Tutorial 6: ID5055 Foundations of Machine Learning

Topics Covered: Naive Bayes Classifier

TASKS

1. Use a Gaussian Naive Bayes Classifier to classify Datasets 1-4 given below; Print confusion matrices for the class-imbalanced datasets 3 & 4
2. **(optional)** Play around with dataset generation parameters (number of features, class separation etc.)
3. Create datasets with number of features - 1000, 2000, 3000, 4000 and 5000. For this question use the same dataset generation parameters as Dataset 1 in notebook. Change only the number of features per datapoint.
4. Use time module to calculate runtime of Naive Bayes for each dataset in Qn3 and plot results

Import Libraries

Import all the necessary libraries.

In [15]:
```
import time
import random
import sklearn
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.manifold import TSNE
from sklearn.metrics import accuracy_score
from sklearn.naive_bayes import GaussianNB
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

In [16]:
```
# set random seeds
random.seed = 42
np.random.seed = 42
sns.set_style('darkgrid')
```

Dataset Generation

In [17]:
```
### DO NOT EDIT ###
def data_gen(n_data, n_class, weights = None, f_tot = 6, f_info = 6, f_red = 0
    X,Y = make_classification(n_samples = n_data,
                              n_features = f_tot,
                              n_classes = n_class,
                              n_informative = f_info,
                              n_redundant = f_red,
                              n_clusters_per_class = 1,
                              weights = weights,
                              hypercube = True,
                              random_state = 42,
                              class_sep= class_sep)
    return X, Y
```

In [18]:
```
### DO NOT EDIT ###
# Creating the datasets
n_samples = 2000
n_classes = 2

# DATASET 1 - 1000 features
X1, Y1 = data_gen(n_data = n_samples,
                  n_class = n_classes,
                  weights = None,
                  f_tot = 1000,
                  f_info = 1000,
                  name = 'data1_nb')

# DATASET 2 - 5000 features
X2, Y2 = data_gen(n_data = n_samples,
                  n_class = n_classes,
                  weights = None,
                  f_tot = 5000,
                  f_info = 5000,
                  name = 'data2_nb')

# DATASET 3 - 20:80 class imbalanced
X3, Y3 = data_gen(n_data = n_samples,
                  n_class = n_classes,
                  weights = [0.2, 0.8],
                  f_tot = 1000,
                  f_info = 1000,
                  name = 'data3_nb')

# DATASET 4 - 10:90 class imbalanced
X4, Y4 = data_gen(n_data = n_samples,
                  n_class = n_classes,
                  weights = [0.05, 0.95],
                  f_tot = 1000,
                  f_info = 1000,
                  name = 'data4_nb')
```

```
In [19]: ### DO NOT EDIT ###
         # splitting each dataset into test and train sets

         X1_train, X1_test, Y1_train, Y1_test = train_test_split(X1, Y1, test_size=0.2,
         X2_train, X2_test, Y2_train, Y2_test = train_test_split(X2, Y2, test_size=0.2,
         X3_train, X3_test, Y3_train, Y3_test = train_test_split(X3, Y3, test_size=0.2,
         X4_train, X4_test, Y4_train, Y4_test = train_test_split(X4, Y4, test_size=0.2,
```

Naive Bayes Classifier

Naive Bayes classifiers are a family of simple probabilistic classifiers which are based on Bayes Theorem. It is a fast and classification method and scales very efficiently with number of features.

Naive Assumption: The main assumption of such classifiers is in assuming that the effect of every feature in a class is independent of other features. This independence assumption gives these classifiers the name.

Training: Training a Naive Bayes classifier involves estimating the class probabilities and the conditional probabilities of features given each class. Once the classifier is trained, it can be used to make predictions. Given a set of feature values, it calculates the probability of the instance belonging to each class and assigns it to the class with the highest probability.

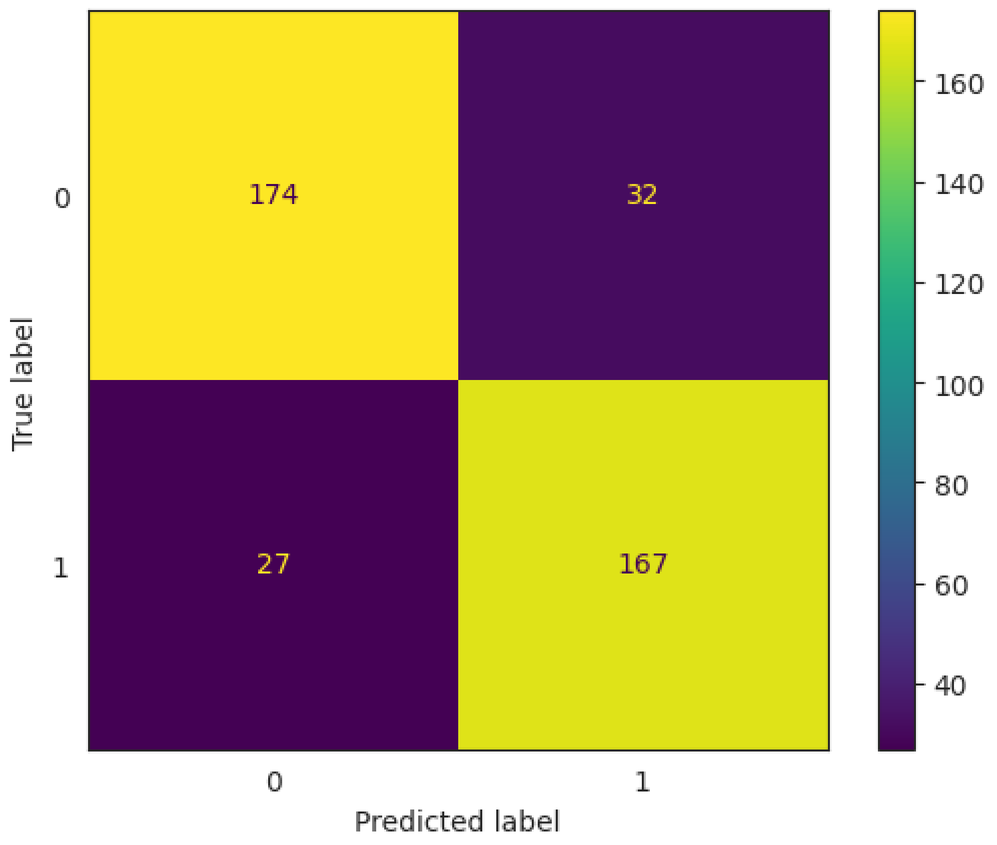
Limitations:This method is however not so reliable when the underlying independence assumption is not true or when the data shows very complex relationships which it cannot capture.

```
In [20]: ### DO NOT EDIT ###
         def NBClassifier(X_train, Y_train, X_test, Y_test, d, conf = True):
             tick = time.time()
             model = GaussianNB()
             model.fit(X_train, Y_train)
             tock = time.time()

             Y_pred = model.predict(X_test)
             acc = accuracy_score(Y_test, Y_pred)
             cm = confusion_matrix(Y_test, Y_pred)

             print('****************************************')
             print('Dataset:', d)
             print(f"Accuracy: {acc:0,.4f}")
             sns.set_style("white")
             if conf:
                 disp = ConfusionMatrixDisplay(confusion_matrix=cm)
                 disp.plot()
                 plt.show()

             return tock-tick
```

Dataset 1

```
In [21]: time1 = NBClassifier(X1_train, Y1_train, X1_test, Y1_test, 1)
         print('Time Taken (seconds):', time1)
```

```
**************************************
Dataset: 1
Accuracy: 0.8525
```

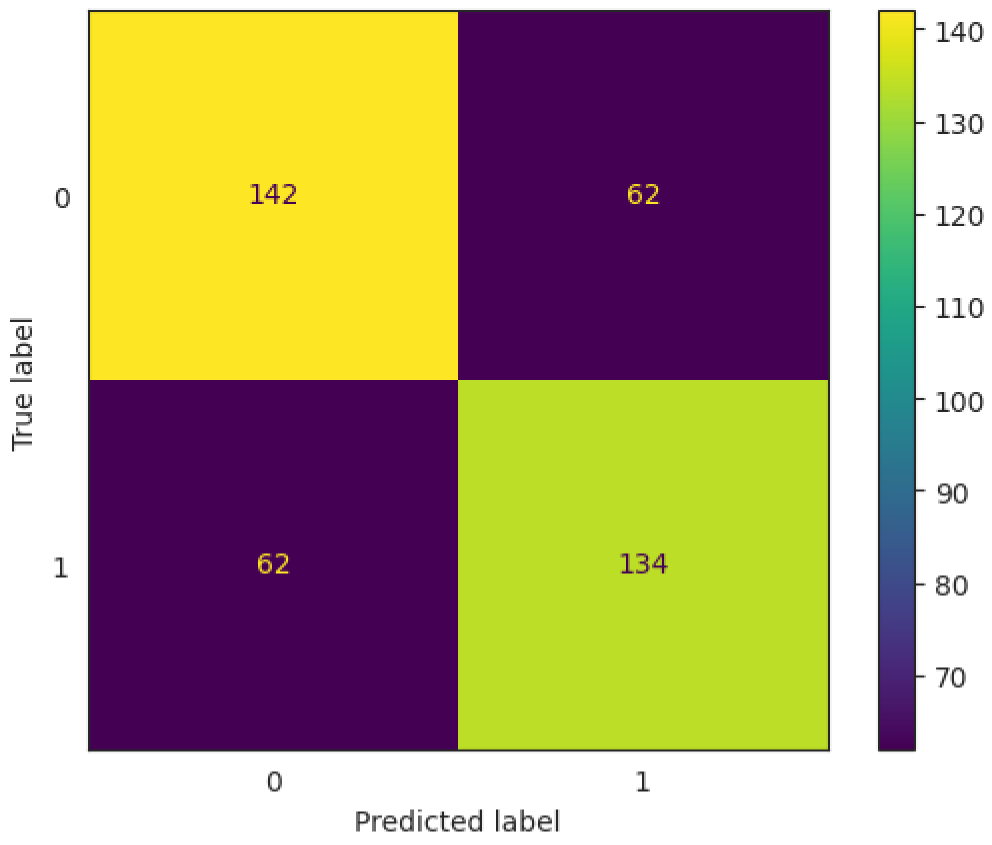


```
Time Taken (seconds): 0.02407526969909668
```

Dataset 2

```
In [22]: time2 = NBClassifier(X2_train, Y2_train, X2_test, Y2_test, 2)
         print('Time Taken (seconds):', time2)
```

```
**************************************
Dataset: 2
Accuracy: 0.6900
```

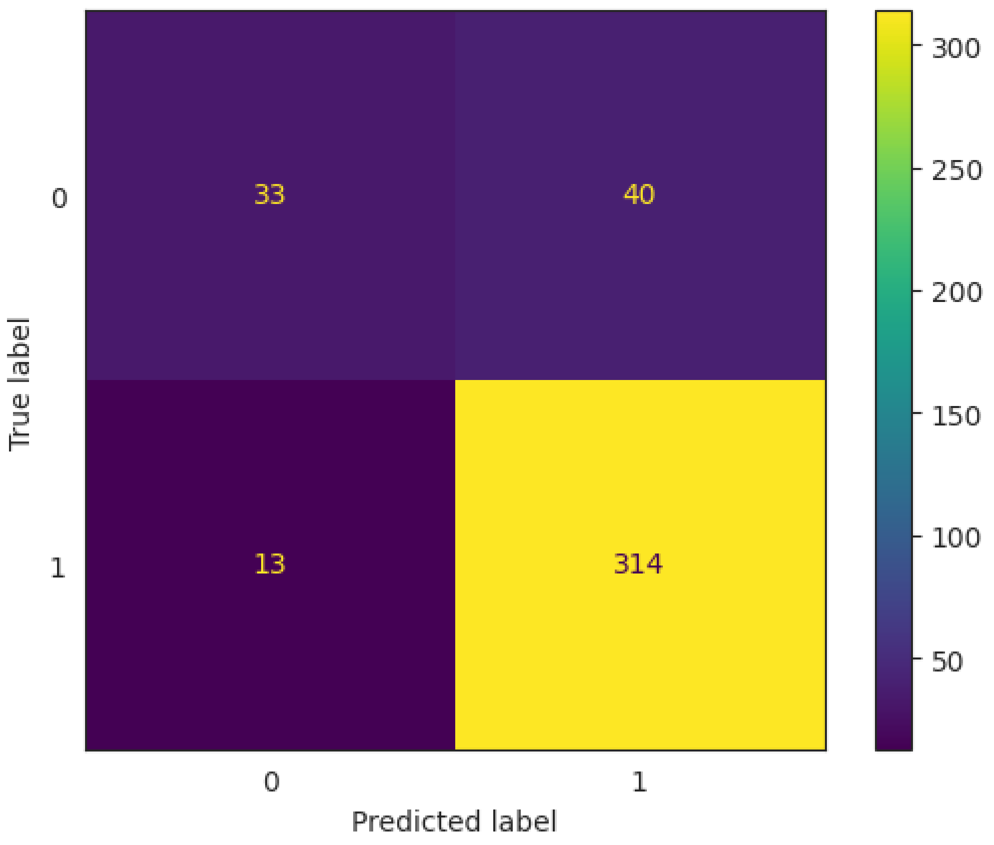


```
Time Taken (seconds): 0.1185297966003418
```

Dataset 3

```
In [23]: time3 = NBClassifier(X3_train, Y3_train, X3_test, Y3_test, 3)
         print('Time Taken (seconds):', time3)
```

```
**************************************
Dataset: 3
Accuracy: 0.8675
```

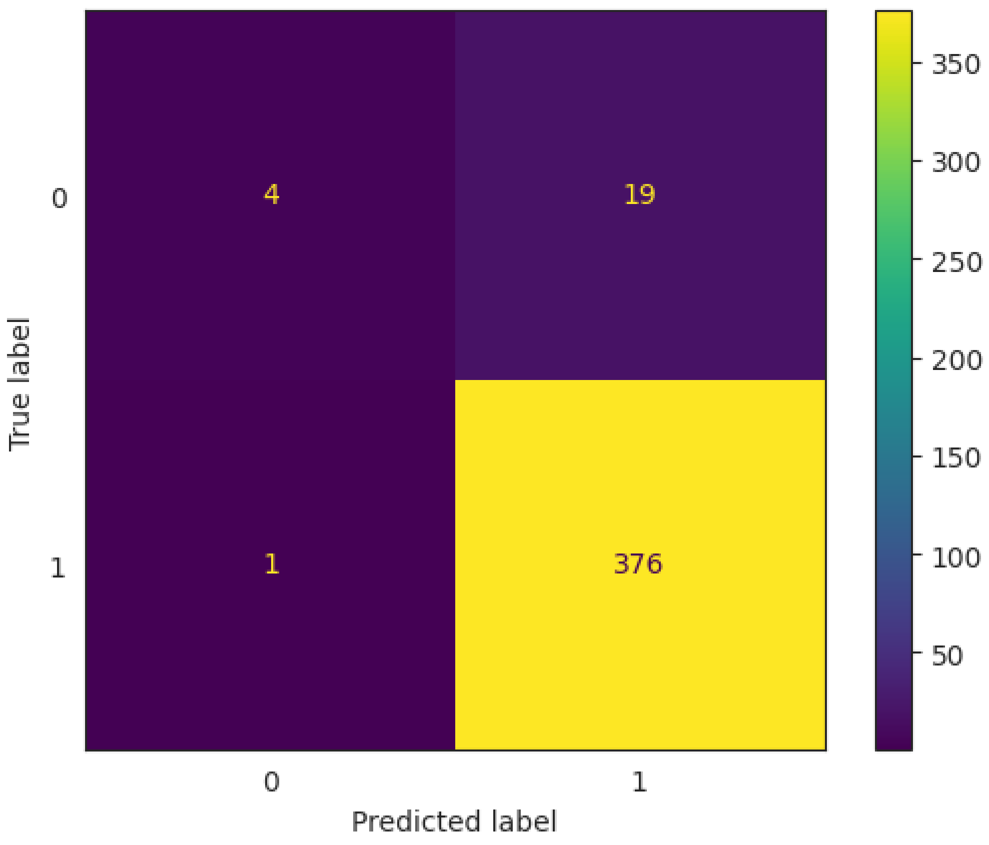


```
Time Taken (seconds): 0.020758867263793945
```

Dataset 4

In [24]:
```
time4 = NBClassifier(X4_train, Y4_train, X4_test, Y4_test, 4)
print('Time Taken (seconds):', time4)
```

```
**************************************
Dataset: 4
Accuracy: 0.9500
```



```
Time Taken (seconds): 0.027128219604492188
```

In [26]:
```
### Write your code here
```

In [ ]:
```

```