

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from keras.utils import np_utils
from scipy.stats import multivariate_normal as mvn
```

```
#Import .py file of general algorithms
from google.colab import files
files.upload()
from general import KNNClassifier as knn
from general import accuracy
from general import confusionMatrix
from general import GaussBayes as gb
from general import GaussNB as ngb
```

Ninguno archivo selec. Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.  
Saving general.py to general.py

## ▼ Work with the data

Import the data, and create the train and test sets. Normalize and visualize your data

```
train_data = pd.read_csv('/content/drive/MyDrive/Enhance It/Training Projects/MNIST Bayes and  
train_data
```

```
test_data = pd.read_csv('/content/drive/MyDrive/Enhance It/Training Projects/MNIST Bayes and
test_data
```

	Unnamed: 0	index	labels	0	1	2	3	4	5	6	...	774	775	776	777	778	779
0	0	0	7	0	0	0	0	0	0	0	...	0	0	0	0	0	(
1	1	1	2	0	0	0	0	0	0	0	...	0	0	0	0	0	(
2	2	2	1	0	0	0	0	0	0	0	...	0	0	0	0	0	(
3	3	3	0	0	0	0	0	0	0	0	...	0	0	0	0	0	(
4	4	4	4	0	0	0	0	0	0	0	...	0	0	0	0	0	(
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
9995	9995	9995	2	0	0	0	0	0	0	0	...	0	0	0	0	0	(
9996	9996	9996	3	0	0	0	0	0	0	0	...	0	0	0	0	0	(
9997	9997	9997	4	0	0	0	0	0	0	0	...	0	0	0	0	0	(
9998	9998	9998	5	0	0	0	0	0	0	0	...	0	0	0	0	0	(
9999	9999	9999	6	0	0	0	0	0	0	0	...	0	0	0	0	0	(

10000 rows × 787 columns

```
X_train = train_data.to_numpy()
X_test = test_data.to_numpy()
x_train = X_train[:,3:].astype('float32')
x_test = X_test[:,3:].astype('float32')
y_train = X_train[:,2]
y_test = X_test[:,2]

print(f"Train set: {x_train.shape},{y_train.shape}")
print(f"Train set: {x_test.shape},{y_test.shape}")
```

```
Train set: (60000, 784),(60000,)
Train set: (10000, 784),(10000,)
```

```
#Normalize the data
x_train /= 255
x_test /= 255
```

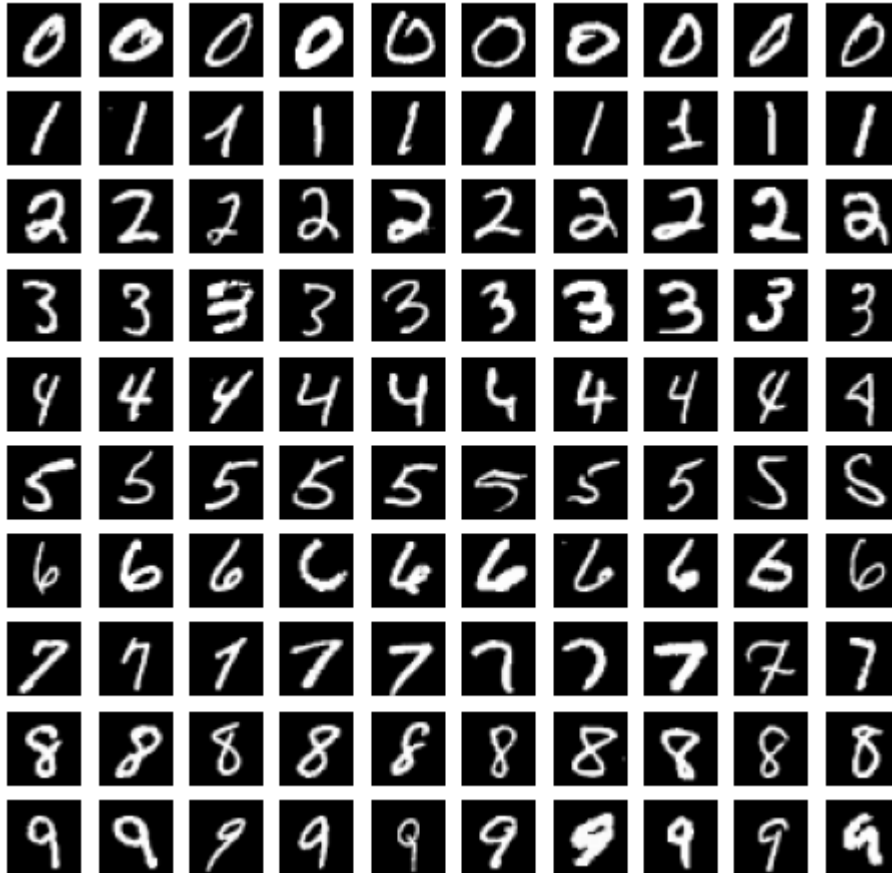
```
#Visualize 10 random training data from every single number
x_vis = X_train[:,3:].reshape(len(x_train),28,28)
```

```
plt.figure(figsize=(8,8))
for i in range(10):
```

```

index = np.where(y_train == i)
index = index[0][np.random.randint(index[0].shape[0], size=10)]
for j in range(10):
    plt.subplot(10,10,i*10+j+1)
    plt.imshow(x_vis[index[j]], cmap='gray')
    plt.axis('off')
plt.show()

```



## ▼ Use of Naive Bayes

```

mnist_naive = nbm.NaiveBayesClassifier()
epsilons = np.linspace(1e-3,1e-1)
naive_accruries = np.zeros(len(epsilons))

for i in range(len(epsilons)):
    print(f'Checking epsilon {i+1} out of {len(epsilons)}...')
    mnist_naive.fit(x_train,y_train,epsilon=epsilons[i])
    y_hat_naive = mnist_naive.predict(x_train)
    naive_accruries[i] = accuracy(y_train,y_hat_naive)
#print(train_acc_naive)

```

```

Checking epsilon 1 out of 50...
Checking epsilon 2 out of 50...
Checking epsilon 3 out of 50...

```

```
Checking epsilon 4 out of 50...
Checking epsilon 5 out of 50...
Checking epsilon 6 out of 50...
Checking epsilon 7 out of 50...
Checking epsilon 8 out of 50...
Checking epsilon 9 out of 50...
Checking epsilon 10 out of 50...
Checking epsilon 11 out of 50...
Checking epsilon 12 out of 50...
Checking epsilon 13 out of 50...
Checking epsilon 14 out of 50...
Checking epsilon 15 out of 50...
Checking epsilon 16 out of 50...
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Checking epsilon 18 out of 50...
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Checking epsilon 21 out of 50...
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Checking epsilon 40 out of 50...
Checking epsilon 41 out of 50...
Checking epsilon 42 out of 50...
Checking epsilon 43 out of 50...
Checking epsilon 44 out of 50...
Checking epsilon 45 out of 50...
Checking epsilon 46 out of 50...
Checking epsilon 47 out of 50...
Checking epsilon 48 out of 50...
Checking epsilon 49 out of 50...
Checking epsilon 50 out of 50...
```

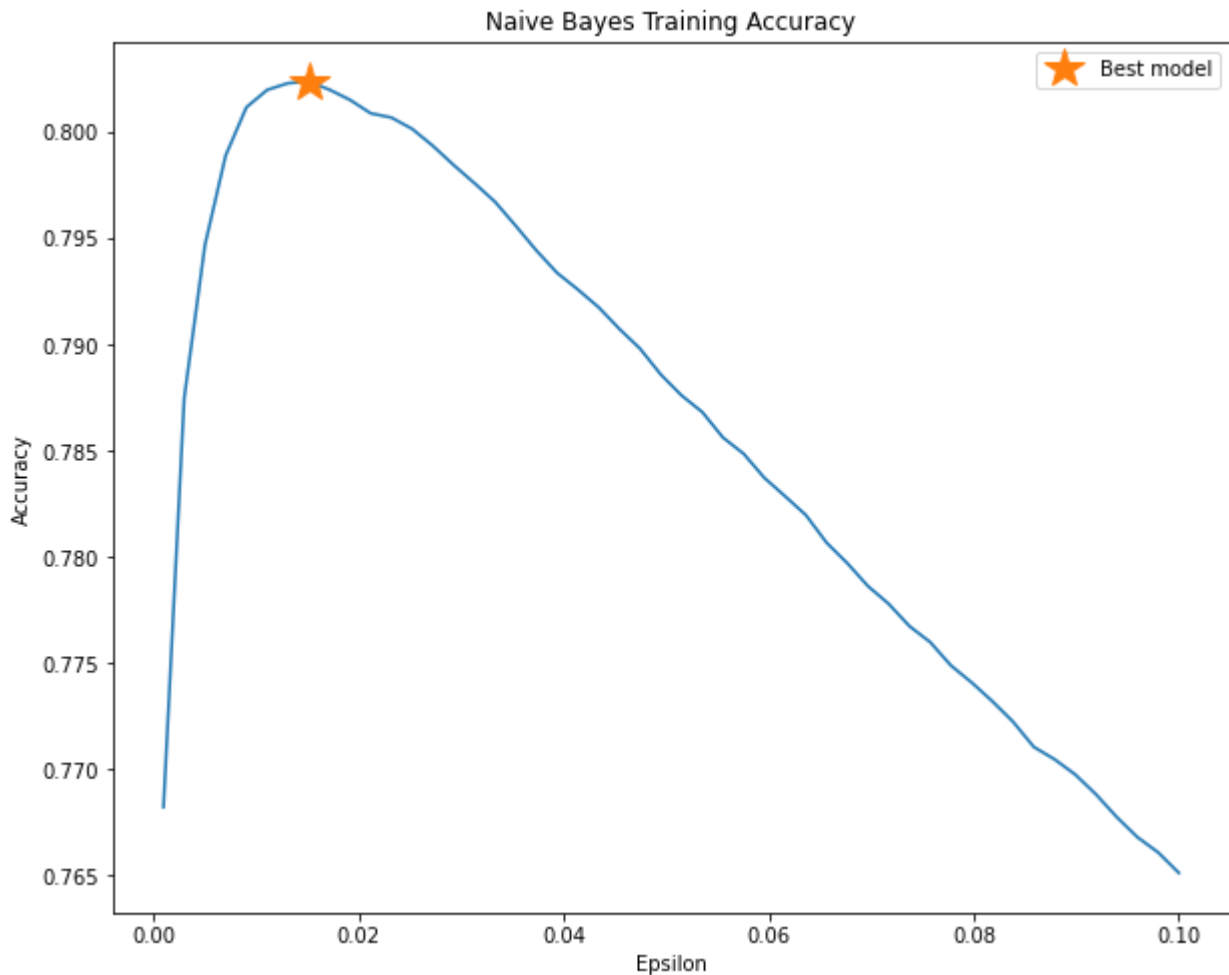
```
max_acc = max(naive_accuracies)
best_e = epsilons[np.where(naive_accuracies == max_acc)]
print(best_e, max_acc)
```

```
plt.figure(figsize=(10,8))
plt.plot(epsilons,naive_accuracies)
```

```
plt.plot(best_e,max_acc,'*',markersize=20,label='Best model')
plt.legend()
plt.xlabel('Epsilon')
plt.ylabel('Accuracy')
plt.title('Naive Bayes Training Accuracy')
```

```
[0.01514286] 0.8024
```

```
Text(0.5, 1.0, 'Naive Bayes Training Accuracy')
```



```
#Check the model with the test set
mnist_naive.fit(x_train,y_train,epsilon=best_e)
test_naive = mnist_naive.predict(x_test)
naive_test_acc = accuracy(y_test,test_naive)

print(f"Training accuracy: {max_acc}      Test accuracy: {naive_test_acc}")
```

```
Training accuracy: 0.8024      Test accuracy: 0.8148
```

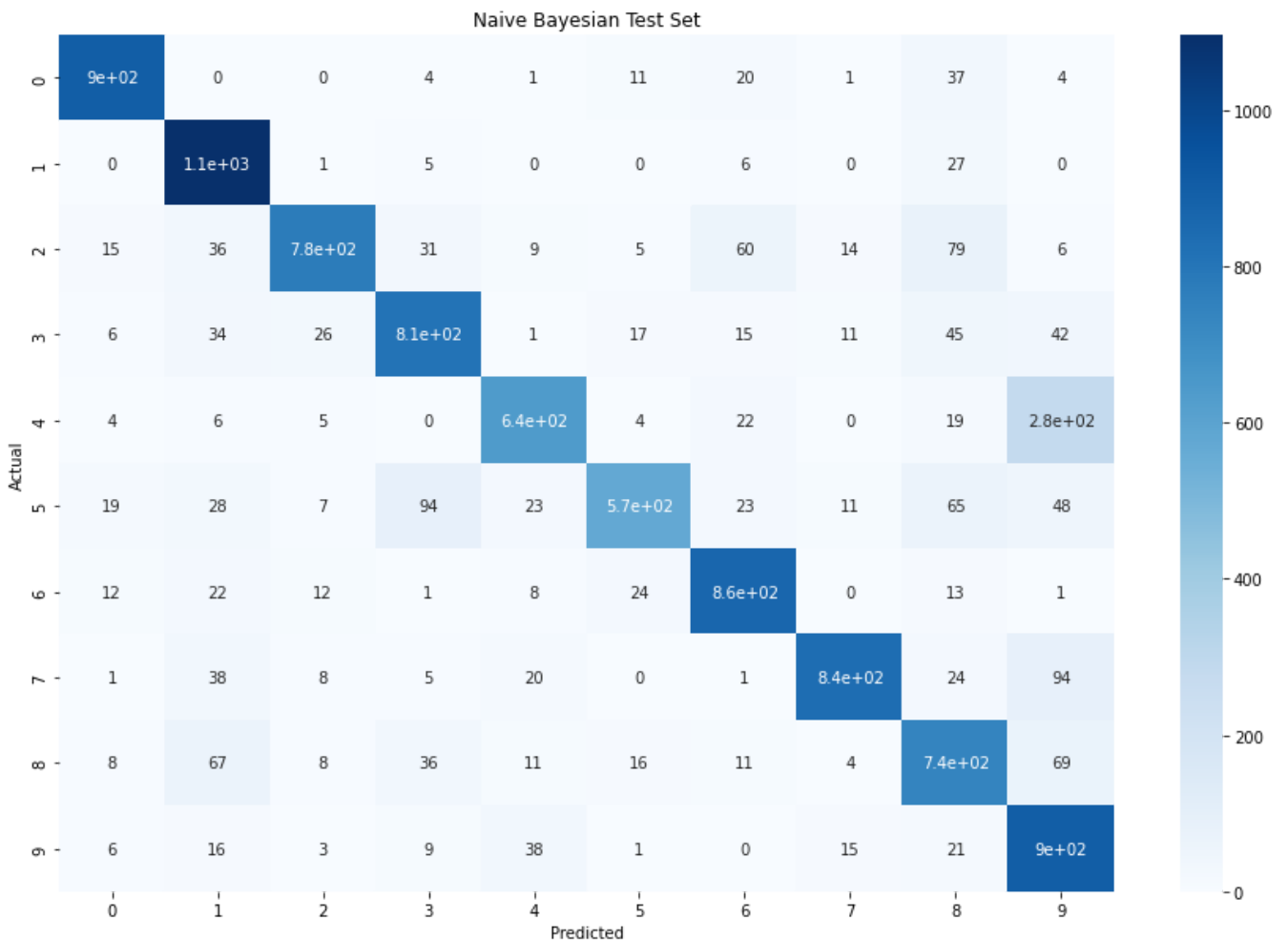
```
#Get the confusion matrix
naive_conf = confusionMatrix(y_test,test_naive)

plt.figure(figsize=(15,10))
conf_plt = sns.heatmap(naive_conf, annot=True, cmap='Blues')
conf_plt.set_title('Naive Bayesian Test Set')
```

```

conf_plt.set_xlabel('Predicted')
conf_plt.set_ylabel('Actual')
conf_plt.xaxis.set_ticklabels(['0','1','2','3','4','5','6','7','8','9'])
conf_plt.yaxis.set_ticklabels(['0','1','2','3','4','5','6','7','8','9'])
plt.show()

```



## ▼ Use of Non-naive Bayes

```

mnist_gauss = gb()
bayes accuracies = np.zeros(len(epsilons))

for i in range(len(epsilons)):
    print(f'Checking epsilon {i+1} out of {len(epsilons)}...')
    mnist_gauss.fit(x_train,y_train,epsilon=epsilons[i])
    y_hat_gauss = mnist_gauss.predict(x_train)

```

```
bayes_accuracies[i] = accuracy(y_train,y_hat_gauss)
#print(train_acc_gauss)
```

```
Checking epsilon 1 out of 50...
Checking epsilon 2 out of 50...
Checking epsilon 3 out of 50...
Checking epsilon 4 out of 50...
Checking epsilon 5 out of 50...
Checking epsilon 6 out of 50...
Checking epsilon 7 out of 50...
Checking epsilon 8 out of 50...
Checking epsilon 9 out of 50...
Checking epsilon 10 out of 50...
Checking epsilon 11 out of 50...
Checking epsilon 12 out of 50...
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Checking epsilon 44 out of 50...
Checking epsilon 45 out of 50...
Checking epsilon 46 out of 50...
Checking epsilon 47 out of 50...
Checking epsilon 48 out of 50...
Checking epsilon 49 out of 50...
Checking epsilon 50 out of 50...
```

```
max_acc = max(bayes_accuracies)
best_e = epsilons[np.where(bayes_accuracies == max_acc)]
```

```

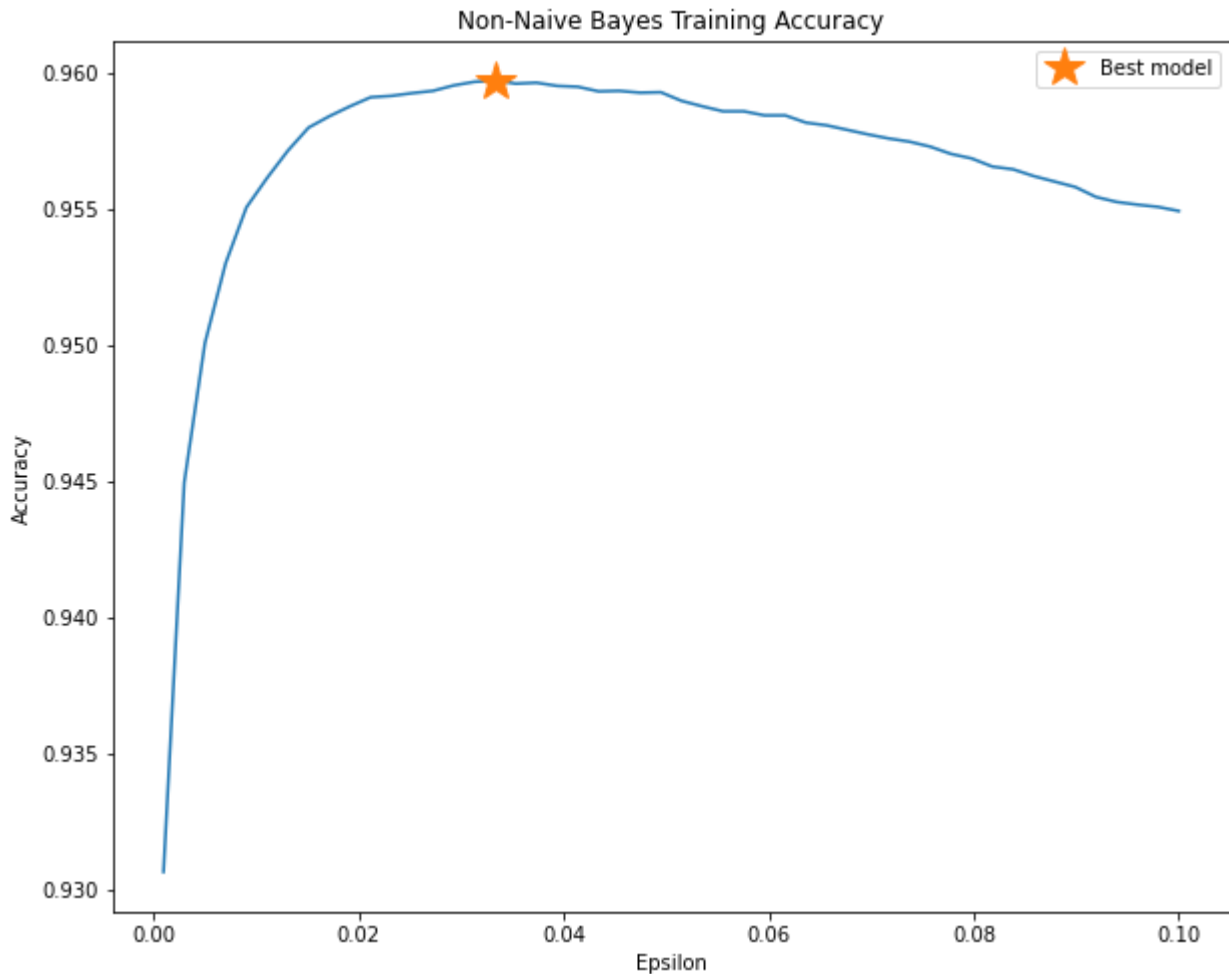
print(best_e, max_acc)

plt.figure(figsize=(10,8))
plt.plot(epsilons,bayes_accuracies)
plt.plot(best_e,max_acc,'*',markersize=20,label='Best model')
plt.legend()
plt.xlabel('Epsilon')
plt.ylabel('Accuracy')
plt.title('Non-Naive Bayes Training Accuracy')

```

```
[0.03332653] 0.9597333333333333
```

```
Text(0.5, 1.0, 'Non-Naive Bayes Training Accuracy')
```



```

#Check the model with the test set
mnist_gauss.fit(x_train,y_train,epsilon=best_e)
test_bayes = mnist_gauss.predict(x_test)
gauss_test_acc = accuracy(y_test,test_bayes)

print(f"Training accuracy: {max_acc}      Test accuracy: {gauss_test_acc}")

```

```
Training accuracy: 0.9597333333333333      Test accuracy: 0.9563
```

```
#Create the confusion matrix
```

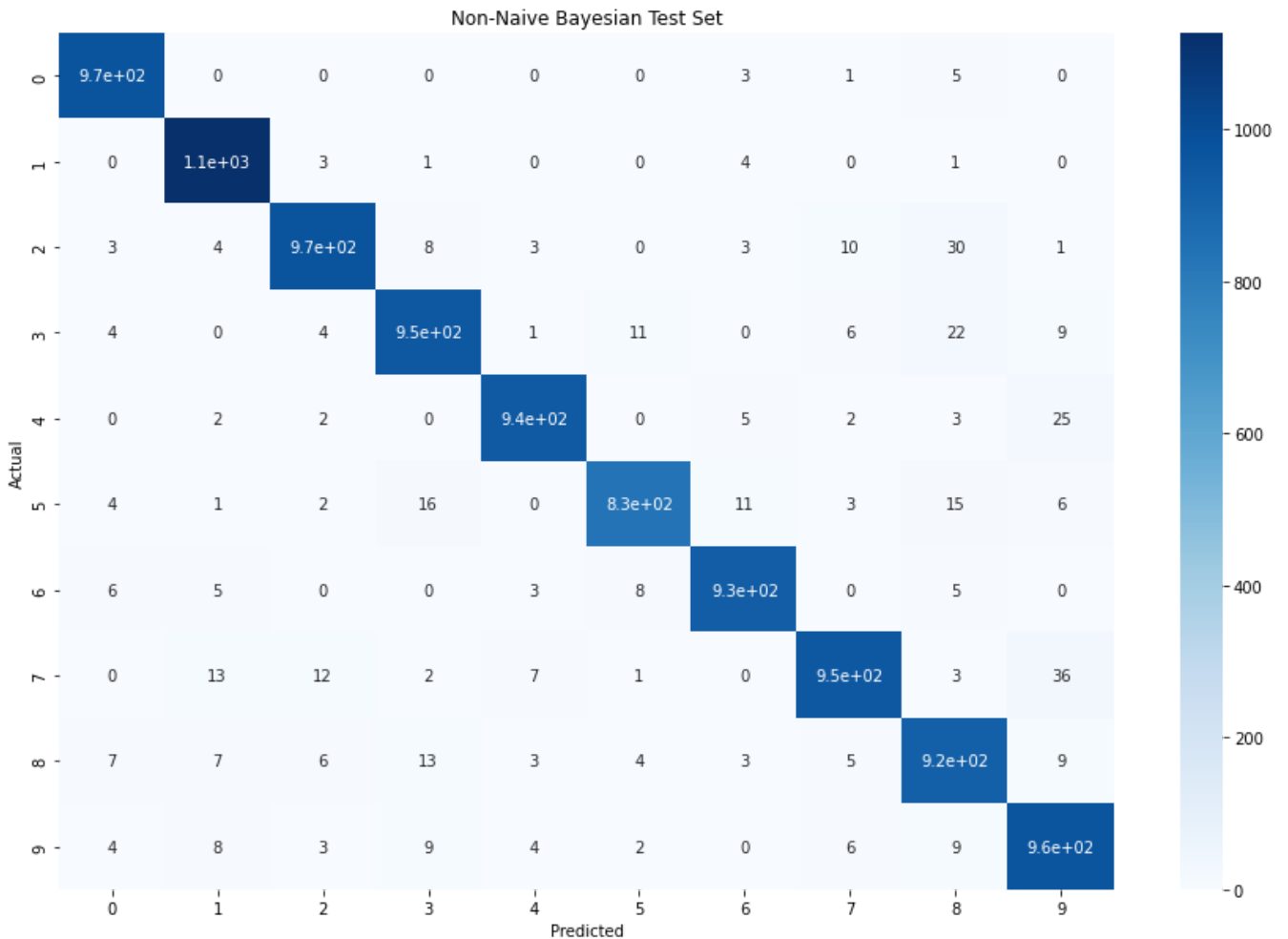


```

bayes_conf = confusionMatrix(y_test,test_bayes)

plt.figure(figsize=(15,10))
conf_plt = sns.heatmap(bayes_conf, annot=True, cmap='Blues')
conf_plt.set_title('Non-Naive Bayesian Test Set')
conf_plt.set_xlabel('Predicted')
conf_plt.set_ylabel('Actual')
conf_plt.xaxis.set_ticklabels(['0','1', '2','3','4','5','6','7','8','9'])
conf_plt.yaxis.set_ticklabels(['0','1', '2','3','4','5','6','7','8','9'])
plt.show()

```



## ▼ Use of KNN

Cannot implement due to high dimensionality

#Reshape the data for x

```
x_train = x_train.reshape(len(x_train),28,28)
x_train.shape
```

```
(60000, 28, 28)
```

```
with tf.device('/device:GPU:0'):
    mnist_knn = knn()
    mnist_knn.fit(x_train,y_train)
```

```
neighbors = [x for x in range(2,11)]
knn_acc = np.zeros(len(neighbors))
```

```
for i in range(len(neighbors)):
    print(f"Checking {i+1} out of {len(neighbors)+1}...")
    y_hat = mnist_knn.predict(x_train, neighbors[i])
    knn_acc[i] = accuracy(y_train,y_hat)
```

```
Checking 1 out of 10...
```

```
-----
KeyboardInterrupt                                Traceback (most recent call last)
```

```
<ipython-input-31-eb89569fa6e3> in <module>()
```

```
      8     for i in range(len(neighbors)):
      9         print(f"Checking {i+1} out of {len(neighbors)+1}...")
---> 10     y_hat = mnist_knn.predict(x_train, neighbors[i])
     11     knn_acc[i] = accuracy(y_train,y_hat)
```

```
/content/general.py in predict(self, x, k, epsilon)
```

```
     54
     55     for i in range(N):
---> 56         dist_sqr = np.sum((self.x - x[i])**2, axis=1) #Get the squared distance of
     57         idxt = np.argsort(dist_sqr)[:k] #Get the indexes of the K nearest neighbor
     58         gamma_k = 1 / (np.sqrt(dist_sqr[idxt]+epsilon)) #Get the weights
```

```
KeyboardInterrupt:
```

SEARCH STACK OVERFLOW

```
max_acc = max(knn_acc)
best_k = neighbors[np.where(knn_acc == max_acc)]
```

```
plt.figure(figsize=(10,8))
plt.plot(neighbors,knn_acc)
plt.plot(best_k,max_acc,'*',markersize=20,label='Best model')
plt.legend()
plt.xlabel('K neighbors')
plt.ylabel('Accuracy')
plt.title('KNN Training Accuracy')
```

```
#Determine the best number of neighbors for the classification
plt.figure(figsize=(10,6))
```

```
plt.plot(neighbors, accuracies)
plt.xlabel('Neighbors')
plt.ylabel('Train accuracy')
```

