Downloading the dataset

```
!pip install opendatasets
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting opendatasets
  Downloading opendatasets-0.1.22-py3-none-any.whl (15 kB)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from opendatasets) (4.65.0)
Requirement already satisfied: kaggle in /usr/local/lib/python3.10/dist-packages (from opendatasets) (1.5.13)
Requirement already satisfied: click in /usr/local/lib/python3.10/dist-packages (from opendatasets) (8.1.3)
Requirement already satisfied: six>=1.10 in /usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets) (1.16.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets) (2022.12.7)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets) (2.27.1)
Requirement already satisfied: python-slugify in /usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets) (8.0.1)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets) (1.26.15)
Requirement already satisfied: python-dateutil in /usr/local/lib/python3.10/dist-packages (from kaggle->opendatasets) (2.8.2)
Requirement already satisfied: text-unidecode>=1.3 in /usr/local/lib/python3.10/dist-packages (from python-slugify->kaggle->opendatasets) (1.3)
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.10/dist-packages (from requests->kaggle->opendatasets) (2.0.12)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->kaggle->opendatasets) (3.4)
Installing collected packages: opendatasets
Successfully installed opendatasets-0.1.22
```

```
import opendatasets as od
dataset_url = 'https://www.kaggle.com/datasets/uciml/sms-spam-collection-dataset'
od.download(dataset_url)
```

```
Downloading sms-spam-collection-dataset.zip to ./sms-spam-collection-dataset

100%|██████████| 211k/211k [00:00<00:00, 52.2MB/s]
```

```
# importing the dependancies
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import nltk
import seaborn as sns
from tqdm.notebook import tqdm
```

```
# importing the dataset
dataset_path = "/content/sms-spam-collection-dataset/spam.csv"

df = pd.read_csv(dataset_path, encoding="latin-1")

# checking the top 5 rows of the dataset
df.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

```
print(f"Shape of the dataset: {df.shape}")
```

```
Shape of the dataset: (5572, 5)
```

Process to follow

1. Data Cleaning
2. EDA
3. Text Preprocessing
4. Model Building
5. Evaluation
6. Improvement
7. Website building
8. Deployment

Data Cleaning

```
# checking the info about the dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 5572 entries, 0 to 5571
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   v1          5572 non-null   object
 1   v2          5572 non-null   object
 2   Unnamed: 2  50 non-null     object
 3   Unnamed: 3  12 non-null     object
 4   Unnamed: 4  6 non-null      object
dtypes: object(5)
memory usage: 217.8+ KB
```

```
# The last three columns has very few values, we can drop those columns
df.drop(columns=['Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'], inplace=True)

# checking the dataset
df.head()
```

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

```
# for more simplicity we can rename the columns
df.rename(columns={'v1':'target', 'v2':'text'}, inplace=True)

# changing the order of the columns
df = df[['text', 'target']]

# checking any 5 samples from the dataset
df.sample(5)
```

	text	target
2701	Hiya, sorry didn't hav signal. I haven't seen ...	ham
1517	Our brand new mobile music service is now live...	spam
891	I am great princess! What are you thinking abo...	ham
4465	Hey u still at the gym?	ham
2325	Apps class varaya elaya.	ham

```
print(f"Checking the distribution of the data:\n{df['target'].value_counts()}")
```

```
Checking the distribution of the data:
ham     4825
```

```
spam     747
Name: target, dtype: int64
```

```
# we can encode the target column
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()

# encoding the target column
df['target'] = encoder.fit_transform(df['target'])

# checking any 5 samples from the dataset
df.sample(5)
```

	text	target
4071	Loans for any purpose even if you have Bad Cre...	1
3563	Do you always celebrate NY's with your family ?	0
2144	FreeMsg: Hey - I'm Buffy. 25 and love to satis...	1
2918	Is xy in ur car when u picking me up?	0
1703	Just taste fish curry :-P	0

```
# checking for the null values
print(f"Total Null values in the dataset:\n{df.isnull().sum()}")
```

```
Total Null values in the dataset:
text      0
target    0
dtype: int64
```

```
# checking the duplicate values
print(f"Total Duplicate rows in the dataset: {df.duplicated().sum()}")
```

```
Total Duplicate rows in the dataset: 403
```

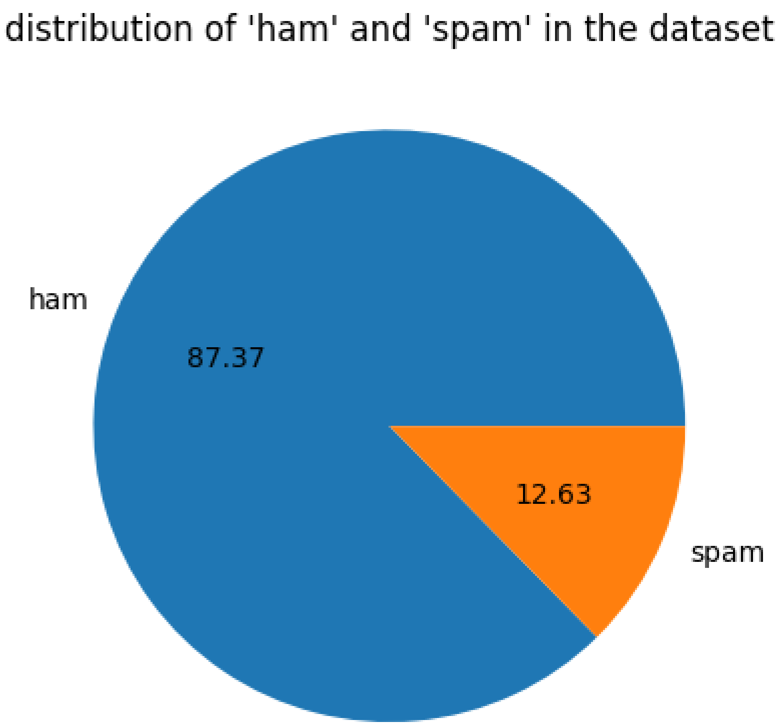
```
print(f"Shape of the dataset before droping the duplicate rows: {df.shape}\n")

# We can remove the duplicate rows
df = df.drop_duplicates(keep='first')
print(f"dupicate rows: {df.duplicated().sum()}\n")

print(f"Shape of the dataset after droping the duplicate rows: {df.shape}")
```

```
Shape of the dataset before droping the duplicate rows: (5572, 2)

dupicate rows: 0

Shape of the dataset after droping the duplicate rows: (5169, 2)
```

EDA

```
# distribution of 'ham' and 'spam' in the dataset
print(f"Distribution:\n{df['target'].value_counts()}\n")

plt.pie(df['target'].value_counts(), labels=['ham', 'spam'], autopct='%0.2f')
plt.title("distribution of 'ham' and 'spam' in the dataset")

print(f"From the above graph we can see, the dataset is imbalanced \n")
```

```
Distribution:
0    4516
1     653
Name: target, dtype: int64

From the above graph we can see, the dataset is imbalanced
```



```
# downloading the punkt sentence tokenizer
nltk.download('punkt')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
True
```

- number of characters in the text
- number of words in the text

- number of sentences in the text

```python
# number of characters in each row of 'text' column
print(f"First row in the 'text' column:\n{df['text'][0]}")

print(f"\ncharacters in the first row of text")

char =[x for x in df['text'][0]]
print(char)

print(f"\n number of characters in first row of 'text' column: {len(char)}")
```

```
First row in the 'text' column:
Go until jurong point, crazy.. Available only in bugis n great world la e buffet...
Cine there got amore wat...

characters in the first row of text
['G', 'o', ' ', 'u', 'n', 't', 'i', 'l', ' ', 'j', 'u', 'r', 'o', 'n', 'g', ' ', 'p',
'o', 'i', 'n', 't', ',', ' ', 'c', 'r', 'a', 'z', 'y', '.', '.', ' ', 'A', 'v', 'a',
'i', 'l', 'a', 'b', 'l', 'e', ' ', 'o', 'n', 'l', 'y', ' ', 'i', 'n', ' ', 'b', 'u',
'g', 'i', 's', ' ', 'n', ' ', 'g', 'r', 'e', 'a', 't', ' ', 'w', 'o', 'r', 'l', 'd', '
', 'l', 'a', ' ', 'e', ' ', 'b', 'u', 'f', 'f', 'e', 't', '.', '.', '.', ' ', 'C', 'i',
'n', 'e', ' ', 't', 'h', 'e', 'r', 'e', ' ', 'g', 'o', 't', ' ', 'a', 'm', 'o', 'r',
'e', ' ', 'w', 'a', 't', '.', '.', '.']

 number of characters in first row of 'text' column: 111
```

```python
# number of characters in each row
df['num_characters'] = df['text'].apply(len)

# checking any 5 random samples from the dataset
df.sample(5)
```

	text	target	num_characters
1865	Call to the number which is available in appoi...	0	100
395	From here after The performance award is calcu...	0	102
2535	Can you pls pls send me a mail on all you know...	0	155
3729	I guess you could be as good an excuse as any,...	0	51
4388	K I'm ready, &lt;#&gt; ?	0	25

```python
# number of words in first row of 'text' column
print(f"First row in the 'text' column:\n{df['text'][0]}")

print(f"\nwords in the first row of text")
word = lambda x: nltk.word_tokenize(x)
print(word(df['text'][0]))
print(f"\n number of words in first row of 'text' column: {len(word(df['text'][0]))}")
```

```
First row in the 'text' column:
Go until jurong point, crazy.. Available only in bugis n great world la e buffet...
Cine there got amore wat...

words in the first row of text
['Go', 'until', 'jurong', 'point', ',', 'crazy', '..', 'Available', 'only', 'in',
'bugis', 'n', 'great', 'world', 'la', 'e', 'buffet', '...', 'Cine', 'there', 'got',
'amore', 'wat', '...']

 number of words in first row of 'text' column: 24
```

word_tokenize --> official_doc --> https://www.nltk.org/_modules/nltk/tokenize.html#word_tokenize

```python
# number of words in each row
df['num_words'] = df['text'].apply(lambda x: len(nltk.word_tokenize(x)))

# checking first 5 rows in the dataset
df.head()
```

	text	target	num_characters	num_words
0	Go until jurong point, crazy.. Available only ...	0	111	24
1	Ok lar... Joking wif u oni...	0	29	8
2	Free entry in 2 a wkly comp to win FA Cup fina...	1	155	37
3	U dun say so early hor... U c already then say...	0	49	13
4	Nah I don't think he goes to usf, he lives aro...	0	61	15

```python
# number of sentence in first row of 'text' column
print(f"First row in the 'text' column:\n{df['text'][0]}")

print(f"\nsentence in the first row of text")
sent = lambda x: nltk.sent_tokenize(x)
print(sent(df['text'][0]))

print(f"\n number of sentence in first row of 'text' column: {len(sent(df['text'][0]))}
```

```
First row in the 'text' column:
Go until jurong point, crazy.. Available only in bugis n great world la e buffet...
Cine there got amore wat...

sentence in the first row of text
['Go until jurong point, crazy..', 'Available only in bugis n great world la e
buffet... Cine there got amore wat...']
```

```
number of sentence in first row of 'text' column: 2
```

sent_tokenize --> official_doc --> https://www.nltk.org/api/nltk.tokenize.sent_tokenize.html#nltk.tokenize.sent_tokenize

```python
# number of sentences in each row
df['num_sentences'] = df['text'].apply(lambda x: len(nltk.sent_tokenize(x)))

# checking first 5 rows in the dataset
df.head()
```

	text	target	num_characters	num_words	num_sentences
0	Go until jurong point, crazy.. Available only ...	0	111	24	2
1	Ok lar... Joking wif u oni...	0	29	8	2
2	Free entry in 2 a wkly comp to win FA Cup fina...	1	155	37	2
3	U dun say so early hor... U c already then say...	0	49	13	1
4	Nah I don't think he goes to usf, he lives aro...	0	61	15	1

```python
# let's compare newly created columns
df[['num_characters', 'num_words', 'num_sentences']].describe()
```

	num_characters	num_words	num_sentences
count	5169.000000	5169.000000	5169.000000
mean	78.977945	18.455794	1.965564
std	58.236293	13.324758	1.448541
min	2.000000	1.000000	1.000000
25%	36.000000	9.000000	1.000000
50%	60.000000	15.000000	1.000000
75%	117.000000	26.000000	2.000000
max	910.000000	220.000000	38.000000

```python
# Now let's compare only 'ham' messages
print(f"ham messages:")
df[df['target']==0][['num_characters', 'num_words', 'num_sentences']].describe()
```

```
ham messages:
```

	num_characters	num_words	num_sentences
count	4516.000000	4516.000000	4516.000000
mean	70.459256	17.123782	1.820195
std	56.358207	13.493970	1.383657
min	2.000000	1.000000	1.000000
25%	34.000000	8.000000	1.000000
50%	52.000000	13.000000	1.000000

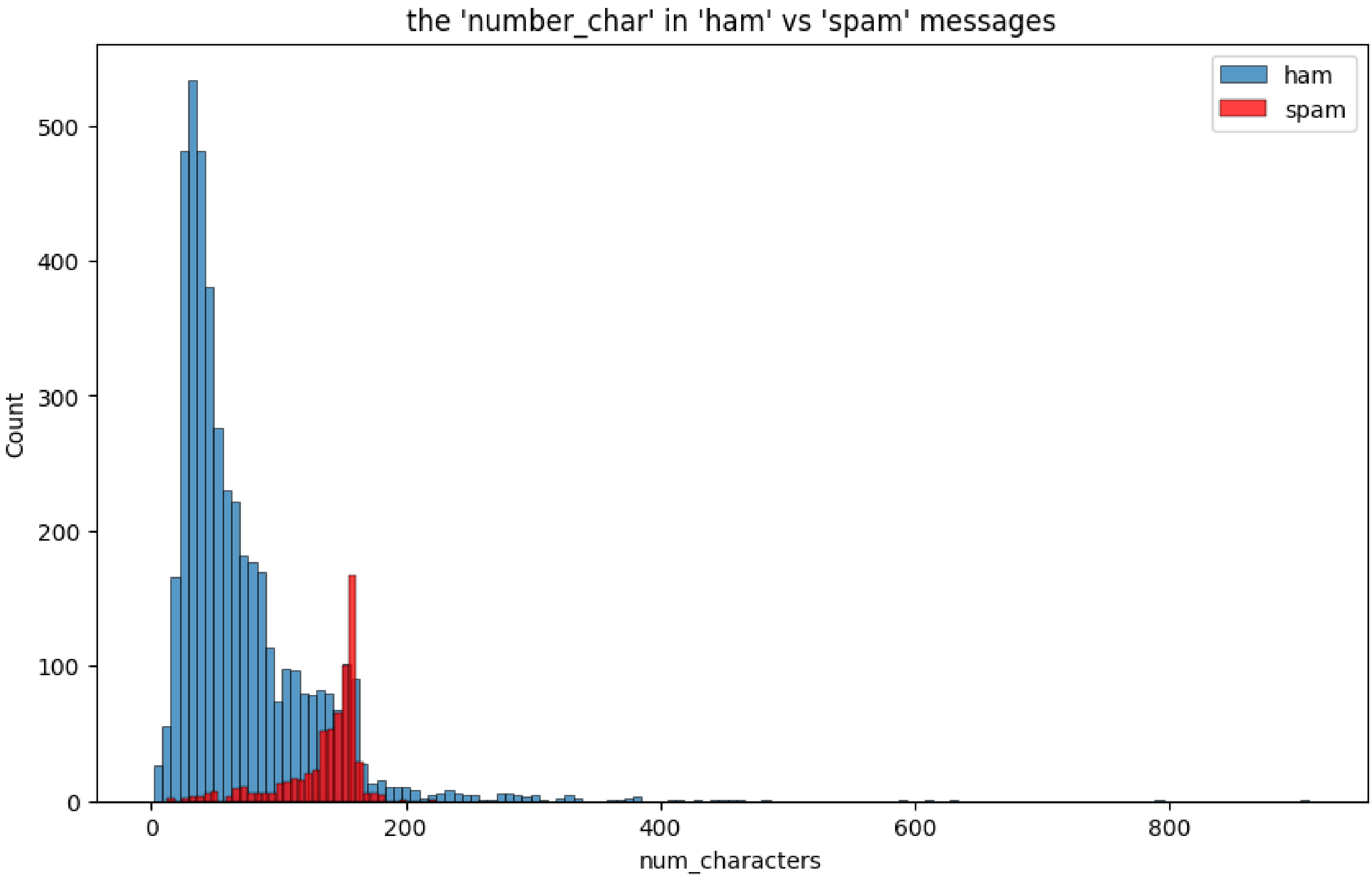
	num_characters	num_words	num_sentences
75%	90.000000	22.000000	2.000000
max	910.000000	220.000000	38.000000

```python
# Now let's compare only 'spam' messages
print(f"Spam messages:")
df[df['target']==1][['num_characters', 'num_words', 'num_sentences']].describe()
```

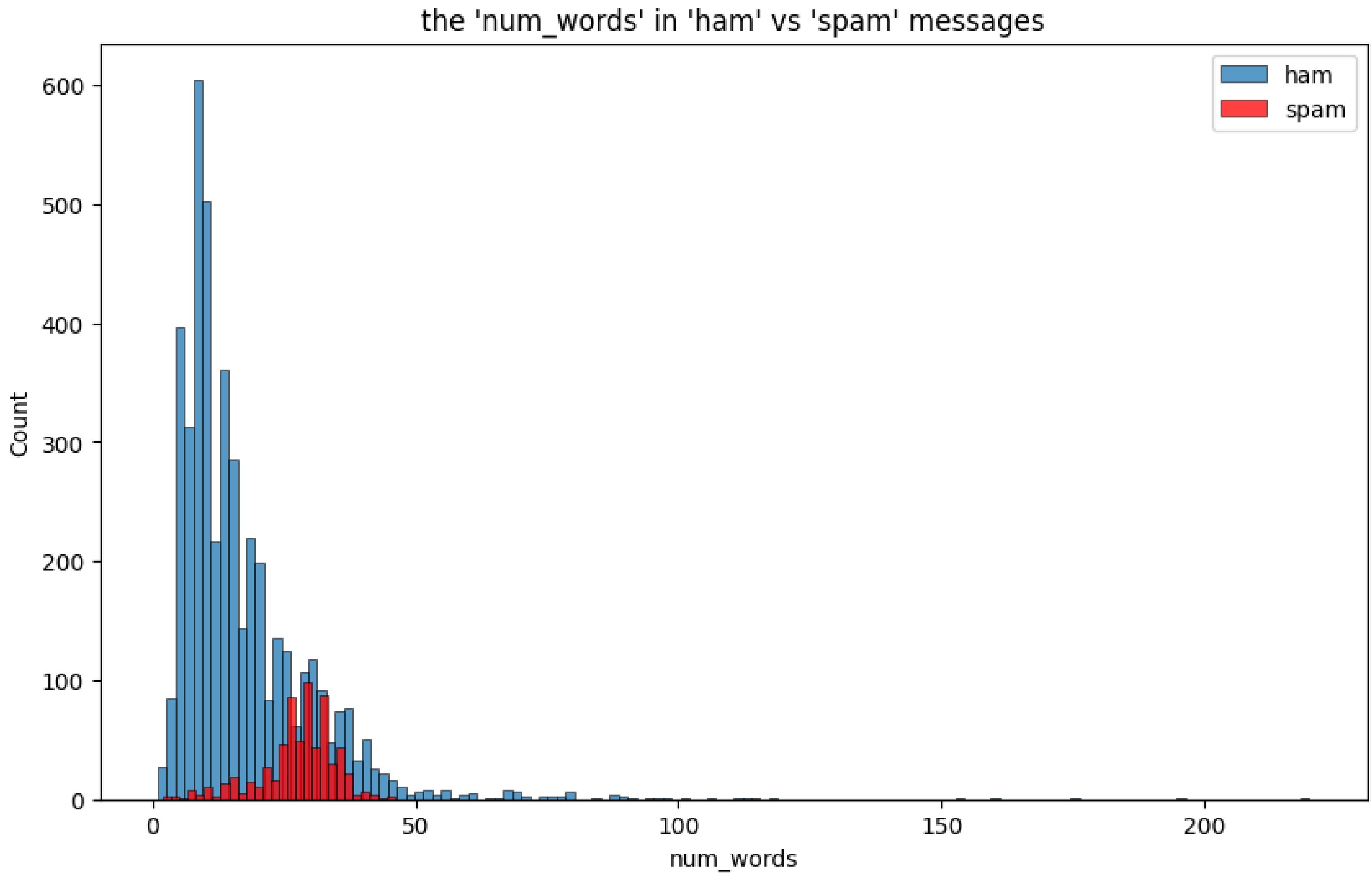
```
Spam messages:
```

	num_characters	num_words	num_sentences
count	653.000000	653.000000	653.000000
mean	137.891271	27.667688	2.970904
std	30.137753	7.008418	1.488425
min	13.000000	2.000000	1.000000
25%	132.000000	25.000000	2.000000
50%	149.000000	29.000000	3.000000
75%	157.000000	32.000000	4.000000
max	224.000000	46.000000	9.000000

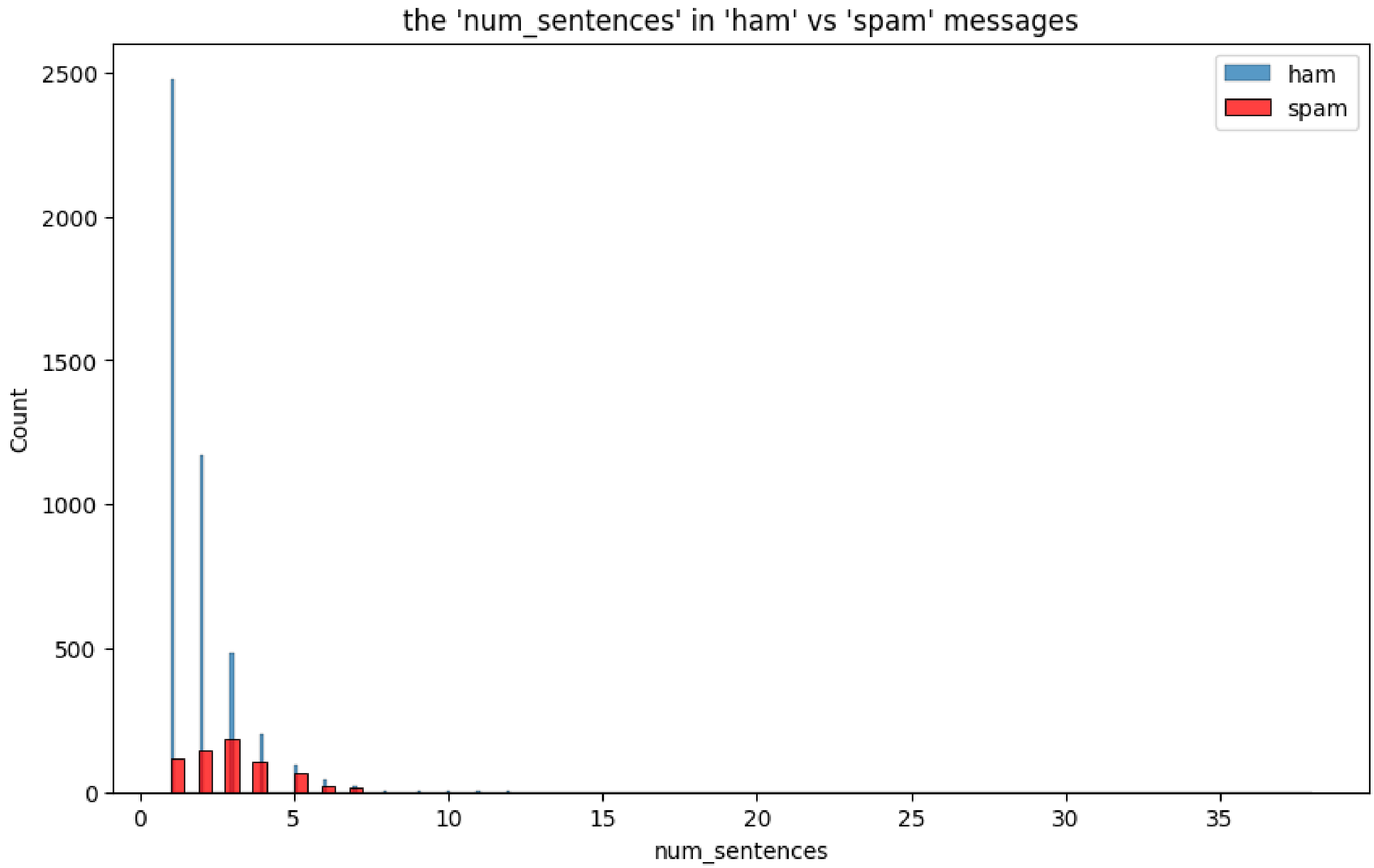
```python
# plotting the 'number_char' in 'ham' vs 'spam' messages
plt.figure(figsize=(10, 6))

sns.histplot(df[df['target']==0]['num_characters'], label='ham')
sns.histplot(df[df['target']==1]['num_characters'], color='red',label='spam')

plt.legend()
plt.title("the 'number_char' in 'ham' vs 'spam' messages");
```



```
# plotting the 'number_words' in 'ham' vs 'spam' messages
plt.figure(figsize=(10, 6))

sns.histplot(df[df['target']==0]['num_words'], label='ham')
sns.histplot(df[df['target']==1]['num_words'], color='red',label='spam')

plt.legend()
plt.title("the 'num_words' in 'ham' vs 'spam' messages");
```

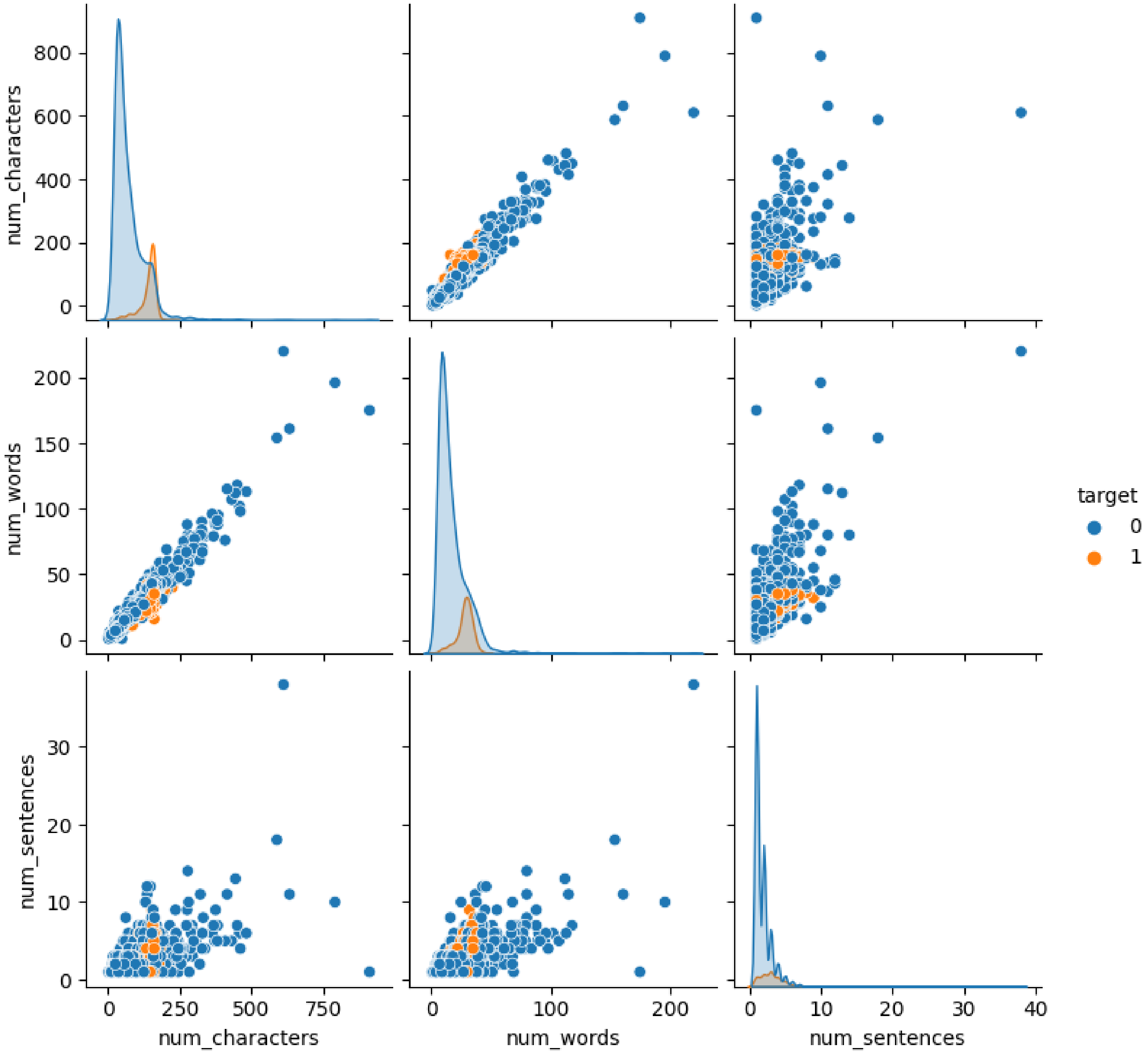


```
# plotting the 'num_sentences' in 'ham' vs 'spam' messages
plt.figure(figsize=(10, 6))

sns.histplot(df[df['target']==0]['num_sentences'], label='ham')
sns.histplot(df[df['target']==1]['num_sentences'], color='red',label='spam')

plt.legend()
plt.title("the 'num_sentences' in 'ham' vs 'spam' messages");
```

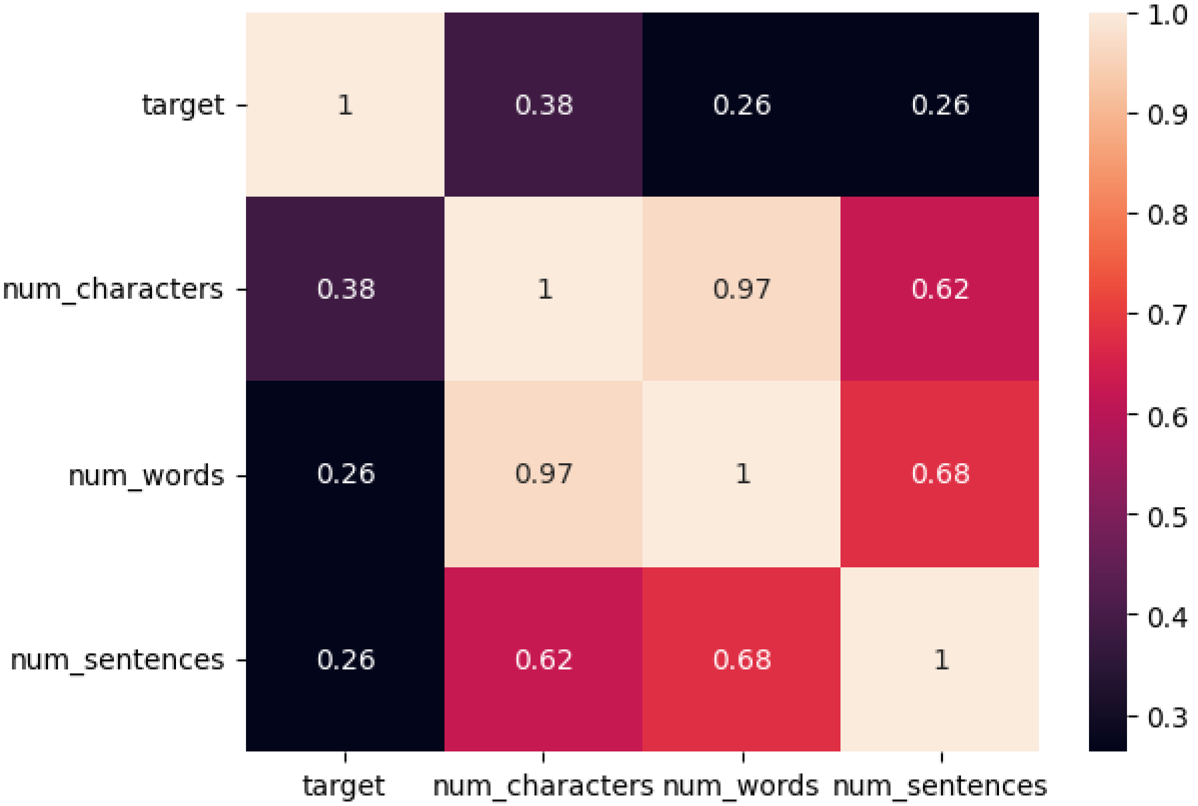


Observation :- The 'spam' messages has maximum charcters and words compare to 'ham' messages

```python
# plotting pair plot
sns.pairplot(df, hue='target');
```



```
sns.heatmap(df[['target', 'num_characters', 'num_words', 'num_sentences']].corr(), anno
```



3. Data Preprocessing

- Lower case
- Tokenizeation
- Removing Special characters
- Removing stop words and punctuation
- Stemming

```
# downloading the stop words from nltk
import nltk
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
True
```

```
# importing stop words from nltk library
from nltk.corpus import stopwords
# stopwords.words('english')
```

```
# puctuations
import string
string.punctuation
```

```
'!"#$%&\'()*+,-./:;<=>?@[\\]^_`{|}~'
```

```
# importing stemming from nltk
from nltk.stem.porter import PorterStemmer
ps = PorterStemmer()

# testing the stemmer
ps.stem('Dancing')
```

```
'danc'
```

```
# we will create a fuction to peform the above mentioned preprocessing

def transform_text(text):
  text = text.lower() # Lower casing the text

  text = nltk.word_tokenize(text) # Tokenization

  # Removing the special characters
  y = []
  for i in text:
    if i.isalnum():
      y.append(i)

  # Removing stop words and punctuation
  text = y[:]
  y.clear()

  for i in text:
    if i not in stopwords.words('english') and i not in string.punctuation:
      y.append(i)

  # stemming
  text = y[:]
  y.clear()

  for i in text:
    y.append(ps.stem(i))

  return " ".join(y)
```

```
print(f"First row in 'text' column before applying preprocessing:\n{df['text'][0]}\n")

print(f"First row in 'text' column after applying preprocessing:\n{transform_text(df['t
```

```
First row in 'text' column before applying preprocessing:
Go until jurong point, crazy.. Available only in bugis n great world la e buffet...
Cine there got amore wat...

First row in 'text' column after applying preprocessing:
go jurong point crazi avail bugi n great world la e buffet cine got amor wat
```

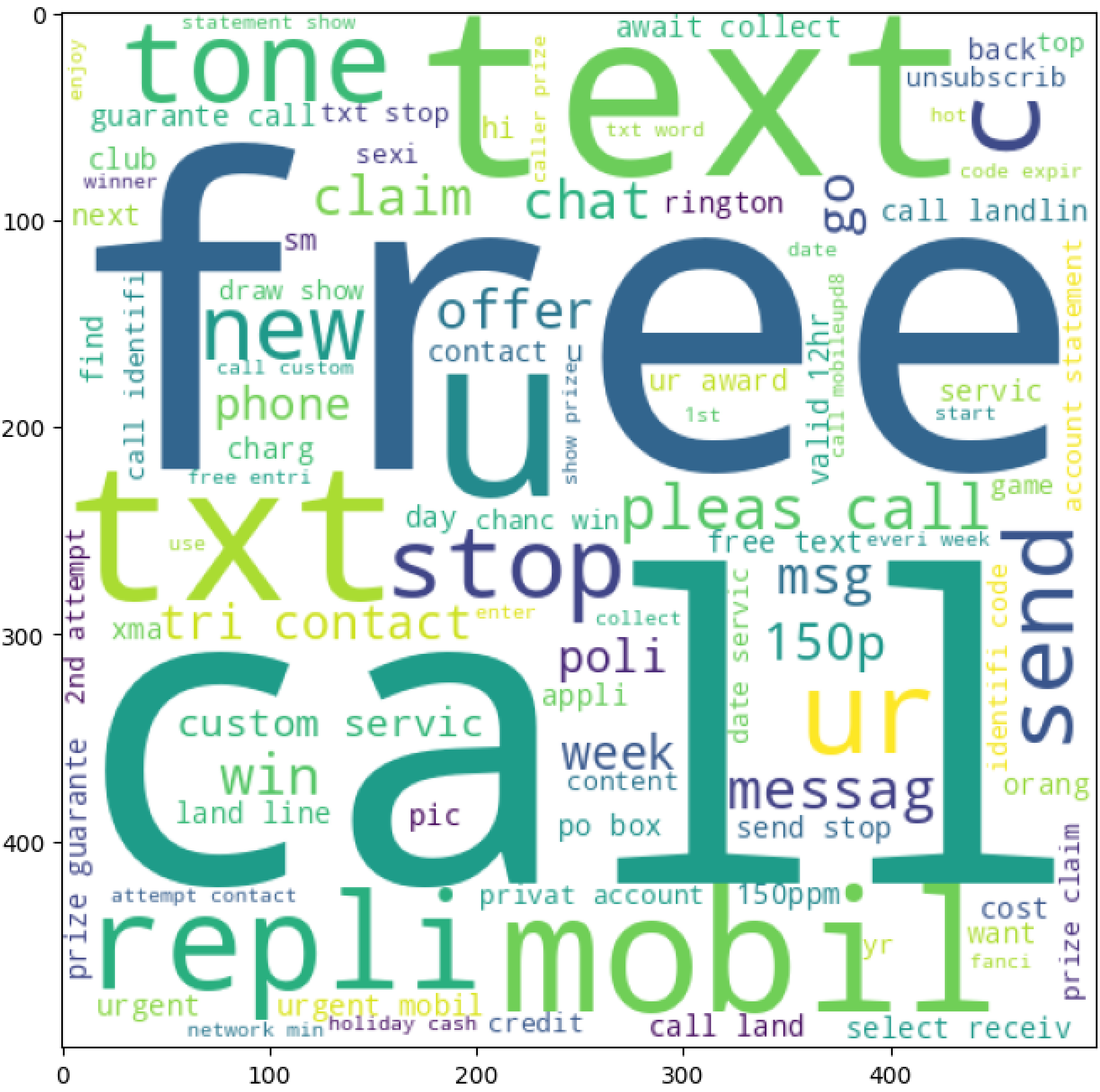
```
# applying transformation on our dataset
df['transformed_text'] = df['text'].apply(transform_text)

# checking the first 5 rows of the dataset
df.head()
```

	text	target	num_characters	num_words	num_sentences	transformed_text
0	Go until jurong point, crazy.. Available only ...	0	111	24	2	go jurong point crazi avail bugi n great world...
1	Ok lar... Joking wif u oni...	0	29	8	2	ok lar joke wif u oni
2	Free entry in 2 a wkly comp to win FA Cup fina...	1	155	37	2	free entri 2 wkli comp win fa cup final tkt 21...
3	U dun say so early hor... U c already then say...	0	49	13	1	u dun say earli hor u c alreadi say
4	Nah I don't think he goes to usf, he lives aro...	0	61	15	1	nah think goe usf live around though

```
# Now we will use wordcloud to see the most frequent words in 'ham' and 'spam' messages

# importing world cloud
from wordcloud import WordCloud
wc = WordCloud(width= 500,
               height = 500,
               min_font_size=10,
               background_color='white')
```

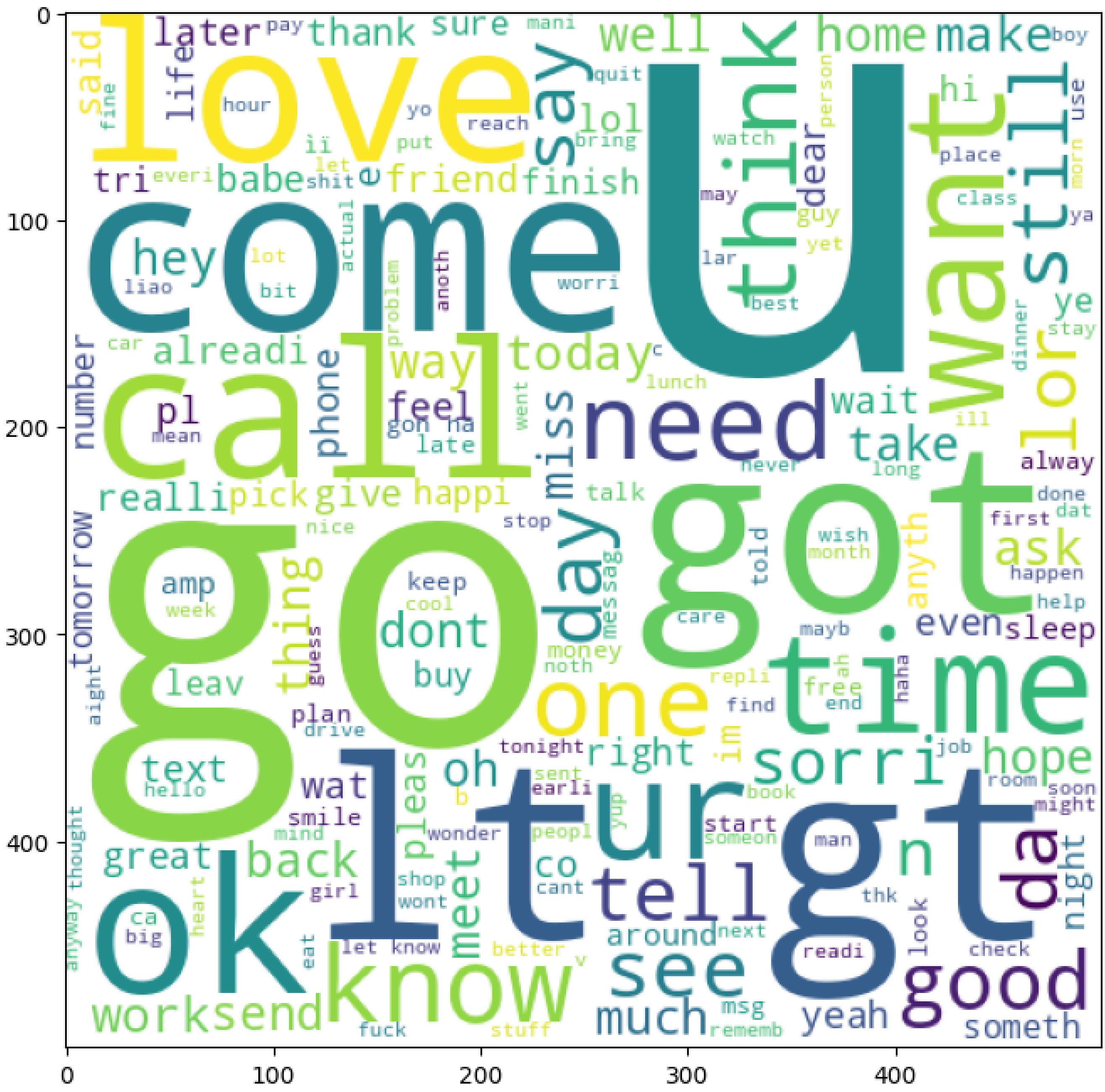
```
# word cloud for 'spam' messages
spam_wc = wc.generate(df[df['target']==1]['transformed_text'].str.cat(sep=" "))

plt.figure(figsize=(15,8))
plt.imshow(spam_wc)
```

```
<matplotlib.image.AxesImage at 0x7f11cc8cf100>
```



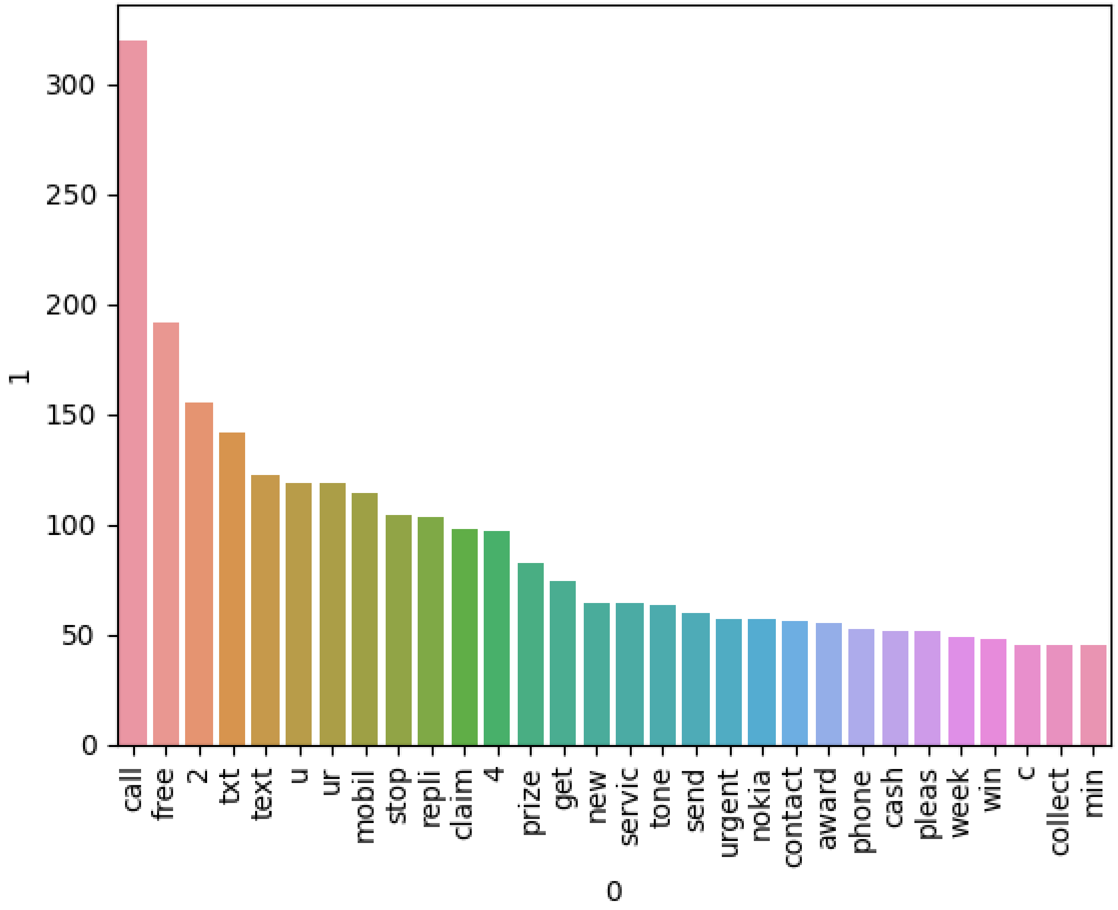
```
# word cloud for 'ham' words
ham_wc = wc.generate(df[df['target']==0]['transformed_text'].str.cat(sep=" "))

plt.figure(figsize=(15,8))
plt.imshow(ham_wc)
```

```
<matplotlib.image.AxesImage at 0x7f11cc959450>
```



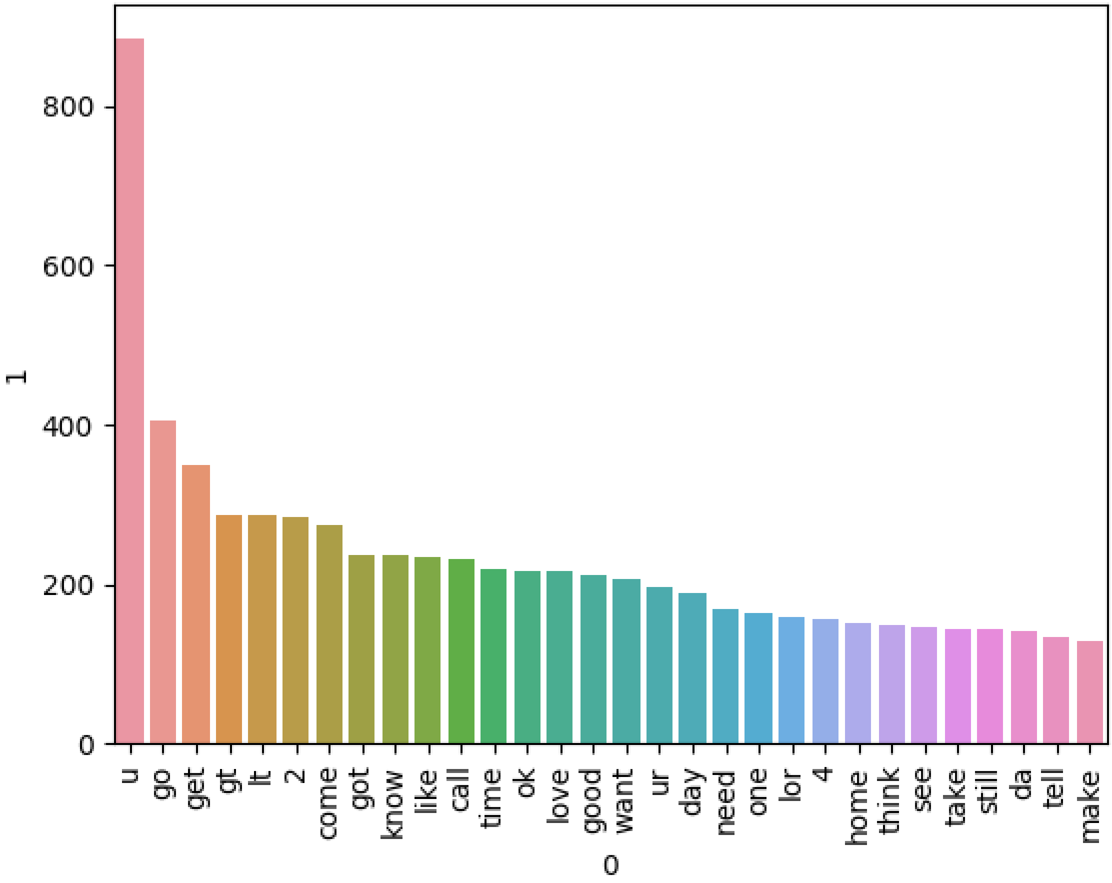
```
# let's find the most occuring word in 'ham' and 'spam' messages

spam_corpus = []
for msg in df[df['target']==1]['transformed_text'].tolist():
  for word in msg.split():
    spam_corpus.append(word)

print(f"The total words in 'spam' messages: {len(spam_corpus)}\n")

from collections import Counter
sns.barplot(x=pd.DataFrame(Counter(spam_corpus).most_common(30))[0],
            y=pd.DataFrame(Counter(spam_corpus).most_common(30))[1])

plt.xticks(rotation='vertical')
plt.show()
```

```
The total words in 'spam' messages: 9939
```



```
ham_corpus = []
for msg in df[df['target']==0]['transformed_text'].tolist():
  for word in msg.split():
    ham_corpus.append(word)

print(f"The total words in 'spam' messages: {len(ham_corpus)}\n")

from collections import Counter
sns.barplot(x=pd.DataFrame(Counter(ham_corpus).most_common(30))[0],
            y=pd.DataFrame(Counter(ham_corpus).most_common(30))[1])

plt.xticks(rotation='vertical')
plt.show()
```

```
The total words in 'spam' messages: 35404
```



Model Building

```
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
cv = CountVectorizer()
tfidf = TfidfVectorizer()
```

```
X = cv.fit_transform(df['transformed_text']).toarray()
X
```

```
array([[0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       ...,
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0],
       [0, 0, 0, ..., 0, 0, 0]])
```

```
X.shape
```

```
(5169, 6708)
```

```
y = df['target'].values
y
```

```
array([0, 0, 1, ..., 0, 0, 0])
```

```
from sklearn.model_selection import train_test_split

# splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2
```

```
from sklearn.naive_bayes import GaussianNB, MultinomialNB, BernoulliNB
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score
```

```
gnb = GaussianNB()
mnb = MultinomialNB()
bnb = BernoulliNB()
```

```
# GaussianNB
gnb.fit(X_train, y_train)
y_pred1 = gnb.predict(X_test)

print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")
```

```
Accuray Score: 0.8800773694390716


Confusion Matrix:
[[792 104]
 [ 20 118]]


Precision Score: 0.5315315315315315
```

```
# MultinomialNB
mnb.fit(X_train, y_train)
y_pred1 = mnb.predict(X_test)

print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")
```

```
Accuray Score: 0.9642166344294004


Confusion Matrix:
[[871  25]
 [ 12 126]]


Precision Score: 0.8344370860927153
```

```
# BernoulliNB
bnb.fit(X_train, y_train)
```

```python
y_pred1 = bnb.predict(X_test)

print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")
```

```
Accuray Score: 0.9700193423597679


Confusion Matrix:
[[893   3]
 [ 28 110]]


Precision Score: 0.9734513274336283
```

```python
# vectroization with tfidf
X = tfidf.fit_transform(df['transformed_text']).toarray()
X
```

```
array([[0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

```python
X.shape
```

```
(5169, 6708)
```

```python
y
```

```
array([0, 0, 1, ..., 0, 0, 0])
```

```python
# splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2
```

```python
# GaussianNB
gnb.fit(X_train, y_train)
y_pred1 = gnb.predict(X_test)

print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")
```

```
Accuray Score: 0.8762088974854932


Confusion Matrix:
```

```
[[793 103]
 [ 25 113]]

Precision Score: 0.5231481481481481
```

```python
# MultinomialNB
mnb.fit(X_train, y_train)
y_pred1 = mnb.predict(X_test)

print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")
```

```
Accuray Score: 0.9593810444874274


Confusion Matrix:
[[896   0]
 [ 42  96]]


Precision Score: 1.0
```

```python
# BernoulliNB
bnb.fit(X_train, y_train)
y_pred1 = bnb.predict(X_test)

print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")
```

```
Accuray Score: 0.9700193423597679


Confusion Matrix:
[[893   3]
 [ 28 110]]


Precision Score: 0.9734513274336283
```

```python
# refering some more algorithms
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.ensemble import BaggingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import AdaBoostClassifier
from xgboost import XGBClassifier
```

```
svc = SVC(kernel='sigmoid', gamma=1.0)
knc = KNeighborsClassifier()
mnb = MultinomialNB()
dtc = DecisionTreeClassifier(max_depth=5)
lrc = LogisticRegression(solver='liblinear', penalty='l1')
rfc = RandomForestClassifier(n_estimators=50, random_state=2)
abc = AdaBoostClassifier(n_estimators=50, random_state=2)
bc = BaggingClassifier(n_estimators=50, random_state=2)
etc = ExtraTreesClassifier(n_estimators=50, random_state=2)
gbdt = GradientBoostingClassifier(n_estimators=50,random_state=2)
xgb = XGBClassifier(n_estimators=50,random_state=2)
```

```
clfs = {
    'SVC' : svc,
    'KN' : knc,
    'NB': mnb,
    'DT': dtc,
    'LR': lrc,
    'RF': rfc,
    'AdaBoost': abc,
    'BgC': bc,
    'ETC': etc,
    'GBDT':gbdt,
    'xgb':xgb
}
```

```
def train_classifier(clf,X_train,y_train,X_test,y_test):
    clf.fit(X_train,y_train)
    y_pred = clf.predict(X_test)
    accuracy = accuracy_score(y_test,y_pred)
    precision = precision_score(y_test,y_pred)

    return accuracy,precision
```

```
# testing the function
train_classifier(svc,X_train,y_train,X_test,y_test)
```

```
(0.9729206963249516, 0.9741379310344828)
```

```
accuracy_scores = []
precision_scores = []

for name,clf in tqdm(clfs.items()):

    current_accuracy,current_precision = train_classifier(clf, X_train,y_train,X_test,y
    print("For ",name)
    print("Accuracy - ",current_accuracy)
    print("Precision - ",current_precision)
    print('\n')

    accuracy_scores.append(current_accuracy)
    precision_scores.append(current_precision)
```

```
  0%|          | 0/11 [00:00<?, ?it/s]
For  SVC
Accuracy -  0.9738878143133463
Precision -  0.9663865546218487


For  KN
Accuracy -  0.9119922630560928
Precision -  1.0


For  NB
Accuracy -  0.97678916827853
Precision -  0.9913793103448276


For  DT
Accuracy -  0.9342359767891683
Precision -  0.8645833333333334


For  LR
Accuracy -  0.9593810444874274
Precision -  0.9528301886792453


For  RF
Accuracy -  0.97678916827853
Precision -  0.9830508474576272


For  AdaBoost
Accuracy -  0.9632495164410058
Precision -  0.9464285714285714


For  BgC
```

```
Accuracy -  0.9584139264990329
Precision -  0.8682170542635659


For  ETC
Accuracy -  0.9758220502901354
Precision -  0.959349593495935


For  GBDT
Accuracy -  0.9526112185686654
Precision -  0.9320388349514563


For  xgb
Accuracy -  0.9738878143133463
Precision -  0.9586776859504132
```

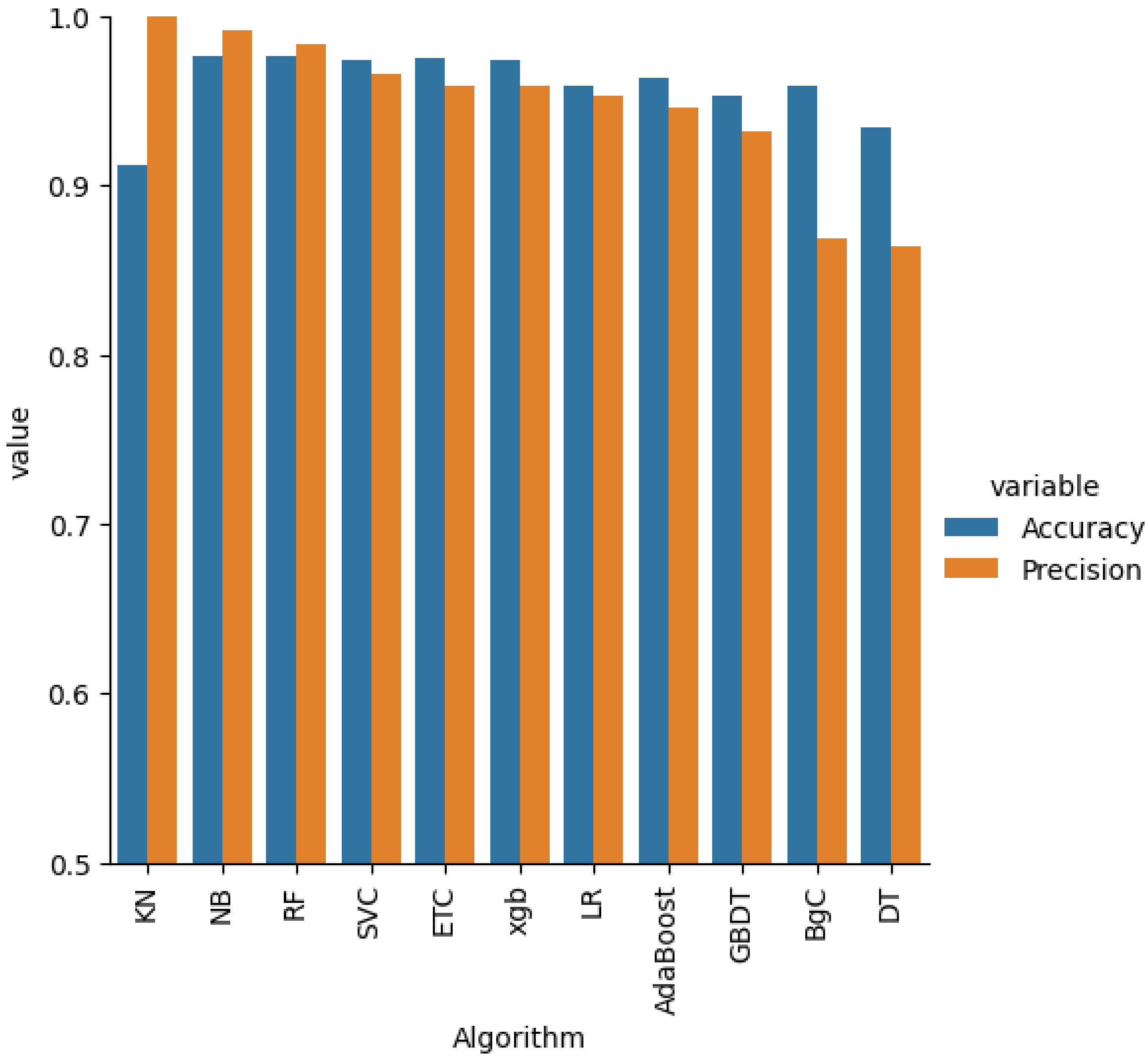
```
performance_df_0 = pd.DataFrame({'Algorithm':clfs.keys(),
                               'Accuracy':accuracy_scores,
                               'Precision':precision_scores}).sort_values('Precision',a

performance_df_0
```

	Algorithm	Accuracy	Precision
1	KN	0.911992	1.000000
2	NB	0.976789	0.991379
5	RF	0.976789	0.983051
0	SVC	0.973888	0.966387
8	ETC	0.975822	0.959350
10	xgb	0.973888	0.958678
4	LR	0.959381	0.952830
6	AdaBoost	0.963250	0.946429
9	GBDT	0.952611	0.932039
7	BgC	0.958414	0.868217
3	DT	0.934236	0.864583

```
performance_df0 = pd.melt(performance_df_0,
                          id_vars='Algorithm')

performance_df0
```

	Algorithm	variable	value
0	KN	Accuracy	0.911992
1	NB	Accuracy	0.976789
2	RF	Accuracy	0.976789
3	SVC	Accuracy	0.973888
4	ETC	Accuracy	0.975822
5	xgb	Accuracy	0.973888
6	LR	Accuracy	0.959381
7	AdaBoost	Accuracy	0.963250
8	GBDT	Accuracy	0.952611
9	BgC	Accuracy	0.958414
10	DT	Accuracy	0.934236
11	KN	Precision	1.000000
12	NB	Precision	0.991379
13	RF	Precision	0.983051
14	SVC	Precision	0.966387
15	ETC	Precision	0.959350
16	xgb	Precision	0.958678
17	LR	Precision	0.952830
18	AdaBoost	Precision	0.946429
19	GBDT	Precision	0.932039
20	BgC	Precision	0.868217
21	DT	Precision	0.864583

```
sns.catplot(x="Algorithm",
            y="value",
            hue="variable",
            data=performance_df0,
            kind='bar',
            height=5)
plt.ylim(0.5, 1.0)
plt.xticks(rotation='vertical')
plt.show()
```



Model Improvement

```
# 1. Change the max_features parameters of TfIdf
# for max_feature = 1000
tfidf = TfidfVectorizer(max_features=1000)

X = tfidf.fit_transform(df['transformed_text']).toarray()

# splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2

# GaussianNB
gnb.fit(X_train, y_train)
y_pred1 = gnb.predict(X_test)
print(f"for GaussianNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# MultinomialNB
mnb.fit(X_train, y_train)
y_pred1 = mnb.predict(X_test)
```

```
print(f"\nfor MultinomialNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# BernoulliNB
bnb.fit(X_train, y_train)
y_pred1 = bnb.predict(X_test)

print(f"\nfor BernoulliNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

accuracy_scores = []
precision_scores = []

for name,clf in tqdm(clfs.items()):

    current_accuracy,current_precision = train_classifier(clf, X_train,y_train,X_test,y

    print("For ",name)
    print("Accuracy - ",current_accuracy)
    print("Precision - ",current_precision)
    print('\n')

    accuracy_scores.append(current_accuracy)
    precision_scores.append(current_precision)
```

```
for GaussianNB
Accuray Score: 0.7804642166344294

Confusion Matrix:
[[687 209]
 [ 18 120]]

Precision Score: 0.364741641337386

for MultinomialNB
Accuray Score: 0.9777562862669246

Confusion Matrix:
[[895   1]
 [ 22 116]]

Precision Score: 0.9914529914529915

for BernoulliNB
```

```
Accuray Score: 0.9835589941972921

Confusion Matrix:
[[893   3]
 [ 14 124]]

Precision Score: 0.9763779527559056
  0%|          | 0/11 [00:00<?, ?it/s]
For  SVC
Accuracy -  0.9690522243713733
Precision -  0.9568965517241379



For  KN
Accuracy -  0.9168278529980658
Precision -  1.0



For  NB
Accuracy -  0.9777562862669246
Precision -  0.9914529914529915



For  DT
Accuracy -  0.9400386847195358
Precision -  0.8725490196078431



For  LR
Accuracy -  0.9613152804642167
Precision -  0.9622641509433962



For  RF
Accuracy -  0.9738878143133463
Precision -  0.944



For  AdaBoost
Accuracy -  0.9632495164410058
Precision -  0.9385964912280702
```

```
For  BgC
Accuracy -  0.9651837524177795
Precision -  0.9047619047619048


For  ETC
Accuracy -  0.97678916827853
Precision -  0.9523809523809523


For  GBDT
Accuracy -  0.9535783365570599
Precision -  0.9411764705882353


For  xgb
Accuracy -  0.9729206963249516
Precision -  0.9583333333333334
```

```
performance_df_1 = pd.DataFrame({'Algorithm':clfs.keys(),
                               'Accuracy':accuracy_scores,
                               'Precision':precision_scores}).sort_values('Precision',a

performance_df_1
```

	Algorithm	Accuracy	Precision
1	KN	0.916828	1.000000
2	NB	0.977756	0.991453
4	LR	0.961315	0.962264
10	xgb	0.972921	0.958333
0	SVC	0.969052	0.956897
8	ETC	0.976789	0.952381
5	RF	0.973888	0.944000
9	GBDT	0.953578	0.941176
6	AdaBoost	0.963250	0.938596
7	BgC	0.965184	0.904762
3	DT	0.940039	0.872549

```
# 1. Change the max_features parameters of TfIdf
# for max_feature = 2000
tfidf = TfidfVectorizer(max_features=2000)
```

```
X = tfidf.fit_transform(df['transformed_text']).toarray()

# splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2

# GaussianNB
gnb.fit(X_train, y_train)
y_pred1 = gnb.predict(X_test)
print(f"for GaussianNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# MultinomialNB
mnb.fit(X_train, y_train)
y_pred1 = mnb.predict(X_test)

print(f"\nfor MultinomialNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# BernoulliNB
bnb.fit(X_train, y_train)
y_pred1 = bnb.predict(X_test)

print(f"\nfor BernoulliNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

accuracy_scores = []
precision_scores = []

for name,clf in tqdm(clfs.items()):

    current_accuracy,current_precision = train_classifier(clf, X_train,y_train,X_test,y

    print("For ",name)
    print("Accuracy - ",current_accuracy)
    print("Precision - ",current_precision)
    print('\n')

    accuracy_scores.append(current_accuracy)
    precision_scores.append(current_precision)
```

```
for GaussianNB
Accuray Score: 0.851063829787234


Confusion Matrix:
[[765 131]
```

```
 [ 23 115]]

Precision Score: 0.46747967479674796

for MultinomialNB
Accuray Score: 0.97678916827853

Confusion Matrix:
[[896   0]
 [ 24 114]]

Precision Score: 1.0

for BernoulliNB
Accuray Score: 0.9864603481624759

Confusion Matrix:
[[895   1]
 [ 13 125]]

Precision Score: 0.9920634920634921
  0%|          | 0/11 [00:00<?, ?it/s]
For  SVC
Accuracy -  0.9758220502901354
Precision -  0.9669421487603306



For  KN
Accuracy -  0.9081237911025145
Precision -  1.0



For  NB
Accuracy -  0.97678916827853
Precision -  1.0



For  DT
Accuracy -  0.9342359767891683
Precision -  0.8365384615384616



For  LR
```

```
Accuracy -  0.9574468085106383
Precision -  0.9607843137254902


For  RF
Accuracy -  0.9748549323017408
Precision -  0.9666666666666667


For  AdaBoost
Accuracy -  0.9613152804642167
Precision -  0.9537037037037037


For  BgC
Accuracy -  0.9564796905222437
Precision -  0.849624060150376


For  ETC
Accuracy -  0.9777562862669246
Precision -  0.9752066115702479


For  GBDT
Accuracy -  0.9526112185686654
Precision -  0.9320388349514563


For  xgb
Accuracy -  0.9690522243713733
Precision -  0.9568965517241379
```

```
performance_df_2 = pd.DataFrame({'Algorithm':clfs.keys(),
                               'Accuracy':accuracy_scores,
                               'Precision':precision_scores}).sort_values('Precision',a

performance_df_2
```

	Algorithm	Accuracy	Precision
1	KN	0.908124	1.000000
2	NB	0.976789	1.000000

	Algorithm	Accuracy	Precision
8	ETC	0.977756	0.975207
0	SVC	0.975822	0.966942
5	RF	0.974855	0.966667
4	LR	0.957447	0.960784
10	xgb	0.969052	0.956897
6	AdaBoost	0.961315	0.953704
9	GBDT	0.952611	0.932039
7	BgC	0.956480	0.849624
3	DT	0.934236	0.836538

```
# 1. Change the max_features parameters of TfIdf
# for max_feature = 3000
tfidf = TfidfVectorizer(max_features=3000)

X = tfidf.fit_transform(df['transformed_text']).toarray()

# splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2

# GaussianNB
gnb.fit(X_train, y_train)
y_pred1 = gnb.predict(X_test)
print(f"for GaussianNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# MultinomialNB
mnb.fit(X_train, y_train)
y_pred1 = mnb.predict(X_test)

print(f"\nfor MultinomialNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# BernoulliNB
bnb.fit(X_train, y_train)
y_pred1 = bnb.predict(X_test)

print(f"\nfor BernoulliNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

accuracy_scores = []
precision_scores = []
```

```
for name,clf in tqdm(clfs.items()):

    current_accuracy,current_precision = train_classifier(clf, X_train,y_train,X_test,y

    print("For ",name)
    print("Accuracy - ",current_accuracy)
    print("Precision - ",current_precision)
    print('\n')

    accuracy_scores.append(current_accuracy)
    precision_scores.append(current_precision)
```

```
for GaussianNB
Accuray Score: 0.8694390715667312

Confusion Matrix:
[[788 108]
 [ 27 111]]

Precision Score: 0.5068493150684932

for MultinomialNB
Accuray Score: 0.9709864603481625

Confusion Matrix:
[[896   0]
 [ 30 108]]

Precision Score: 1.0

for BernoulliNB
Accuray Score: 0.9835589941972921

Confusion Matrix:
[[895   1]
 [ 16 122]]

Precision Score: 0.991869918699187
  0%|          | 0/11 [00:00<?, ?it/s]
For  SVC
Accuracy -  0.9758220502901354
Precision -  0.9747899159663865



For  KN
```

```
Accuracy -  0.9052224371373307
Precision -  1.0


For  NB
Accuracy -  0.9709864603481625
Precision -  1.0


For  DT
Accuracy -  0.9274661508704062
Precision -  0.8118811881188119


For  LR
Accuracy -  0.9584139264990329
Precision -  0.9702970297029703


For  RF
Accuracy -  0.9758220502901354
Precision -  0.9829059829059829


For  AdaBoost
Accuracy -  0.960348162475822
Precision -  0.9292035398230089


For  BgC
Accuracy -  0.9584139264990329
Precision -  0.8682170542635659


For  ETC
Accuracy -  0.9748549323017408
Precision -  0.9745762711864406


For  GBDT
Accuracy -  0.9468085106382979
Precision -  0.9191919191919192
```

```
For  xgb
Accuracy -  0.9671179883945842
Precision -  0.9333333333333333
```

```
performance_df_3 = pd.DataFrame({'Algorithm':clfs.keys(),
                               'Accuracy':accuracy_scores,
                               'Precision':precision_scores}).sort_values('Precision',a

performance_df_3
```

	Algorithm	Accuracy	Precision
1	KN	0.905222	1.000000
2	NB	0.970986	1.000000
5	RF	0.975822	0.982906
0	SVC	0.975822	0.974790
8	ETC	0.974855	0.974576
4	LR	0.958414	0.970297
10	xgb	0.967118	0.933333
6	AdaBoost	0.960348	0.929204
9	GBDT	0.946809	0.919192
7	BgC	0.958414	0.868217
3	DT	0.927466	0.811881

```
# 1. Change the max_features parameters of TfIdf
# for max_feature = 1500
tfidf = TfidfVectorizer(max_features=1500)

X = tfidf.fit_transform(df['transformed_text']).toarray()

# splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2

# GaussianNB
gnb.fit(X_train, y_train)
y_pred1 = gnb.predict(X_test)
print(f"for GaussianNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# MultinomialNB
mnb.fit(X_train, y_train)
y_pred1 = mnb.predict(X_test)
```

```
print(f"\nfor MultinomialNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# BernoulliNB
bnb.fit(X_train, y_train)
y_pred1 = bnb.predict(X_test)

print(f"\nfor BernoulliNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

accuracy_scores = []
precision_scores = []

for name,clf in tqdm(clfs.items()):

    current_accuracy,current_precision = train_classifier(clf, X_train,y_train,X_test,y

    print("For ",name)
    print("Accuracy - ",current_accuracy)
    print("Precision - ",current_precision)
    print('\n')

    accuracy_scores.append(current_accuracy)
    precision_scores.append(current_precision)
```

```
for GaussianNB
Accuray Score: 0.8259187620889749

Confusion Matrix:
[[738 158]
 [ 22 116]]

Precision Score: 0.4233576642335766

for MultinomialNB
Accuray Score: 0.97678916827853

Confusion Matrix:
[[895   1]
 [ 23 115]]

Precision Score: 0.9913793103448276

for BernoulliNB
```

```
Accuray Score: 0.9835589941972921

Confusion Matrix:
[[893   3]
 [ 14 124]]

Precision Score: 0.9763779527559056
  0%|          | 0/11 [00:00<?, ?it/s]
For  SVC
Accuracy -  0.9738878143133463
Precision -  0.9663865546218487



For  KN
Accuracy -  0.9119922630560928
Precision -  1.0



For  NB
Accuracy -  0.97678916827853
Precision -  0.9913793103448276



For  DT
Accuracy -  0.9313346228239845
Precision -  0.8526315789473684



For  LR
Accuracy -  0.9593810444874274
Precision -  0.9528301886792453



For  RF
Accuracy -  0.97678916827853
Precision -  0.9830508474576272



For  AdaBoost
Accuracy -  0.9632495164410058
Precision -  0.9464285714285714
```

```
For  BgC
Accuracy -  0.9584139264990329
Precision -  0.8682170542635659


For  ETC
Accuracy -  0.9758220502901354
Precision -  0.959349593495935


For  GBDT
Accuracy -  0.9526112185686654
Precision -  0.9320388349514563


For  xgb
Accuracy -  0.9738878143133463
Precision -  0.9586776859504132
```

```
performance_df_4 = pd.DataFrame({'Algorithm':clfs.keys(),
                                'Accuracy':accuracy_scores,
                                'Precision':precision_scores}).sort_values('Precision',a

performance_df_4
```

	Algorithm	Accuracy	Precision
1	KN	0.911992	1.000000
2	NB	0.976789	0.991379
5	RF	0.976789	0.983051
0	SVC	0.973888	0.966387
8	ETC	0.975822	0.959350
10	xgb	0.973888	0.958678
4	LR	0.959381	0.952830
6	AdaBoost	0.963250	0.946429
9	GBDT	0.952611	0.932039
7	BgC	0.958414	0.868217
3	DT	0.931335	0.852632

```
performance_df_4 = performance_df_4.rename(columns={
    'Accuracy':'Accuracy_1500_ft',
    'Precision':'Precision_1500_ft'
})
```

```
performance_df_3 = performance_df_3.rename(columns={
    'Accuracy':'Accuracy_3000_ft',
    'Precision':'Precision_3000_ft'
})

performance_df_2 = performance_df_2.rename(columns={
    'Accuracy':'Accuracy_2000_ft',
    'Precision':'Precision_2000_ft'
})

performance_df_1 = performance_df_1.rename(columns={
    'Accuracy':'Accuracy_1000_ft',
    'Precision':'Precision_1000_ft'
})

performance_df_0 = performance_df_0.rename(columns={
    'Accuracy':'Accuracy_max_ft',
    'Precision':'Precision_max_ft'
})
```

```
df1 = pd.merge(performance_df_0, performance_df_3, on='Algorithm', how='left')
df2 = pd.merge(df1, performance_df_2, on='Algorithm', how='right')
df3 = pd.merge(df2, performance_df_4, on='Algorithm', how='right')
df4 = pd.merge(df3, performance_df_1, on='Algorithm', how='right')
df4
```

	Algorithm	Accuracy_max_ft	Precision_max_ft	Accuracy_3000_ft	Precision_3000_ft	Accuracy_2000_ft	Precision_20
0	KN	0.911992	1.000000	0.905222	1.000000	0.908124	1.00
1	NB	0.976789	0.991379	0.970986	1.000000	0.976789	1.00
2	LR	0.959381	0.952830	0.958414	0.970297	0.957447	0.96
3	xgb	0.973888	0.958678	0.967118	0.933333	0.969052	0.95
4	SVC	0.973888	0.966387	0.975822	0.974790	0.975822	0.96
5	ETC	0.975822	0.959350	0.974855	0.974576	0.977756	0.97
6	RF	0.976789	0.983051	0.975822	0.982906	0.974855	0.96
7	GBDT	0.952611	0.932039	0.946809	0.919192	0.952611	0.93
8	AdaBoost	0.963250	0.946429	0.960348	0.929204	0.961315	0.95
9	BgC	0.958414	0.868217	0.958414	0.868217	0.956480	0.84
10	DT	0.934236	0.864583	0.927466	0.811881	0.934236	0.83

```
# 2. Model Improvement, adding 'num_characters' into input set
# As per above dataframe, we got better result with max_feature=2000

tfidf = TfidfVectorizer(max_features=2000)

X = tfidf.fit_transform(df['transformed_text']).toarray()
```

```python
# appending the num_characters column to X
X = np.hstack((X, df['num_characters'].values.reshape(-1,1)))

# splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=2

# GaussianNB
gnb.fit(X_train, y_train)
y_pred1 = gnb.predict(X_test)
print(f"for GaussianNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# MultinomialNB
mnb.fit(X_train, y_train)
y_pred1 = mnb.predict(X_test)

print(f"\nfor MultinomialNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

# BernoulliNB
bnb.fit(X_train, y_train)
y_pred1 = bnb.predict(X_test)

print(f"\nfor BernoulliNB")
print(f"Accuray Score: {accuracy_score(y_test, y_pred1)}\n")
print(f"Confusion Matrix:\n{confusion_matrix(y_test, y_pred1)}\n")
print(f"Precision Score: {precision_score(y_test, y_pred1)}")

accuracy_scores = []
precision_scores = []

for name,clf in tqdm(clfs.items()):

    current_accuracy,current_precision = train_classifier(clf, X_train,y_train,X_test,y

    print("For ",name)
    print("Accuracy - ",current_accuracy)
    print("Precision - ",current_precision)
    print('\n')

    accuracy_scores.append(current_accuracy)
    precision_scores.append(current_precision)
```

```
for GaussianNB
Accuray Score: 0.8849129593810445


Confusion Matrix:
```

```
[[798  98]
 [ 21 117]]

Precision Score: 0.5441860465116279

for MultinomialNB
Accuray Score: 0.9661508704061895

Confusion Matrix:
[[896   0]
 [ 35 103]]

Precision Score: 1.0

for BernoulliNB
Accuray Score: 0.9864603481624759

Confusion Matrix:
[[895   1]
 [ 13 125]]

Precision Score: 0.9920634920634921
```

```
  0%|          | 0/11 [00:00<?, ?it/s]
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
For  SVC
Accuracy -  0.8665377176015474
Precision -  0.0



For  KN
Accuracy -  0.9342359767891683
Precision -  0.8181818181818182



For  NB
Accuracy -  0.9661508704061895
Precision -  1.0



For  DT
```

```
Accuracy -  0.9468085106382979
Precision -  0.8807339449541285


For  LR
Accuracy -  0.9632495164410058
Precision -  0.9716981132075472


For  RF
Accuracy -  0.971953578336557
Precision -  0.9658119658119658


For  AdaBoost
Accuracy -  0.9632495164410058
Precision -  0.923728813559322


For  BgC
Accuracy -  0.9593810444874274
Precision -  0.8582089552238806


For  ETC
Accuracy -  0.9777562862669246
Precision -  0.967479674796748


For  GBDT
Accuracy -  0.9487427466150871
Precision -  0.9207920792079208


For  xgb
Accuracy -  0.9690522243713733
Precision -  0.9568965517241379
```

```
performance_df_5 = pd.DataFrame({'Algorithm':clfs.keys(),
                               'Accuracy':accuracy_scores,
                               'Precision':precision_scores}).sort_values('Precision',a
```

```
performance_df_5 = performance_df_5.rename(columns={"Accuracy":"Accuracy_num_char",
                                                    "Precision":"Precision_num_char"})
```

```
pd.merge(performance_df_2, performance_df_5, on='Algorithm', how='left')
```

	Algorithm	Accuracy_2000_ft	Precision_2000_ft	Accuracy_num_char	Precision_num_char
0	KN	0.908124	1.000000	0.934236	0.818182
1	NB	0.976789	1.000000	0.966151	1.000000
2	ETC	0.977756	0.975207	0.977756	0.967480
3	SVC	0.975822	0.966942	0.866538	0.000000
4	RF	0.974855	0.966667	0.971954	0.965812
5	LR	0.957447	0.960784	0.963250	0.971698
6	xgb	0.969052	0.956897	0.969052	0.956897
7	AdaBoost	0.961315	0.953704	0.963250	0.923729
8	GBDT	0.952611	0.932039	0.948743	0.920792
9	BgC	0.956480	0.849624	0.959381	0.858209
10	DT	0.934236	0.836538	0.947776	0.903846

The accuracy dropped after adding 'num_characters' in the input set

```
# model improvement #3
# Creating voting classifier (the combination of best performing algorithms)
svc = SVC(kernel='sigmoid', gamma=1.0, probability=True)
mnb = MultinomialNB()
etc = ExtraTreesClassifier(n_estimators=50, random_state=2)

from sklearn.ensemble import VotingClassifier
```

```
voting = VotingClassifier(estimators=[('svc',svc),
                                      ('nb', mnb),
                                      ('et', etc)],
                          voting='soft')
```

```
voting.fit(X_train, y_train)
```

```
VotingClassifier(estimators=[('svc',
SVC(gamma=1.0, kernel='sigmoid',
probability=True)),
('nb', MultinomialNB()),
('et',
ExtraTreesClassifier(n_estimators=50,
random_state=2))],
voting='soft')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
VotingClassifier

```
VotingClassifier(estimators=[('svc',
SVC(gamma=1.0, kernel='sigmoid',
probability=True)),
('nb', MultinomialNB()),
('et',
ExtraTreesClassifier(n_estimators=50,
random_state=2))],
voting='soft')
```

svc
SVC

```
SVC(gamma=1.0, kernel='sigmoid', probability=True)
```

nb
MultinomialNB

```
MultinomialNB()
```

et
ExtraTreesClassifier

```
ExtraTreesClassifier(n_estimators=50, random_state=2)
```

```
y_pred = voting.predict(X_test)
print(f"Accuray:{accuracy_score(y_test, y_pred)}")
print(f"Precision:{precision_score(y_test, y_pred)}")
```

```
Accuray:0.960348162475822
```

```
Precision:1.0
```

```
# model improvement #04
# Applying stacking

estimators = [('svc',svc),
              ('nb', mnb),
              ('et', etc)]
final_estimator = RandomForestClassifier()

from sklearn.ensemble import StackingClassifier

clf = StackingClassifier(estimators=estimators,
                         final_estimator=final_estimator)
```

```
# training the model
clf.fit(X_train, y_train)
```

```python
# testing the model
y_pred = clf.predict(X_test)

print(f"Accuray:{accuracy_score(y_test, y_pred)}")
print(f"Precision:{precision_score(y_test, y_pred)}")
```

```
Accuray:0.9758220502901354
Precision:0.937984496124031
```

```python
# saving the model and vectorizer
import pickle
pickle.dump(tfidf, open('vectorizer.pkl','wb'))
pickle.dump(mnb, open('model.pkl', 'wb'))
```