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.

Setup

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import GaussianNB
```

In [2]:

```
np.random.seed(0)
sns.set()
```

In [3]:

```
!wget https://gist.githubusercontent.com/netj/8836201/raw/6f9306ad21398ea43cba4f7d5
```

```
--2022-04-12 14:47:15--  https://gist.githubusercontent.com/netj/8836201/raw/6f9306ad
398ea43cba4f7d537619d0e07d5ae3/iris.csv
Resolving gist.githubusercontent.com (gist.githubusercontent.com)... 185.199.109.133, 1
85.199.110.133, 185.199.108.133, ...
Connecting to gist.githubusercontent.com (gist.githubusercontent.com)|185.199.109.133|:
443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 3975 (3.9K) [text/plain]
Saving to: ‘iris.csv.1’

iris.csv.1          100%[===================>]   3.88K  --.-KB/s    in 0.001s

2022-04-12 14:47:15 (2.94 MB/s) - ‘iris.csv.1’ saved [3975/3975]
```

Loading the dataset

In [4]:

```
df = pd.read_csv('./iris.csv')
```

In [5]:

```
df.shape
```

Out[5]:

```
(150, 5)
```

In [6]:

```
df.head()
```

Out[6]:

	sepal.length	sepal.width	petal.length	petal.width	variety
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

	sepal.length	sepal.width	petal.length	petal.width	variety
4	5.0	3.6	1.4	0.2	Setosa

In [7]:

```
df.head()
```

Out[7]:

	sepal.length	sepal.width	petal.length	petal.width	variety
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

In [8]:

```
df['variety'].unique()
```

Out[8]:

```
array(['Setosa', 'Versicolor', 'Virginica'], dtype=object)
```

In [9]:

```
le = LabelEncoder()
le.fit(["Setosa", "Versicolor", "Virginica"])
```

Out[9]:

```
LabelEncoder()
```

In [10]:

```
variety = df['variety']
variety = le.transform(variety)
```

In [11]:

```
df['variety'] = variety
```

In [12]:

```
df
```

Out[12]:

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

150 rows × 5 columns

Splitting into Train and Test data

In [13]:
```
X, Y = df.drop('variety', axis='columns'), df['variety']
```

In [14]:
```
X
```

Out[14]:

	sepal.length	sepal.width	petal.length	petal.width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

In [15]:
```
Y
```

Out[15]:
```
0      0
1      0
2      0
3      0
4      0
      ..
145    2
146    2
147    2
148    2
149    2
Name: variety, Length: 150, dtype: int64
```

In [16]:
```
X_train, X_val, Y_train, Y_val = train_test_split(X, Y, stratify=Y, random_state=0)
```

In [17]:
```
X_train.shape, X_val.shape, Y_train.shape, Y_val.shape
```

Out[17]:
```
((112, 4), (38, 4), (112,), (38,))
```

Training the Naive Bayes Classifier

In [18]:
```
model = GaussianNB()
```

In [19]:
```
model.fit(X_train, Y_train)
```

Out[19]:
```
GaussianNB()
```

Evaluation

In [20]:
```
Y_pred = model.predict(X_val)
```

In [21]:
```
accuracy = accuracy_score(Y_val, Y_pred)
```

In [22]:
```
print("Accuracy of Naive Bayes Classfier : ", accuracy * 100)
```

```
Accuracy of Naive Bayes Classfier :  97.36842105263158
```

Confusion Matrix

In [23]:
```
cm = confusion_matrix(Y_val, Y_pred)
```

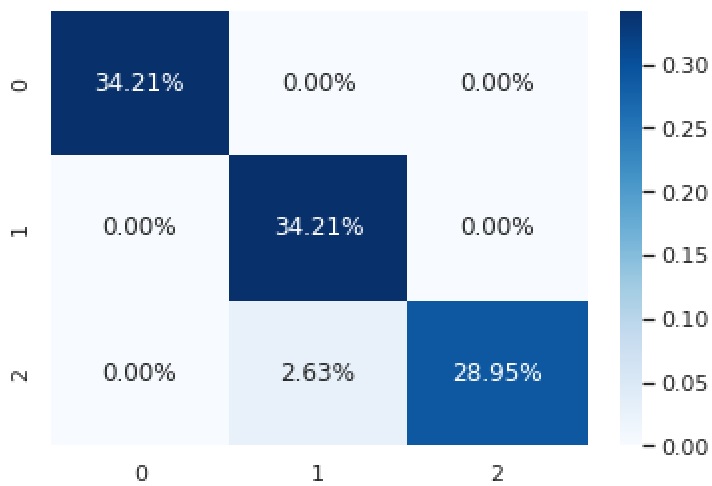
In [24]:
```
cm
```

Out[24]:
```
array([[13,  0,  0],
       [ 0, 13,  0],
       [ 0,  1, 11]])
```

In [25]:
```
np.sum(cm, axis=1)
```

Out[25]:
```
array([13, 13, 12])
```

In [26]:
```
sns.heatmap(cm/np.sum(cm), annot=True, fmt='.2%', cmap='Blues')
plt.show()
```



We need to get the TP, TN, FP, FN, Precision and Recall for each class

In [27]:
```
def evaluate_metrics_for_class(cm, class_no):
    row_sums, col_sums = np.sum(cm, axis=1), np.sum(cm, axis=0)
    TP, FP, FN = cm[class_no][class_no], row_sums[class_no] - cm[class_no][class_no],
    TN = np.sum(cm) - TP - FP - FN
    precision = TP / (TP + FP)
    recall = TP / (TP + FN)
    return TP, FP, FN, TN, precision, recall
```

In [28]:
```
TP_Setosa, FP_Setosa, FN_Setosa, TN_Setosa, precision_Setosa, recall_Setosa = evalu
```

In [29]:
```
print("For Class Setosa")
print("TP : ", TP_Setosa)
print("FP : ", FP_Setosa)
```

```
print("FN : ", FN_Setosa)
print("TN : ", TN_Setosa)
print("Precision : ", precision_Setosa)
print("Recall : ", recall_Setosa)
```

```
For Class Setosa
TP :  13
FP :  0
FN :  0
TN :  25
Precision :  1.0
Recall :  1.0
```

In [30]:

```
TP_Versicolor, FP_Versicolor, FN_Versicolor, TN_Versicolor, precision_Versicolor, r
```

In [31]:

```
print("For Class Versicolor")
print("TP : ", TP_Versicolor)
print("FP : ", FP_Versicolor)
print("FN : ", FN_Versicolor)
print("TN : ", TN_Versicolor)
print("Precision : ", precision_Versicolor)
print("Recall : ", recall_Versicolor)
```

```
For Class Versicolor
TP :  13
FP :  0
FN :  1
TN :  24
Precision :  1.0
Recall :  0.9285714285714286
```

In [32]:

```
TP_Virginica, FP_Virginica, FN_Virginica, TN_Virginica, precision_Virginica, recall
```

In [33]:

```
print("For Class Virginica")
print("TP : ", TP_Virginica)
print("FP : ", FP_Virginica)
print("FN : ", FN_Virginica)
print("TN : ", TN_Virginica)
print("Precision : ", precision_Virginica)
print("Recall : ", recall_Virginica)
```

```
For Class Virginica
TP :  11
FP :  1
FN :  0
TN :  26
Precision :  0.9166666666666666
Recall :  1.0
```