2.3
120 6.9 3.2 5.7 2.3 94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 <th>44</th> <th>5.1</th> <th>3.8</th> <th>1.9</th> <th>0.4</th>	44	5.1	3.8	1.9	0.4
94 5.6 2.7 4.2 1.3 5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3	29	4.7	3.2	1.6	0.2
5 5.4 3.9 1.7 0.4 102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	120	6.9	3.2	5.7	2.3
102 7.1 3.0 5.9 2.1 51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	94	5.6	2.7	4.2	1.3
51 6.4 3.2 4.5 1.5 78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	5	5.4	3.9	1.7	0.4
78 6.0 2.9 4.5 1.5 42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	102	7.1	3.0	5.9	2.1
42 4.4 3.2 1.3 0.2 92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	51	6.4	3.2	4.5	1.5
92 5.8 2.6 4.0 1.2 66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	78	6.0	2.9	4.5	1.5
66 5.6 3.0 4.5 1.5 31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	42	4.4	3.2	1.3	0.2
31 5.4 3.4 1.5 0.4 35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	92	5.8	2.6	4.0	1.2
35 5.0 3.2 1.2 0.2 90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	66	5.6	3.0	4.5	1.5
90 5.5 2.6 4.4 1.2 84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	31	5.4	3.4	1.5	0.4
84 5.4 3.0 4.5 1.5 77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	35	5.0	3.2	1.2	0.2
77 6.7 3.0 5.0 1.7 40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	90	5.5	2.6	4.4	1.2
40 5.0 3.5 1.3 0.3 125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	84	5.4	3.0	4.5	1.5
125 7.2 3.2 6.0 1.8 99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	77	6.7	3.0	5.0	1.7
99 5.7 2.8 4.1 1.3 33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	40	5.0	3.5	1.3	0.3
33 5.5 4.2 1.4 0.2 19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	125	7.2	3.2	6.0	1.8
19 5.1 3.8 1.5 0.3 73 6.1 2.8 4.7 1.2	99	5.7	2.8	4.1	1.3
73 6.1 2.8 4.7 1.2	33	5.5	4.2	1.4	0.2
	19	5.1	3.8	1.5	0.3
146 6.3 2.5 5.0 1.9	73	6.1	2.8	4.7	1.2
	146	6.3	2.5	5.0	1.9

```
In [5]:
from sklearn.preprocessing import LabelEncoder
la_object = LabelEncoder()
y = la_object.fit_transform(y)
У
Out[5]:
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
    In [6]:
from sklearn.naive bayes import GaussianNB
model = GaussianNB()
model.fit(X_train, y_train)
Out[6]:
GaussianNB()
In [7]:
y_predicted = model.predict(X_test)
In [8]:
y_predicted
Out[8]:
'versicolor', 'setosa', 'virginica', 'versicolor', 'versicolor',
    'setosa', 'versicolor', 'versicolor', 'setosa', 'setosa',
    'versicolor', 'versicolor', 'virginica', 'setosa', 'virginica',
    'versicolor', 'setosa', 'setosa', 'versicolor', 'virginica'],
   dtype='<U10')
In [9]:
model.score(X_test,y_test)
Out[9]:
0.966666666666667
In [10]:
```

from sklearn.metrics import confusion matrix,classification report

cm = confusion_matrix(y_test, y_predicted)

```
In [11]:
```

cm

Out[11]:

In [12]:

```
# classification report for precision, recall f1-score and accuracy
cl_report=classification_report(y_test,y_predicted)
```

In [13]:

```
cl_report
```

Out[13]:

```
precision
                            recall f1-score
                                                support\n\n
                                                                 setosa
          1.00
1.00
                    1.00
                                 11\n versicolor
                                                        1.00
                                                                  0.92
0.96
                                   0.86
                                              1.00
                                                        0.92
                                                                     6\n\n
            13\n
                   virginica
                                    0.97
                                                30\n
                                                       macro avg
                                                                       0.95
accuracy
0.97
          0.96
                      30\nweighted avg
                                              0.97
                                                        0.97
                                                                  0.97
30\n'
```

In [20]:

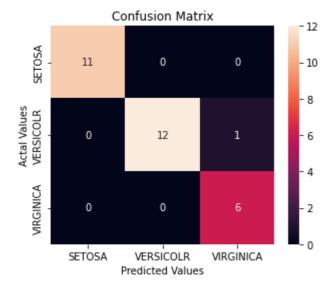
```
recall f1-score
           precision
                                            support\n\n
#Setosa
              1.00
                        1.00
                                   1.00
                                               11\n
              1.00
                        0.92
                                   0.96
                                               13\n
#Versicolor
#Virginica
              0.86
                        1.00
                                   0.92
                                                6\n\n
#accuracy
                                     0.97
                                                 30\n
#macro avg
                 0.95
                           0.97
                                      0.96
                                                  30\n
#weighted avg
                 0.97
                           0.97
                                      0.97
                                                  30\n
```

https://www.analyticsvidhya.com/blog/2021/06/confusion-matrix-for-multi-class-classification/ (https://www.analyticsvidhya.com/blog/2021/06/confusion-matrix-for-multi-class-classification/)

In [16]:

In [17]:

```
#Plotting the confusion matrix
import seaborn as sns
plt.figure(figsize=(5,4))
sns.heatmap(cm_df, annot=True)
plt.title('Confusion Matrix')
plt.ylabel('Actal Values')
plt.xlabel('Predicted Values')
plt.show()
```



In [18]:

```
def accuracy_cm(tp,fn,fp,tn):
    return (tp+tn)/(tp+fp+tn+fn)

def precision_cm(tp,fn,fp,tn):
    return tp/(tp+fp)

def recall_cm(tp,fn,fp,tn):
    return tp/(tp+fn)

def f1_score(tp,fn,fp,tn):
    return (2/((1/recall_cm(tp,fn,fp,tn))+precision_cm(tp,fn,fp,tn)))

def error_rate_cm(tp,fn,fp,tn):
    return 1-accuracy_cm(tp,fn,fp,tn)
```

In [19]:

```
#For Virginica
tp = cm[2][2]
fn = cm[2][0]+cm[2][1]
fp = cm[0][2]+cm[1][2]
tn = cm[0][0]+cm[0][1]+cm[1][0]+cm[1][1]
print("For Virginica \n")
print("Accuracy : ",accuracy_cm(tp,fn,fp,tn))
print("Precision : ",precision_cm(tp,fn,fp,tn))
print("Recall : ",recall_cm(tp,fn,fp,tn))
print("F1-Score : ",f1_score(tp,fn,fp,tn))
print("Error rate : ",error_rate_cm(tp,fn,fp,tn))
```

For Virginica

Accuracy : 0.966666666666667 Precision : 0.8571428571428571

Recall : 1.0 F1-Score : 1.0769230769230769 Error rate : 0.033333333333333333