| Date | 02-11-2022 |
|--------------|---|
| Team ID | PNT2022TMID43024 |
| Project Name | Real time communication powered by Ai for specially Abled |

ASSIGNMENT-4

Problem Statement:

Over recent years, as the popularity of mobile phone devices has increased, Short Message Service (SMS) has grown into a multi-billion dollar industry. At the same time, reduction in the cost of messaging services has resulted in growth in unsolicited commercial advertisements (spams) being sent to mobile phones. Due to Spam SMS, Mobile service providers suffer from some sort of financial problems as well as it reduces calling time for users. Unfortunately, if the user accesses such Spam SMS they may face the problem of virus or malware. When SMS arrives at mobile it will disturb mobile user privacy and concentration. It may lead to frustration for the user. So Spam SMS is one of he major issues in the wireless communication world and it grows day by day.

Solution:

Dataset: Spam Data = 13.21%, ham Data = 86.78%

Import Python libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.naive_bayes import MultinomialNB
```

Import SMS Data

```
In [2]:
df = pd.read_csv('../input/spamraw.csv')
```

df.head()

Out[2]:

| 046[2]. | | |
|---------|------|---|
| | type | text |
| 0 | ham | Hope you are having a good week. Just checking in |
| 1 | ham | Kgive back my thanks. |
| 2 | ham | Am also doing in cbe only. But have to pay. |
| 3 | spam | complimentary 4 STAR Ibiza Holiday or £10,000 |
| 4 | spam | okmail: Dear Dave this is your final notice to |

Exploratory Data Analysis (EDA)

In [3]:

#Find count and unique messages count of all the messages
df.describe()

Out[3]:

| <u>oucloj.</u> | | |
|----------------|------|------------------------|
| | type | text |
| count | 5559 | 5559 |
| unique | 2 | 5156 |
| top | ham | Sorry, I'll call later |

| | type | text |
|------|------|------|
| freq | 4812 | 30 |

#Extract SPAM messages

spam_messages = df[df["type"]=="spam"]
spam_messages.head() #Display first 5 rows of SPAM messages

Out[4]:

| | type | text |
|----|------|--|
| 3 | spam | complimentary 4 STAR Ibiza Holiday or £10,000 |
| 4 | spam | okmail: Dear Dave this is your final notice to |
| 8 | spam | Marvel Mobile Play the official Ultimate Spide |
| 19 | spam | U can WIN £100 of Music Gift Vouchers every we |
| 34 | spam | U have won a nokia 6230 plus a free digital ca |

#Find count and unique messages count of SPAM messages. spam_messages.describe()

Out[5]:

| | type | text |
|-------|------|------|
| count | 747 | 747 |

| | type | text |
|--------|------|--|
| unique | 1 | 653 |
| top | spam | Please call our customer service representativ |
| freq | 747 | 4 |

```
In [6]:
linkcode
#Plot the counts of HAM (non SPAM) vs SPAM
sns.countplot(data = df, x= df["type"]).set_title("Amount of spam and no-spam
messages")
plt.show()
```

Splitting the SMS data into Test and Train data

```
In [7]:
data_train, data_test, labels_train, labels_test =
train_test_split(df.text,df.type,test_size=0.2,random_state=0)
print("data_train, labels_train : ",data_train.shape, labels_train.shape)
print("data_test, labels_test: ",data_test.shape, labels_test.shape)
data_train, labels_train : (4447,) (4447,)
data_test, labels_test: (1112,) (1112,)

Extraction & CountVectorize
```

The CountVectorizer provides a simple way to both tokenize a collection of text documents and build a vocabulary of known words, but also to encode new documents using that vocabulary.

```
In [8]:
vectorizer = CountVectorizer()
#fit & transform
# fit: build dict (i.e. word->wordID)
# transform: convert document (i.e. each line in the file) to word vector
data_train_count = vectorizer.fit_transform(data_train)
data_test_count = vectorizer.transform(data_test)
```

Modelling & training

Multinomial Naive Bayes is a specialized version of Naive Bayes that is designed more for text documents. Whereas simple naive Bayes would model a document as the presence and absence of particular words, multinomial naive bayes explicitly models the word counts and adjusts the underlying calculations to deal with in.

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

```
In [9]:
clf = MultinomialNB()
clf.fit(data_train_count, labels_train)
predictions = clf.predict(data_test_count)
predictions

Out[9]:
array(['ham', 'ham', 'ham', ..., 'ham', 'ham', 'ham'],
dtype='<U4')

Results and Accuracy

In [10]:
print ("accuracy_score : ", accuracy_score(labels_test, predictions))
accuracy_score : 0.9901079136690647</pre>
```

Confusion Matrix

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known. It allows the visualization of the performance of an algorithm.

```
In [11]:
print ("confusion matrix : \n", confusion matrix(labels test, predictions))
confusion matrix :
 [[979
          01
 [ 11 122]]
In [12]:
print (classification_report(labels_test, predictions))
                precision
                             recall f1-score
                                                     support
          ham
                     0.99
                                 1.00
                                            0.99
                                                         979
         spam
                      1.00
                                 0.92
                                            0.96
                                                         133
```

| micro | avg | 0.99 | 0.99 | 0.99 | 1112 |
|----------|-----|------|------|------|------|
| macro | avg | 0.99 | 0.96 | 0.98 | 1112 |
| weighted | avg | 0.99 | 0.99 | 0.99 | 1112 |