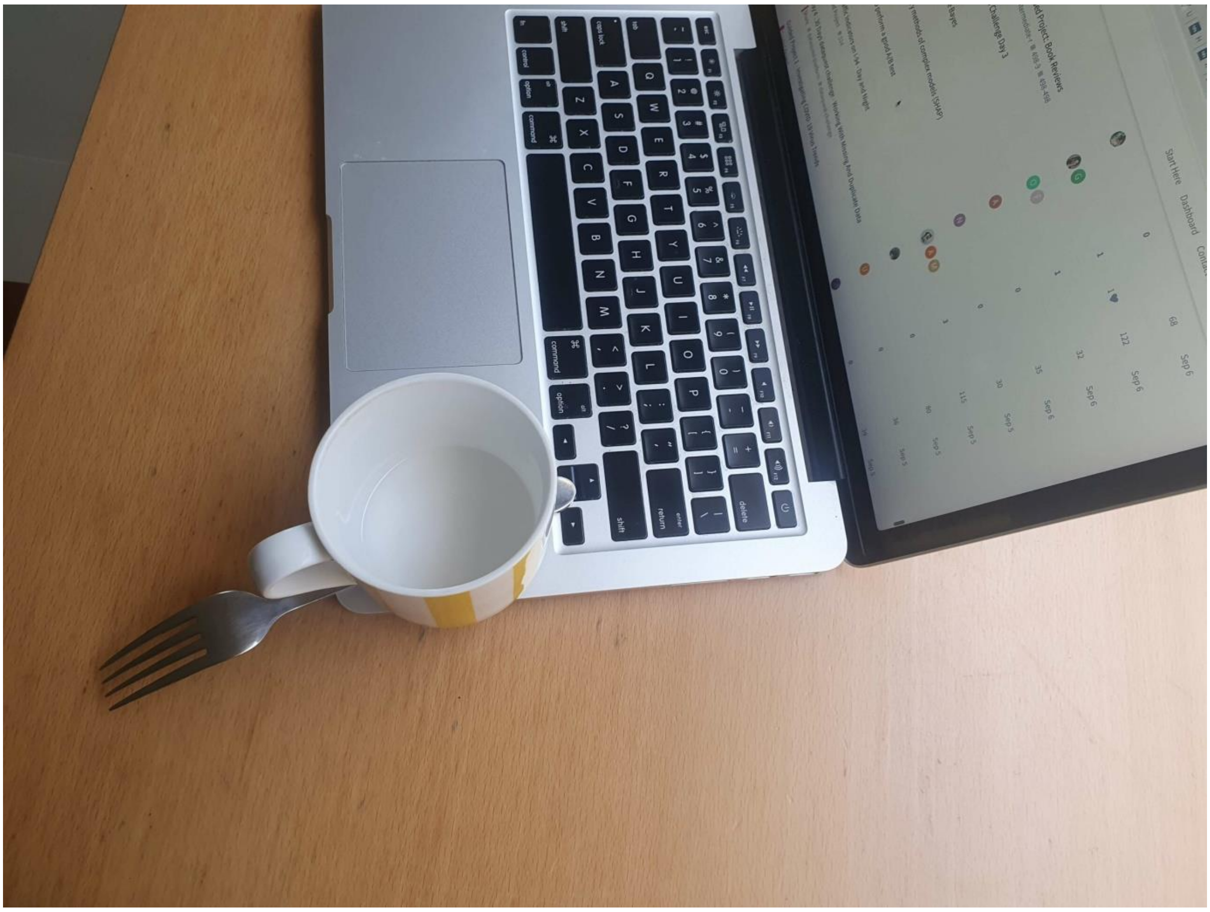
Malignant Comments Classifier



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Internship:- **23**

Acknowledgment:-

- *First, I would like to express my gratitude towards Flip Robo Technologies for their kind co- operation and encouragement which help me in completion of this project.*

- *I would like to express my special gratitude and thanks to industry persons and my mentor Miss. Sapna Verma for giving me such attention and time as and whenever required.*

- *Research papers that helped me in this project was as follows:*

  - https://medium.com/@dobko_m/nlp-text-data-cleaning-and-preprocessing-ea3ffe0406c1
  - https://towardsdatascience.com/your-guide-to-natural-language-processing-nlp-48ea2511f6e1

- *Articles that helped me in this project was as follows:*

  - TF-IDF Vectorizer scikit-learn. Deep understanding TfidfVectorizer by… | by Mukesh Chaudhary | Medium

Introduction:-

Business Problem Framing:-

- *The proliferation of social media enables people to express their opinions widely online. However, at the same time, this has resulted in the emergence of conflict and hate, making online environments uninviting for users. Although researchers have found that hate is a problem across multiple platforms, there is a lack of models for online hate detection.*

- *Online hate, described as abusive language, aggression, cyberbullying, hatefulness and many others has been identified as a major threat on online social media platforms. Social media platforms are the most prominent grounds for such toxic behaviour.*

- *There has been a remarkable increase in the cases of cyberbullying and trolls on various social media platforms. Many celebrities and influences are facing backlashes from people and have to come across hateful and offensive comments. This can take a toll on anyone and affect them mentally leading to depression, mental illness, self-hatred and suicidal thoughts.*

- *Internet comments are bastions of hatred and vitriol. While online anonymity has provided a new outlet for aggression and hate speech, machine learning can be used to fight it. The problem we sought to solve was the tagging of internet comments that are aggressive towards other users. This means that insults to third parties such as celebrities will be tagged as unoffensive, but "u are an idiot" is clearly offensive.*

- *Our goal is to build a prototype of online hate and abuse comment classifier which can used to classify hate and offensive comments so that it can be controlled and restricted from spreading hatred and cyberbullying.*

Conceptual Background of the Domain Problem

- *In the past few years its seen that the cases related to social media hatred have increased exponentially. The social media is turning into a dark venomous pit for people now a days. Online hate is the result of difference in opinion, race, religion, occupation, nationality etc.*

- *In social media the people spreading or involved in such kind of activities uses filthy languages, aggression, images etc. to offend and gravely hurt the person on the other side. This is one of the major concerns now.*

- *The result of such activities can be dangerous. It gives mental trauma to the victims making their lives miserable. People who are not well aware of mental health online hate or cyber bullying become life threatening for them. Such cases are also at rise. It is also taking its toll on religions. Each and every day we can see an incident of fighting between people of different communities or religions due to offensive social media posts.*

- *Online hate, described as abusive language, aggression, Cyber-bullying, hatefulness, insults, personal attacks, provocation, racism, sexism, threats, or toxicity has been identified as a major threat on online social media platforms. These kinds of activities must be checked for a better future.*

Motivation for the Problem Undertaken

The project was the first provided to me by FlipRobo as a part of the internship programme. The exposure to real world data and the opportunity to deploy my skillset in solving a real time problem has been the primary objective. However, the motivation for taking this project was that it is relatively a new field of research. Here we have many options but less concrete solutions. The main motivation is to build a prototype of online hate and abuse comment classifier which can used to classify hate and offensive comments so that it can be controlled and restricted from spreading hatred and Cyber-bullying.

Analytical Problem Framing

Data Sources and their formats

The data was provided by FlipRobo in CSV format. After loading the training dataset into Jupyter Notebook using Pandas and it can be seen that there are eight columns named as:
“ id, comment_text, “malignant, highly_malignant, rude, threat, abuse, loathe**”.**

There are 8 columns in the dataset provided:
The description of each of the column is given below:

- **Malignant:** It is the Label column, which includes values 0 and 1, denoting if the comment is malignant or not.
- **Highly Malignant:** It denotes comments that are highly malignant and hurtful.
- **Rude:** It denotes comments that are very rude and offensive.
- **Threat:** It contains indication of the comments that are giving any threat to someone.
- **Abuse:** It is for comments that are abusive in nature.
- **Loathe:** It describes the comments which are hateful and loathing in nature.
- **ID:** It includes unique Ids associated with each comment text given.
- **Comment text:** This column contains the comments extracted from various social media platforms.

Data Processing

Importing the Required Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Giving the training and the testing data to the model.

```
train = pd.read_csv("train.csv")
test = pd.read_csv("test.csv")
```

```
train
```

	id	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
0	0000997932d777bf	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0
1	000103f0d9cfb60f	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0
2	000113f07ec002fd	Hey man, I'm really not trying to edit war. It...	0	0	0	0	0	0
3	0001b41b1c6bb37e	"\nMore\nI can't make any real suggestions on ...	0	0	0	0	0	0
4	0001d958c54c6e35	You, sir, are my hero. Any chance you remember...	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...
159566	ffe987279560d7ff	":::::And for the second time of asking, when ...	0	0	0	0	0	0
159567	ffea4adeee384e90	You should be ashamed of yourself \n\nThat is ...	0	0	0	0	0	0
159568	ffee36eab5c267c9	Spitzer \n\nUmm, theres no actual article for ...	0	0	0	0	0	0
159569	fff125370e4aaaf3	And it looks like it was actually you who put ...	0	0	0	0	0	0
159570	fff46fc426af1f9a	"\nAnd ... I really don't think you understand...	0	0	0	0	0	0

159571 rows × 8 columns

Here as I can see that there is no need of "ID" so, here I am dr opping this column.

```
train = train.drop(columns = ["id"])
train
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
0	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0
1	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0
2	Hey man, I'm really not trying to edit war. It...	0	0	0	0	0	0

```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159571 entries, 0 to 159570
Data columns (total 7 columns):
 #   Column            Non-Null Count   Dtype 
---  ------            --------------   ----- 
 0   comment_text      159571 non-null  object
 1   malignant         159571 non-null  int64 
 2   highly_malignant  159571 non-null  int64 
 3   rude              159571 non-null  int64 
 4   threat            159571 non-null  int64 
 5   abuse             159571 non-null  int64 
 6   loathe            159571 non-null  int64 
dtypes: int64(6), object(1)
memory usage: 8.5+ MB
```

Here, I can see that the column , "Comment_text " is object typ e and the rest are int type.

```
train.describe().T
```

	count	mean	std	min	25%	50%	75%	max
malignant	159571.0	0.095844	0.294379	0.0	0.0	0.0	0.0	1.0
highly_malignant	159571.0	0.009996	0.099477	0.0	0.0	0.0	0.0	1.0
rude	159571.0	0.052948	0.223931	0.0	0.0	0.0	0.0	1.0
threat	159571.0	0.002996	0.054650	0.0	0.0	0.0	0.0	1.0
abuse	159571.0	0.049364	0.216627	0.0	0.0	0.0	0.0	1.0
loathe	159571.0	0.008805	0.093420	0.0	0.0	0.0	0.0	1.0

```
train.isnull().sum()
```

```
comment_text        0
malignant           0
highly_malignant    0
rude                0
threat              0
abuse               0
loathe              0
dtype: int64
```

Here, I can see that there are no null values present in the dataset,

```
train.duplicated().sum()
```

```
0
```

Here, I can see that there are also no duplicate values present in the dataset.

Value counts of the few columns, for both the positive and negative comments(where 0 is positive and 1 is negative words):-

```
train["malignant"].value_counts()
```

```
0    144277
1     15294
Name: malignant, dtype: int64
```

```
train["highly_malignant"].value_counts()
```

```
0    157976
1      1595
Name: highly_malignant, dtype: int64
```

```
train["rude"].value_counts()
```

```
0    151122
1      8449
Name: rude, dtype: int64
```

```
train["abuse"].value_counts()
```

```
0    151694
1      7877
Name: abuse, dtype: int64
```

```
train['length']= train['comment_text'].str.len()
train
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe	length
0	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0	264
1	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0	112
2	Hey man, I'm really not trying to edit war. It...	0	0	0	0	0	0	233
3	"\nMore\nI can't make any real suggestions on ...	0	0	0	0	0	0	622
4	You, sir, are my hero. Any chance you remember...	0	0	0	0	0	0	67
...	...	...	...	...	...	...	...	...
159566	":::::And for the second time of asking, when ...	0	0	0	0	0	0	295
159567	You should be ashamed of yourself \n\nThat is ...	0	0	0	0	0	0	99
159568	Spitzer \n\nUmm, theres no actual article for ...	0	0	0	0	0	0	81
159569	And it looks like it was actually you who put ...	0	0	0	0	0	0	116
159570	"\nAnd ... I really don't think you understand...	0	0	0	0	0	0	189

159571 rows × 8 columns

Here, I have calculated the length of each comment.

```
# convert to lower case
train['comment_text']= train['comment_text'].str.lower()

# replace email address
train['comment_text']= train['comment_text'].str.replace(r'^.+@[^\.].*\.[a-z]{2,}$', 'emailaddr')

# replace web address
train['comment_text']= train['comment_text'].str.replace(r'^http\://[a-zA-Z0-9\-\.]+\.[a-zA-Z]{2,3}(/\S*)?$','webaddress')

# replace money symbols
train['comment_text']=train['comment_text'].str.replace(r'£|\$', 'moneysymb')

# replace 10 digit phone numbers with 'phonenumber'
train['comment_text']=train['comment_text'].str.replace(r'^\(?[\d]{3}\)?[\s-]?[\d]{3}[\s-]?[\d]{4}$','phonenumbr')

# replace normal numbers with 'numbr'
train['comment_text']= train['comment_text'].str.replace(r'\d+(\.\d+)?','numbr')

#handling all the punctuation in the comment's
train['comment_text'] = train['comment_text'].apply(lambda x: ' '.join(
    term for term in x.split() if term not in string.punctuation))

#Giving the stopwords and a few extra words along with the pre-defined stopwords
stop_words = set(stopwords.words('english') + ['u', 'ü', 'ur', '4', '2', 'im', 'dont', 'doin', 'ure'])
train['comment_text'] = train['comment_text'].apply(lambda x: ' '.join(
    term for term in x.split() if term not in stop_words))

# Used the Lemmatizer in the column, "Comment_text"
lem=WordNetLemmatizer()
train['comment_text'] = train['comment_text'].apply(lambda x: ' '.join(
 lem.lemmatize(t) for t in x.split()))
```

```
train['clean_length'] = train.comment_text.str.len()
train
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe	length	clean_length
0	explanation edits made username hardcore metal...	0	0	0	0	0	0	264	180
1	d'aww! match background colour i'm seemingly s...	0	0	0	0	0	0	112	111
2	hey man, i'm really trying edit war. guy const...	0	0	0	0	0	0	233	149
3	can't make real suggestion improvement wondere...	0	0	0	0	0	0	622	397
4	you, sir, hero. chance remember page that's on?	0	0	0	0	0	0	67	47
...	...	...	...	...	...	...	...	...	...
159566	":::::and second time asking, view completely ...	0	0	0	0	0	0	295	211
159567	ashamed horrible thing put talk page. numbr.numbr	0	0	0	0	0	0	99	49
159568	spitzer umm, there actual article prostitution...	0	0	0	0	0	0	81	68
159569	look like actually put speedy first version de...	0	0	0	0	0	0	116	60
159570	... really think understand. came idea bad rig...	0	0	0	0	0	0	189	129

159571 rows × 9 columns

```
# Total length removal
print ('Origian Length', train.length.sum())
print ('Clean Length', train.clean_length.sum())
```

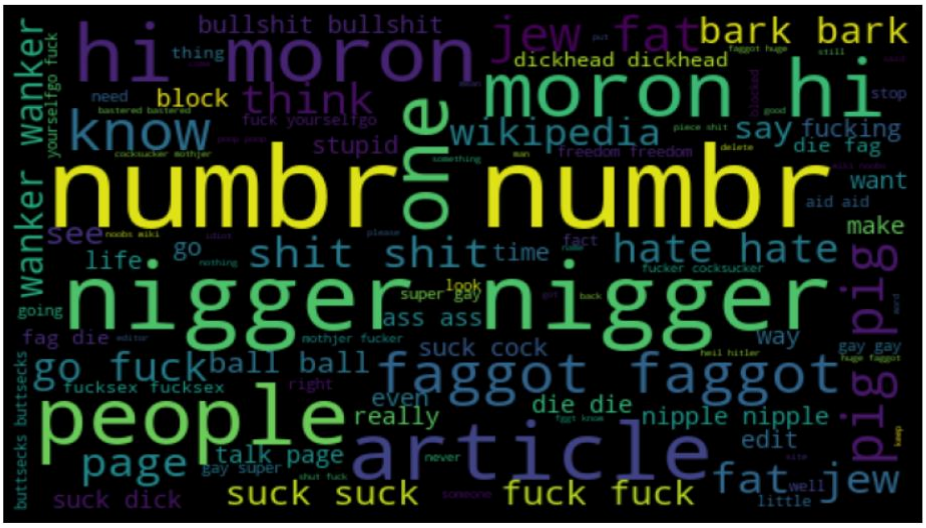
```
Origian Length 62893130
Clean Length 43577387
```

Here, I can see the the orginal length and then the cleaned length.

Visualization:-

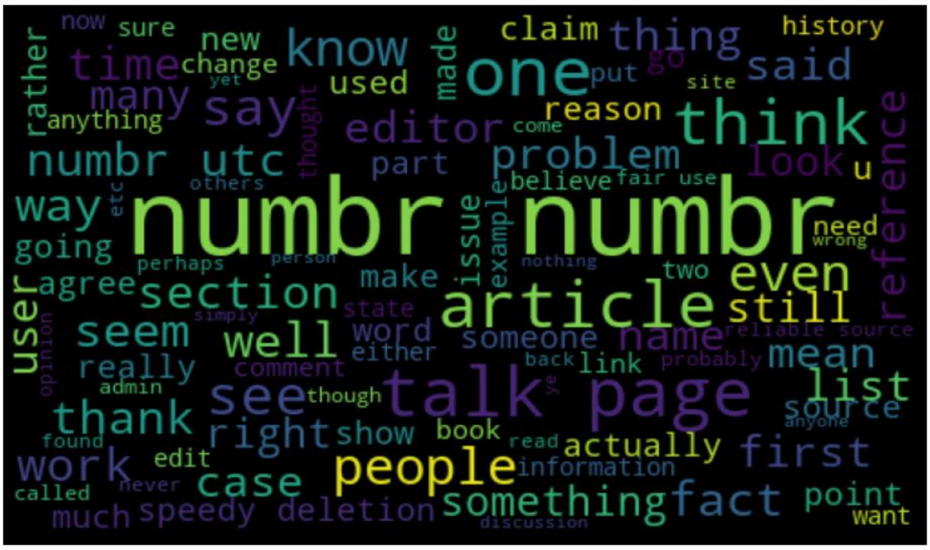
Malignant Words

```
from wordcloud import WordCloud
hams = train['comment_text'][train['malignant']==1]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Non-Malignant Words

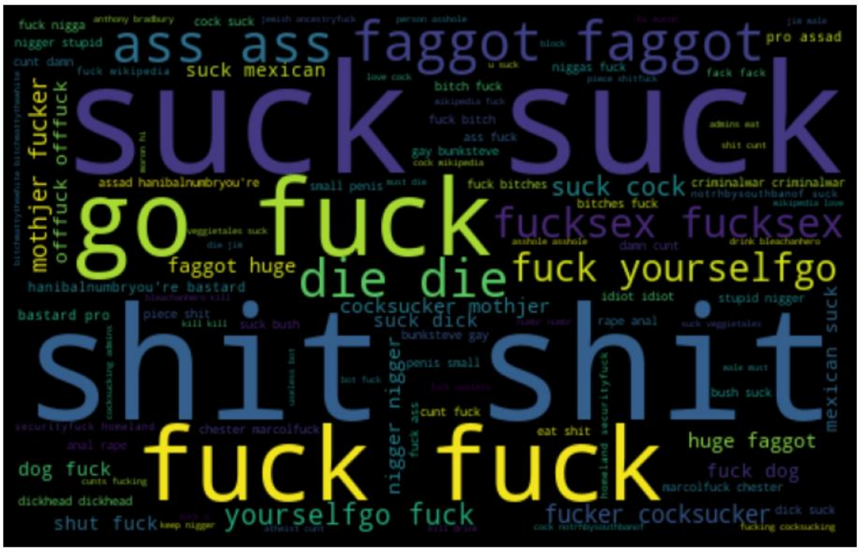
```
hams = train['comment_text'][train['malignant']==0]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Here, is the WordCloud of 100, "Non-Malignant Words".

Highly Malignant Words

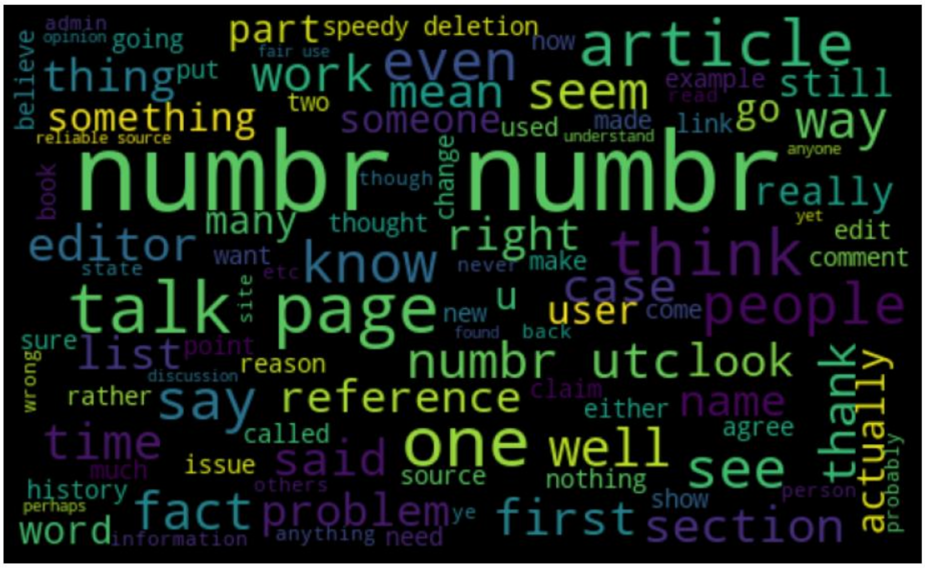
```
hams = train['comment_text'][train['highly_malignant']==1]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Here, is the WordCloud of 100, "Highly Malignant" words.

Highly Non-Malignant Words

```
hams = train['comment_text'][train['highly_malignant']==0]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Here, is the WordCloud of 100, "Highly Non-Malignant" words.

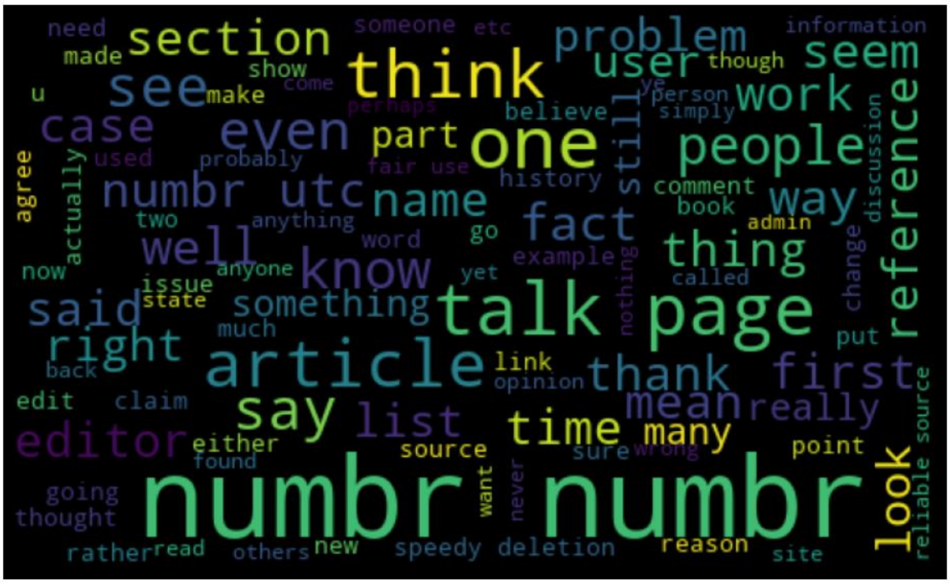
Rude Words

```
hams = train['comment_text'][train['rude']==1]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

Here, is the WordCloud of 100, "Rude" words.

Non-Rude Words

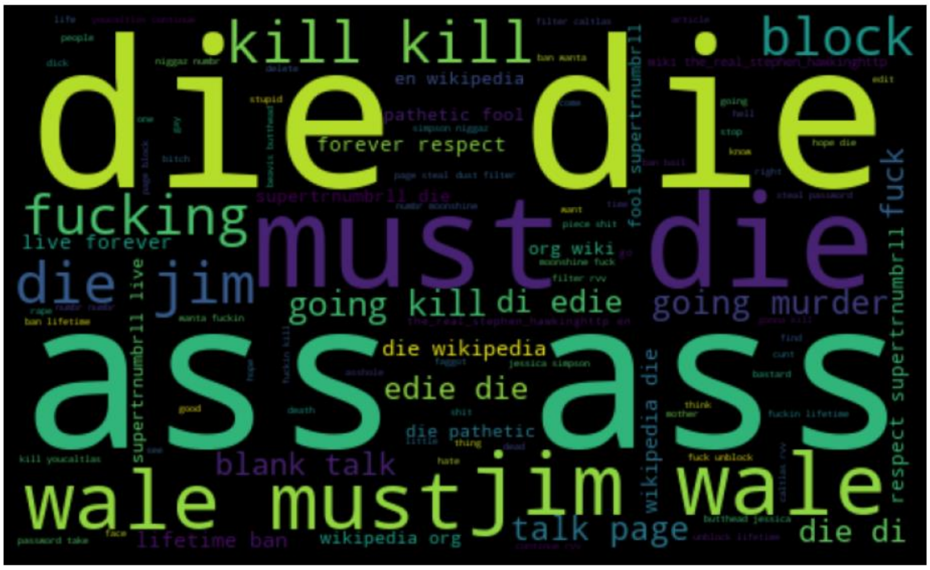
```
hams = train['comment_text'][train['rude']==0]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Here, is the WordCloud of 100, "Non-Rude" words.

Threatning Words ¶

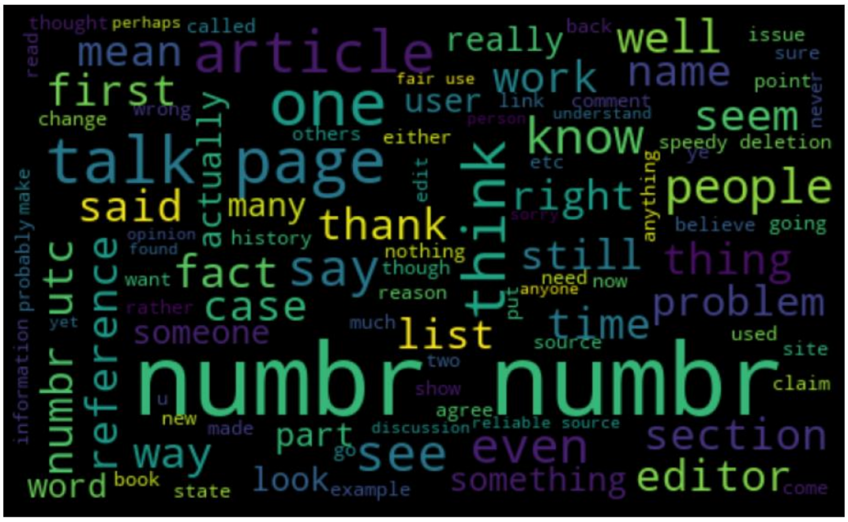
```
hams = train['comment_text'][train['threat']==1]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Here, is the WordCloud of 100, "Threatning" words.

Non-Threatning Words

```
hams = train['comment_text'][train['threat']==0]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Here, is the WordCloud of 100, "Non-Threatning" words.

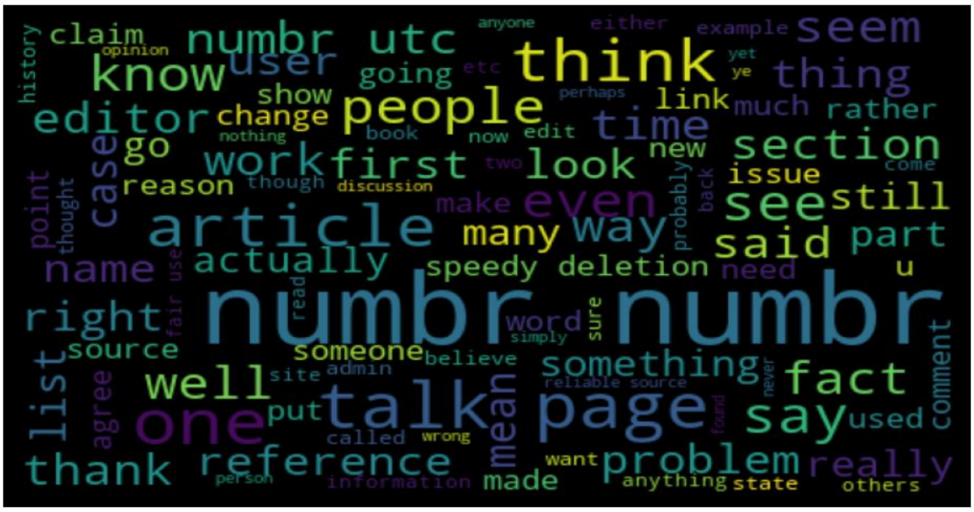
Abusive Words

```
hams = train['comment_text'][train['abuse']==1]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

Here, is the WordCloud of 100, "Abusive" words.

Non-Abusive Words ¶

```
hams = train['comment_text'][train['abuse']==0]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Here, is the WordCloud of 100, "Non-Abusive" words.

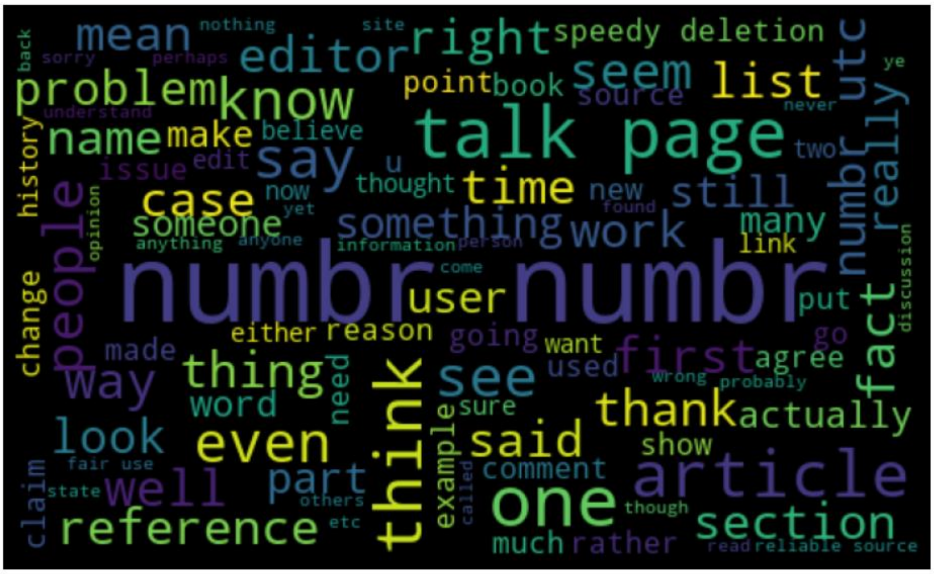
Loathe Words

```
hams = train['comment_text'][train['loathe']==1]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

Here, is the WordCloud of 100, "Loathe" words.

Non Loathy Words

```
hams = train['comment_text'][train['loathe']==0]
spam_cloud = WordCloud(width=500,height=300,background_color='black',max_words=100).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Here, is the WordCloud of 100, "Non-Loathy" words.

Test CSV

```
test
```

	id	comment_text
0	00001cee341fdb12	Yo bitch Ja Rule is more succesful then you'll...
1	0000247867823ef7	== From RfC == \n\n The title is fine as it is...
2	00013b17ad220c46	" \n\n == Sources == \n\n * Zawe Ashton on Lap...
3	00017563c3f7919a	:If you have a look back at the source, the in...
4	00017695ad8997eb	I don't anonymously edit articles at all.
...	...	...
153159	fffcd0960ee309b5	. \n i totally agree, this stuff is nothing bu...
153160	fffd7a9a6eb32c16	== Throw from out field to home plate. == \n\n...
153161	fffda9e8d6fafa9e	" \n\n == Okinotorishima categories == \n\n I ...
153162	fffe8f1340a79fc2	" \n\n == ""One of the founding nations of the...
153163	ffffce3fb183ee80	" \n :::Stop already. Your bullshit is not wel...

153164 rows × 2 columns

```
test.duplicated().sum()
```

```
0
```

```
test.isnull().sum()
```

```
id              0
comment_text    0
dtype: int64
```

```
test['length'] = test['comment_text'].str.len()
test
```

	id	comment_text	length
0	00001cee341fdb12	Yo bitch Ja Rule is more succesful then you'll...	367
1	0000247867823ef7	== From RfC == \n\n The title is fine as it is...	50
2	00013b17ad220c46	" \n\n == Sources == \n\n * Zawe Ashton on Lap...	54
3	00017563c3f7919a	:If you have a look back at the source, the in...	205
4	00017695ad8997eb	I don't anonymously edit articles at all.	41
...	...	...	...
153159	fffcd0960ee309b5	. \n i totally agree, this stuff is nothing bu...	60
153160	fffd7a9a6eb32c16	== Throw from out field to home plate. == \n\n...	198
153161	fffda9e8d6fafa9e	" \n\n == Okinotorishima categories == \n\n I ...	423
153162	fffe8f1340a79fc2	" \n\n == ""One of the founding nations of the...	502
153163	ffffce3fb183ee80	" \n :::Stop already. Your bullshit is not wel...	141

153164 rows × 3 columns

Here, I have calculated the length of the Comment_text.

```
In [43]: #Converting the text into Lower Case
test['comment_text'] = test['comment_text'].str.lower()

#Replace email address
test['comment_text'] = test['comment_text'].str.replace(r'^.+@[^\.].*\.[a-z]{2,}$','emailaddress')

# Replace web address
test['comment_text'] = test['comment_text'].str.replace(r'^http\://[a-zA-Z0-9\-\.]+\.[a-zA-Z]{2,3}(/\S*)?$','webaddress')

# Replace money symbols
test['comment_text'] = test['comment_text'].str.replace(r'£|\$', 'dollers')

# Replace 10 digit phone numbers (formats include paranthesis, spaces, no spaces, dashes) with 'phonenumber'
test['comment_text'] = test['comment_text'].str.replace(r'^\(?[\d]{3}\)?[\s-]?[\d]{3}[\s-]?[\d]{4}$','phonenumber')

#Handling all the punctuation in the comment's
test['comment_text'] = test['comment_text'].apply(lambda x: ' '.join(term for term in x.split() if term not in string.punctuatior

#Giving the stopwords and a few extra words along with the pre-defined stopwords
stop_words = set(stopwords.words('english') + ['u', 'ü', 'ur', '4', '2', 'im', 'dont', 'doin', 'ure'])
test['comment_text'] = test['comment_text'].apply(lambda x: ' '.join(term for term in x.split() if term not in stop_words))


# Used the Lemmatizer in the column, "Comment_text"
lem=WordNetLemmatizer()
test['comment_text'] = test['comment_text'].apply(lambda x: ' '.join(lem.lemmatize(t) for t in x.split()))

test['clean_length'] = test.comment_text.str.len()
test
```

Out[43]:

	id	comment_text	length	clean_length
0	00001cee341fdb12	yo bitch ja rule succesful ever whats hating s...	367	249
1	0000247867823ef7	== rfc == title fine is, imo.	50	29
2	00013b17ad220c46	== source == zawe ashton lapland —	54	34

```
print ('Origial Length:', test.length.sum())
print ('Clean Length:', test.clean_length.sum())
```

```
Origial Length: 55885733
Clean Length: 38993729
```

Here, I can see the the orginal length and then the cleaned length.

Importing important libraries required for the Model Building.

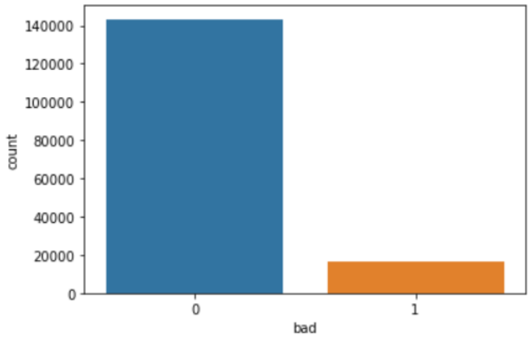
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report,roc_curve,roc_auc_score,auc,f1_score
from sklearn.model_selection import cross_val_score,GridSearchCV
```

```
target_columns = ['malignant','highly_malignant','rude','threat','abuse','loathe']
target_data = train[target_columns]

train['bad'] = train[target_columns].sum(axis =1)
print(train['bad'].value_counts())
train['bad'] = train['bad'] > 0
train['bad'] = train['bad'].astype(int)
print(train['bad'].value_counts())
```

```
0    143346
1      6360
3      4209
2      3480
4      1760
5       385
6        31
Name: bad, dtype: int64
0    143346
1     16225
Name: bad, dtype: int64
```

In [47]:
```
sns.countplot(train['bad'])
plt.show()
```



In [48]:
```
#  Convert text into vectors using TF-IDF
from sklearn.feature_extraction.text import TfidfVectorizer
tf_vec = TfidfVectorizer(max_features = 10000, stop_words='english')
features = tf_vec.fit_transform(train['comment_text'])
x = features
x
```

Out[48]:
```
<159571x10000 sparse matrix of type '<class 'numpy.float64'>'
	with 3366447 stored elements in Compressed Sparse Row format>
```

```
y= train['bad']
x_train,x_test,y_train,y_test = train_test_split(x,y,random_state=56,test_size=.30)
```

In [53]:
```
# Logistic Regression
LG = LogisticRegression()
#for trainoing data
LG.fit(x_train, y_train)
y_pred_train = LG.predict(x_train)
print('Training accuracy is {}'.format(accuracy_score(y_train, y_pred_train)))

# for testing data
y_pred_test = LG.predict(x_test)
print('Test accuracy is {}'.format(accuracy_score(y_test,y_pred_test)))
print(confusion_matrix(y_test,y_pred_test))
print(classification_report(y_test,y_pred_test))
```

```
Training accuracy is 0.9595967734715619
Test accuracy is 0.9553392379679144
[[42729   221]
 [ 1917  3005]]
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     42950
           1       0.93      0.61      0.74      4922

    accuracy                           0.96     47872
   macro avg       0.94      0.80      0.86     47872
weighted avg       0.95      0.96      0.95     47872
```

```python
# DecisionTree Regression
DTC = DecisionTreeClassifier()
#for trainoing data
DTC.fit(x_train, y_train)
y_pred_train = DTC.predict(x_train)
print('Training accuracy is {}'.format(accuracy_score(y_train, y_pred_train)))

# for testing data
y_pred_test = DTC.predict(x_test)
print('Test accuracy is {}'.format(accuracy_score(y_test,y_pred_test)))
print(confusion_matrix(y_test,y_pred_test))
print(classification_report(y_test,y_pred_test))
```

```
Training accuracy is 0.9988898736783678
Test accuracy is 0.9394009024064172
[[41578  1372]
 [ 1529  3393]]
              precision    recall  f1-score   support

           0       0.96      0.97      0.97     42950
           1       0.71      0.69      0.70      4922

    accuracy                           0.94     47872
   macro avg       0.84      0.83      0.83     47872
weighted avg       0.94      0.94      0.94     47872
```

```python
# KNeighborsClassifier
knn = KNeighborsClassifier()
#for trainoing data
knn.fit(x_train, y_train)
y_pred_train = knn.predict(x_train)
print('Training accuracy is {}'.format(accuracy_score(y_train, y_pred_train)))

# for testing data
y_pred_test = knn.predict(x_test)
print('Test accuracy is {}'.format(accuracy_score(y_test,y_pred_test)))
print(confusion_matrix(y_test,y_pred_test))
print(classification_report(y_test,y_pred_test))
```

```
Training accuracy is 0.9296591733139956
Test accuracy is 0.9181567513368984
[[42604   346]
 [ 3572  1350]]
              precision    recall  f1-score   support

           0       0.92      0.99      0.96     42950
           1       0.80      0.27      0.41      4922

    accuracy                           0.92     47872
   macro avg       0.86      0.63      0.68     47872
weighted avg       0.91      0.92      0.90     47872
```

```python
# Random Forest Regression
RF = RandomForestClassifier()
#for trainoing data
RF.fit(x_train, y_train)
y_pred_train = RF.predict(x_train)
print('Training accuracy is {}'.format(accuracy_score(y_train, y_pred_train)))

# for testing data
y_pred_test = RF.predict(x_test)
print('Test accuracy is {}'.format(accuracy_score(y_test,y_pred_test)))
print(confusion_matrix(y_test,y_pred_test))
print(classification_report(y_test,y_pred_test))
```

```
Training accuracy is 0.9988809210467416
Test accuracy is 0.9553183489304813
[[42416   534]
 [ 1605  3317]]
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     42950
           1       0.86      0.67      0.76      4922

    accuracy                           0.96     47872
   macro avg       0.91      0.83      0.87     47872
weighted avg       0.95      0.96      0.95     47872
```

```python
# AdaBoostClassifier Regression
ada = AdaBoostClassifier()
#for trainoing data
ada.fit(x_train, y_train)
y_pred_train = ada.predict(x_train)
print('Training accuracy is {}'.format(accuracy_score(y_train, y_pred_train)))

# for testing data
y_pred_test = ada.predict(x_test)
print('Test accuracy is {}'.format(accuracy_score(y_test,y_pred_test)))
print(confusion_matrix(y_test,y_pred_test))
print(classification_report(y_test,y_pred_test))
```

```
Training accuracy is 0.9463737365598618
Test accuracy is 0.9454169451871658
[[42587   363]
 [ 2250  2672]]
              precision    recall  f1-score   support

           0       0.95      0.99      0.97     42950
           1       0.88      0.54      0.67      4922

    accuracy                           0.95     47872
   macro avg       0.92      0.77      0.82     47872
weighted avg       0.94      0.95      0.94     47872
```

```python
# xgboost Regression
xgb = XGBClassifier()
#for trainoing data
xgb.fit(x_train, y_train)
y_pred_train = xgb.predict(x_train)
print('Training accuracy is {}'.format(accuracy_score(y_train, y_pred_train)))

# for testing data
y_pred_test = xgb.predict(x_test)
print('Test accuracy is {}'.format(accuracy_score(y_test,y_pred_test)))
print(confusion_matrix(y_test,y_pred_test))
print(classification_report(y_test,y_pred_test))
```

```
Training accuracy is 0.9614410155865316
Test accuracy is 0.9526445521390374
[[42686   264]
 [ 2003  2919]]
              precision    recall  f1-score   support

           0       0.96      0.99      0.97     42950
           1       0.92      0.59      0.72      4922

    accuracy                           0.95     47872
   macro avg       0.94      0.79      0.85     47872
weighted avg       0.95      0.95      0.95     47872
```

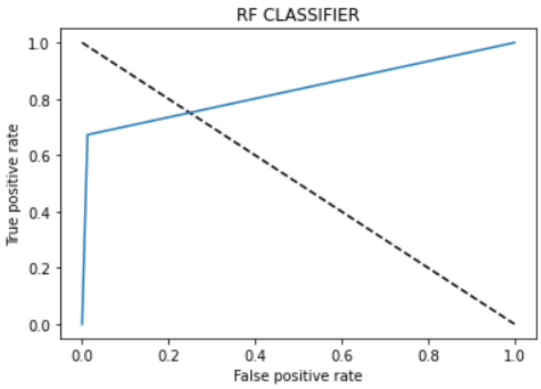
```python
# Hypertuning the model with Random forest Classifier:
RF = RandomForestClassifier()
RF.fit(x_train, y_train)
y_pred_train = RF.predict(x_train)
print('Training accuracy is {}'.format(accuracy_score(y_train, y_pred_train)))
y_pred_test = RF.predict(x_test)
print('Test accuracy is {}'.format(accuracy_score(y_test,y_pred_test)))
cvs=cross_val_score(RF, x, y, cv=5, scoring='accuracy').mean()
print('cross validation score :',cvs*100)
print(confusion_matrix(y_test,y_pred_test))
print(classification_report(y_test,y_pred_test))
```

```
Training accuracy is 0.9988809210467416
Test accuracy is 0.9550676804812834
cross validation score : 95.67026562878806
[[42410   540]
 [ 1611  3311]]
              precision    recall  f1-score   support

           0       0.96      0.99      0.98     42950
           1       0.86      0.67      0.75      4922

    accuracy                           0.96     47872
   macro avg       0.91      0.83      0.87     47872
weighted avg       0.95      0.96      0.95     47872
```

```python
fpr,tpr,thresholds=roc_curve(y_test,y_pred_test)
roc_auc=auc(fpr,tpr)
plt.plot([0,1],[1,0],'k--')
plt.plot(fpr,tpr,label = 'RF Classifier')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('RF CLASSIFIER')
plt.show()
```



In [61]:
```python
test_data = tf_vec.fit_transform(test['comment_text'])
test_data
```

Out[61]:
```
<153164x10000 sparse matrix of type '<class 'numpy.float64'>'
	with 2848168 stored elements in Compressed Sparse Row format>
```

In [62]:
```python
test['malignant']=RF.predict(test_data)
test['highly_malignant']=RF.predict(test_data)
test['rude']=RF.predict(test_data)
test['threat']=RF.predict(test_data)
test['abuse']=RF.predict(test_data)
test['loathe']=RF.predict(test_data)
test[['id','comment_text','malignant','highly_malignant','rude','threat','abuse','loathe']].to_csv('Malignant_comment_submission.
```

In [63]:
```python
test
```

Out[63]:

	id	comment_text	length	clean_length	malignant	highly_malignant	rude	threat	abuse	loathe
0	00001cee341fdb12	yo bitch ja rule succesful ever whats hating s...	367	249	0	0	0	0	0	0
1	0000247867823ef7	== rfc == title fine is, imo.	50	29	0	0	0	0	0	0
2	00013b17ad220c46	== source == zawe ashton lapland —	54	34	0	0	0	0	0	0
3	00017563c3f7919a	:if look back source, information updated corr...	205	117	0	0	0	0	0	0
4	00017695ad8997eb	anonymously edit article all.	41	29	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...
153159	fffcd0960ee309b5	totally agree, stuff nothing too-long-crap	60	42	0	0	0	0	0	0
153160	fffd7a9a6eb32c16	== throw field home plate. == get faster throw...	198	117	0	0	0	0	0	0
153161	fffda9e8d6fafa9e	== okinotorishima category == see change agree...	423	293	1	1	1	1	1	1

```
In [64]: submission = pd.read_csv(r'Malignant_comment_submission.csv')
         submission.shape

Out[64]: (153164, 8)

In [65]: import joblib
         joblib.dump(RF,"MalignantComment Prediction.pkl")

Out[65]: ['MalignantComment Prediction.pkl']

In [66]: submission.sample(50)

Out[66]:
```

	id	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
12584	15227e5d5f8bb701	==one link== noticed discussion ongoing yester...	0	0	0	0	0	0
42939	47327a760d277939	== jfhq-ncr == said mhwp page would willing re...	1	1	1	1	1	1
18594	1f40c8c78cd1bda3	bot posted	0	0	0	0	0	0
60166	640ba329d78b3a4f	"someone exchanged word ""poopy"" word ""nomin...	0	0	0	0	0	0
112516	bbc676cac49aed70	== please re-lock == hi, could please restore ...	0	0	0	0	0	0
82943	8a4f5ffdbb6a6df9	realm ""completely unsubstantiated rumour"", i...	0	0	0	0	0	0
127267	d49fc016d628ba41	español veáse aquí para mi pagina de discusion...	0	0	0	0	0	0
101591	a986e346a6269e6e	alexhead8835 shut >:(	0	0	0	0	0	0

Conclusion:-

Key Findings and Conclusions of the Study

- Online hate, described as abusive language, aggression, cyberbullying, hatefulness and many others has been identified as a major threat on online social media platforms. Social media platforms are the most prominent grounds for such toxic behaviour.
- From the above analysis the below mentioned results were achieved which depicts the chances and conditions of a comment being a hateful comment or a normal comment.
- With the increasing popularity of social media, more and more people consume feeds from social media and due differences they spread hate comments to instead of love and harmony. It has strong negative impacts on individual users and broader society.

Learning Outcomes of the Study in respect of Data Science

It is possible to classify the comments content into the required categories of Malignant and Non Malignant. However, using this kind of project an awareness can be created to know what is good and bad. It will help to stop spreading hatred among people.

Limitations of this work and Scope for Future Work

- Machine Learning Algorithms like Decision Tree Classifier took enormous amount of time to build the model and Ensemble techniques were taking a lot more time thus I have not included Ensemble models.
- Using Hyper-parameter tuning would have resulted in some more accuracy.
- Every effort has been put on it for perfection but nothing is perfect and this project is of no exception. There are certain areas which can be enhanced. Comment detection is an emerging research area with few public datasets. So, a lot of works need to be done on this field.

ThankYou