#### SPAM CLASSIFIER

#### Introduction

The upsurge in the volume of unwanted emails called spam has created an intense need for the development of more dependable and robust anti spam filters. Any promotional messages or advertisements that end up in our inbox can be categorized as spam as they don't provide any value and often irritates us.

#### Import the required packages

```
%matplotlib inline
import matplotlib.pyplot as plt
import csv
import sklearn
import pickle
from wordcloud import WordCloud
import pandas as pd
import numpy as np
import nltk
from nltk.corpus import stopwords
from sklearn.feature extraction.text import CountVectorizer,
TfidfTransformer
from sklearn.tree import DecisionTreeClassifier
from sklearn.model selection import
GridSearchCV,train test split,StratifiedKFold,cross val score,learning
curve
```

## **Loading the Dataset**

data = pd.read\_csv('dataset/spam.csv', encoding='latin-1')
data.head()

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy Available only	NaN	NaN	NaN
1	ham	Ok lar Joking wif u oni	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina	NaN	NaN	NaN
3	ham	U dun say so early hor U c already then say	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro	NaN	NaN	NaN

## Removing unwanted columns

From the above figure, we can see that there are some unnamed columns and the label and text column name is not intuitive so let's fix those in this step.

```
data = data.drop(["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"],
axis=1)
data = data.rename(columns={"v2": "text", "v1":"label"})
data[1990:2000]
```

	label	text
1990	ham	HI DARLIN IVE JUST GOT BACK AND I HAD A REALLY
1991	ham	No other Valentines huh? The proof is on your
1992	spam	Free tones Hope you enjoyed your new content
1993	ham	Eh den sat u book e kb liao huh
1994	ham	Have you been practising your curtsey?
1995	ham	Shall i come to get pickle
1996	ham	Lol boo I was hoping for a laugh
1997	ham	YEH I AM DEF UP4 SOMETHING SAT
1998	ham	Well, I have to leave for my class babe Yo
1999	ham	LMAO where's your fish memory when I need it?

data['label'].value\_counts()

# OUTPUT

ham 4825

spam 747

Name: label, dtype: int64

## **Preprocessing and Exploring the Dataset**

# Import nltk packages and Punkt Tokenizer Models import nltk nltk.download("punkt") import warnings warnings ('ignore')

## Build word cloud to see which message is spam and which is not

```
ham_words = "
spam_words = "

# Creating a corpus of spam messages
for val in data[data['label'] == 'spam'].text:
    text = val.lower()
```

```
tokens = nltk.word_tokenize(text)
for words in tokens:
   spam_words = spam_words + words + ' '
```

```
# Creating a corpus of ham messages
for val in data[data['label'] == 'ham'].text:

text = text.lower()

tokens = nltk.word_tokenize(text)

for words in tokens:

ham_words = ham_words + words + ''
```

let's use the above functions to create Spam word cloud and ham word cloud.

```
spam_wordcloud = WordCloud(width=500,
height=300).generate(spam_words)
ham_wordcloud = WordCloud(width=500,
height=300).generate(ham_words)
#Spam Word cloud
plt.figure(figsize=(10,8), facecolor='w')
plt.imshow(spam_wordcloud)
plt.axis("off")
plt.tight_layout(pad=0)
plt.show()
#Creating Ham wordcloud
```

```
plt.figure(figsize=(10,8), facecolor='g')
plt.imshow(ham_wordcloud)
plt.axis("off")
plt.tight_layout(pad=0)
plt.show()
```

From the spam word cloud, we can see that "free" is most often used in spam.

Now, we can convert the spam and ham into 0 and 1 respectively so that the machine can understand.

	label	text	
0	0	Go until jurong point, crazy Available only	
1	0	Ok lar Joking wif u oni	
2	1	Free entry in 2 a wkly comp to win FA Cup fina	
3	0	U dun say so early hor U c already then say	
4	0	Nah I don't think he goes to usf, he lives aro	
5	1	FreeMsg Hey there darling it's been 3 week's n	
6	0	Even my brother is not like to speak with me	
7	0	As per your request 'Melle Melle (Oru Minnamin	
8	1	WINNER!! As a valued network customer you have	
9	1	Had your mobile 11 months or more? U R entitle	

## Removing punctuation and stopwords from the messages

Punctuation and stop words do not contribute anything to our model, so we have to remove them. Using the NLTK library we can easily do it.

```
import nltk
nltk.download('stopwords')
```

```
#remove the punctuations and stopwords
import string
def text_process(text):

text = text.translate(str.maketrans(", ", string.punctuation))
text = [word for word in text.split() if word.lower() not in
stopwords.words('english')]

return " ".join(text)

data['text'] = data['text'].apply(text_process)
data.head()
```

text	label	
Go jurong point crazy Available bugis n great	0	0
Ok lar Joking wif u oni	0	1
Free entry 2 wkly comp win FA Cup final tkts 2	1	2
U dun say early hor U c already say	0	3
Nah dont think goes usf lives around though	0	4

Now, create a data frame from the processed data before moving to the next step.

```
text = pd.DataFrame(data['text'])
label = pd.DataFrame(data['label'])
```

#### **Converting words to vectors**

We can convert words to vectors using either Count Vectorizer or by using TF-IDF Vectorizer.

TF-IDF is better than Countvectorizer because it not only focuses on the frequency of words present in the corpus but also provides the importance of the words. We can then remove the words that are less important for analysis, hence making the model building less complex by reducing the input dimensions.

## Converting words to vectors using TF-IDF Vectorizer

```
#convert the text data into vectors
from sklearn.feature_extraction.text import TfidfVectorizer

vectorizer = TfidfVectorizer()
vectors = vectorizer.fit_transform(data['text'])
vectors.shape

# OUTPUT
(5572, 9376)
#features = word_vectors
features = vectors
```

#### Splitting into training and test set

```
#split the dataset into train and test set X_{train}, X_{test}, y_{train}, y_{test} = train_{test} split(features, data['label'], test size=0.15, random\ state=111)
```

#### Classifying using sklearn's pre-built classifiers

```
#import sklearn packages for building classifiers from sklearn.linear_model import LogisticRegression from sklearn.svm import SVC from sklearn.naive_bayes import MultinomialNB from sklearn.tree import DecisionTreeClassifier from sklearn.neighbors import KNeighborsClassifier from sklearn.ensemble import RandomForestClassifier from sklearn.metrics import accuracy_score
```

```
#initialize multiple classification models

svc = SVC(kernel='sigmoid', gamma=1.0)

knc = KNeighborsClassifier(n_neighbors=49)

mnb = MultinomialNB(alpha=0.2)

dtc = DecisionTreeClassifier(min_samples_split=7, random_state=111)

lrc = LogisticRegression(solver='liblinear', penalty='l1')

rfc = RandomForestClassifier(n_estimators=31, random_state=111)
```

```
#create a dictionary of variables and models

clfs = {'SVC' : svc, 'KN' : knc, 'NB': mnb, 'DT': dtc, 'LR': lrc, 'RF': rfc}
```

```
#fit the data onto the models

def train(clf, features, targets):
    clf.fit(features, targets)

def predict(clf, features):
    return (clf.predict(features))

pred_scores_word_vectors = []

for k,v in clfs.items():
    train(v, X_train, y_train)
    pred = predict(v, X_test)
    pred_scores_word_vectors.append((k, [accuracy_score(y_test, pred)]))
```

### **Predictions using TFIDF Vectorizer algorithm**

```
pred_scores_word_vectors

# OUTPUT
[('SVC', [0.9784688995215312]),
('KN', [0.9330143540669856]),
```

```
('NB', [0.9880382775119617]),
 ('DT', [0.9605263157894737]),
 ('LR', [0.9533492822966507]),
 ('RF', [0.9796650717703349])]
Model predictions
#write functions to detect if the message is spam or not
def find(x):
  if x == 1:
    print ("Message is SPAM")
  else:
     print ("Message is NOT Spam")
newtext = \lceil "Free\ entry" \rceil
integers = vectorizer.transform(newtext)
x = mnb.predict(integers)
find(x)
# OUTPUT
Message is SPAM
```

#### **Evaluating Classification Results with Confusion Matrix**

```
from sklearn.metrics import confusion_matrix
import seaborn as sns
# Naive Bayes

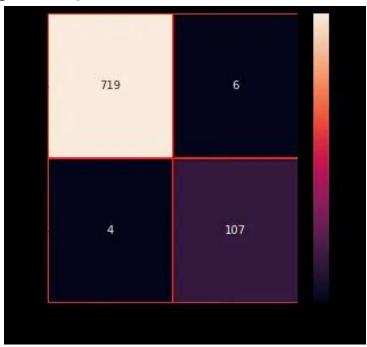
y_pred_nb = mnb.predict(X_test)

y_true_nb = y_test

cm = confusion_matrix(y_true_nb, y_pred_nb)

f, ax = plt.subplots(figsize = (5,5))
```

```
sns.heatmap(cm,annot = True,linewidths=0.5,linecolor="red",fmt =
".0f",ax=ax)
plt.xlabel("y_pred_nb")
plt.ylabel("y_true_nb")
plt.show()
```



from the confusion matrix, we can see that the Naive Bayes model is balanced.

# Build word cloud to see which message is spam and which is not spam

```
ham_words = "
spam_words = "
# Creating a corpus of spam messages
for val in data[data['label'] == 'spam'].text:
    text = val.lower()
```

```
tokens = nltk.word tokenize(text)
  for words in tokens:
    spam words = spam words + words + ''
# Creating a corpus of ham messages
for val in data[data['label'] == 'ham'].text:
  text = text.lower()
  tokens = nltk.word tokenize(text)
  for words in tokens:
    ham words = ham words + words + ''
let's use the above functions to create Spam word cloud and ham word
cloud.
spam wordcloud = WordCloud(width=500,
height=300).generate(spam words)
ham wordcloud = WordCloud(width=500,
height=300).generate(ham words)
#Spam Word cloud
```

plt.figure(figsize=(10,8), facecolor='w')

plt.imshow(spam wordcloud)

plt.tight layout(pad=0)

plt.axis("off")

plt.show()



#Creating Ham wordcloud

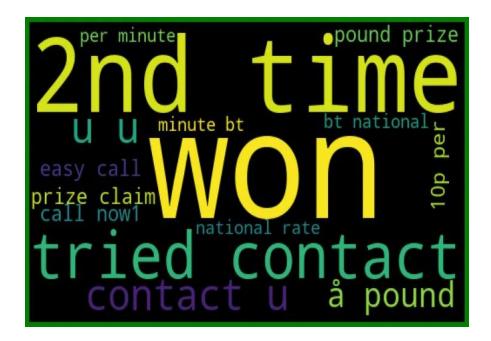
plt.figure(figsize=(10,8), facecolor='g')

plt.imshow(ham\_wordcloud)

plt.axis("off")

plt.tight\_layout(pad=0)

plt.show()



#### ham-word-cloud

From the spam word cloud, we can see that "free" is most often used in spam.

Now, we can convert the spam and ham into 0 and 1 respectively so that the machine can understand.

data = data.replace(['ham','spam'],[0, 1])
data.head(10)

text		label	
Go until jurong point, crazy Available only	0	0	
Ok lar Joking wif u oni	0	1	
Free entry in 2 a wkly comp to win FA Cup fina	1	2	
U dun say so early hor U c already then say	0	3	
Nah I don't think he goes to usf, he lives aro	0	4	
FreeMsg Hey there darling it's been 3 week's n	1	5	
Even my brother is not like to speak with me	0	6	
As per your request 'Melle Melle (Oru Minnamin	0	7	
VINNER!! As a valued network customer you have	1	8	
Had your mobile 11 months or more? U R entitle	1	9	

## Conclusion

Spam classifier using AI is a powerful tool for automatically identifying and filtering out unwanted or malicious emails, messages, and content. By leveraging machine learning algorithms and natural language processing, it can effectively distinguish between legitimate and spam communications, ultimately enhancing user experience, privacy, and security.