MACHINE LEARNING APPLIED: MALAIGNANT COMMENTS CLASSIFICATION.

Submitted by:

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ACKNOWLEDGMENT

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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

Online platforms and social media become the place where people share the thoughts freely without any partiality and overcoming all the race people share their thoughts and ideas among the crowd.

Social media is a computer-based technology that facilitates the sharing of ideas, thoughts, and information through the building of virtual networks and communities. By design, social media is Internet-based and gives users quick electronic communication of content. Content includes personal information, documents, videos, and photos. Users engage with social media via a computer, tablet, or smartphone via web-based software or applications.

While social media is ubiquitous in America and Europe, Asian countries like India lead the list of social media usage. More than 3.8 billion people use social media.

In this huge online platform or an online community there are some people or some motivated mob wilfully bully others to make them not to share their thought in rightful way. They bully others in a foul language which among the civilized society is seen as ignominy. And when innocent individuals are being bullied by these mob these individuals are going silent without speaking anything. So, ideally the motive of this disgraceful mob is achieved.

To solve this problem, we are now building a model that identifies all the foul language and foul words, using which the online platforms like social media principally stops these mob using the foul language in an online community or even block them or block them from using this foul language.

Review of Literature

The purpose of the literature review is to:

1. Identify the foul words or foul statements that are being used.
2. Stop the people from using these foul languages in online public forum.

To solve this problem, we are now building a model using our machine language technique that identifies all the foul language and foul words, using which the online platforms like social media principally stops these mob using the foul language in an online community or even block them or block them from using this foul language.

I have used 10 different Classification algorithms and shortlisted the best on basis on the metrics of performance and I have chosen one algorithm and build a model in that algorithm.

Motivation for the Problem Undertaken

The project was the first provided to me by Flip Robo Technologies 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 motivation.

Analytical Problem Framing

Mathematical/ Analytical Modeling of the Problem

I start analysis on this project in importing the data set and simple play around with the data and identifying the characteristics of each column.

```
In [6]:  1 ## Data type:
         2 df.dtypes
```

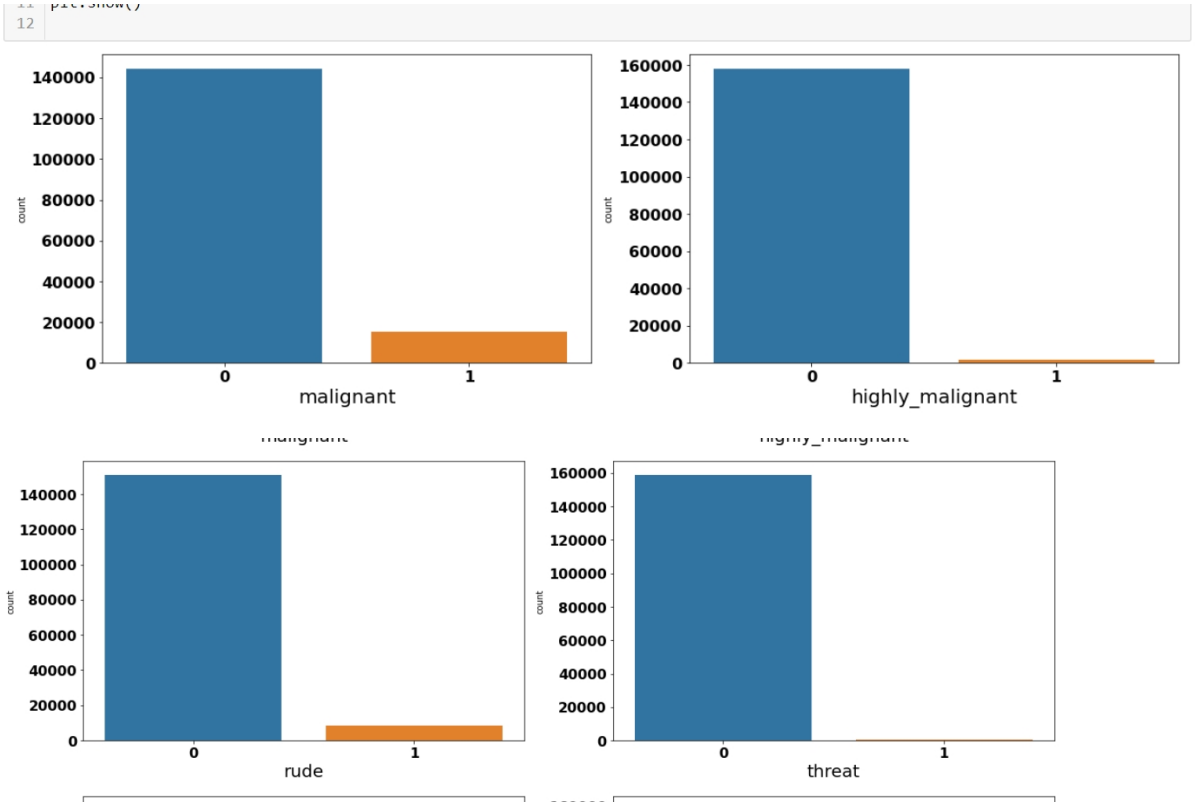
```
Out[6]: id                  object
        comment_text        object
        malignant            int64
        highly_malignant     int64
        rude                 int64
        threat               int64
        abuse                int64
        loathe               int64
        dtype: object
```

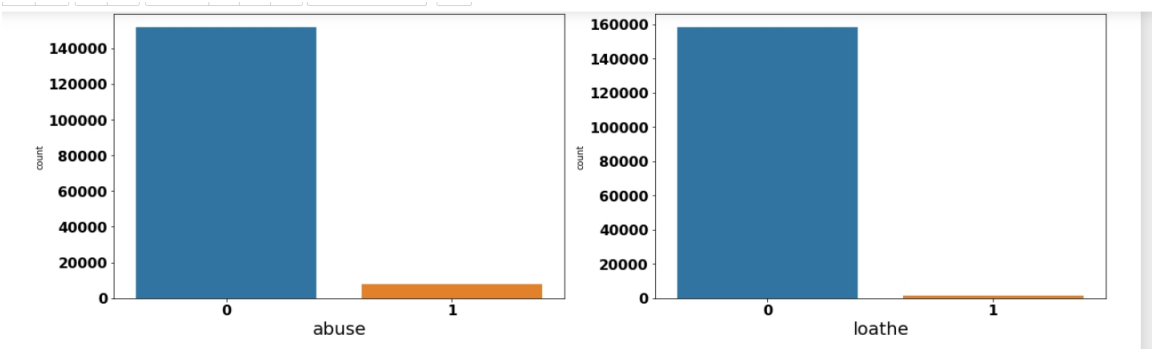
Apart from id and comment_text,rest columns datatype is int.

In the first stoke of analysis I understood that there are 8 columns in total in which 6 are numerical column with binary data 0's and 1's and 'id' data which has all unique values "comment text" have string values.

Since 'id' have all unique values, it won't be helpful in analysis to I have dropped id column.

Post dropping 'id' I tried to understand data from 'malignant', 'highly_malignant', 'rude', 'threat', 'abuse', 'loathe columns by plotting them in count plot.





Observations:- -> Most of the comments are malignant followed by rude and abuse. -> Highly_malignant, loathe and threat are very less in count.

Key observation:

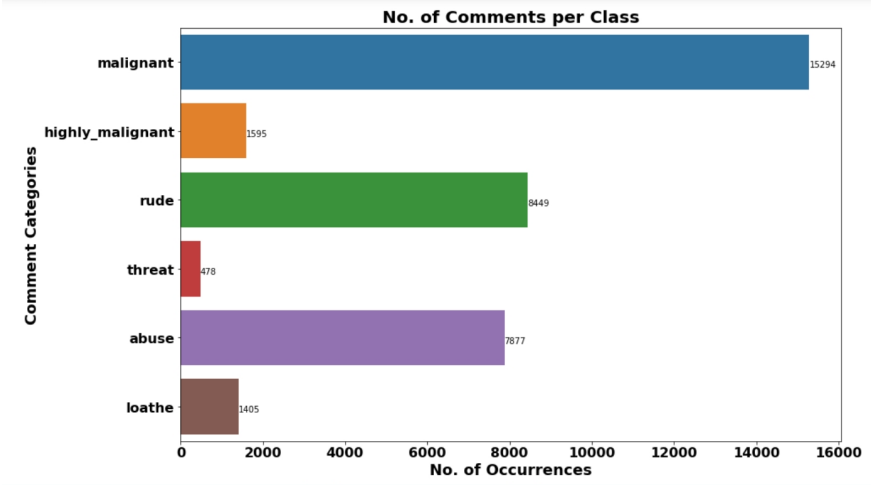
we can see that there only minimum number of columns in 'malignant', 'highly_malignant', 'rude', 'threat', 'abuse', 'loathe' and remaining all in 0.

In [12]:
```
#Checking the percentage of the comments
non_malignant = df[(df['malignant']!=1) & (df['highly_malignant']!=1) & (df['rude']!=1) &
                   (df['threat']!=1) & (df['abuse']!=1) & (df['loathe']!=1)]
percent=len(non_malignant)/len(df)*100
print('Percentage of good/neutral comments = ',percent)
print('Percentage of negative comments = ', (100-percent))
```

```
Percentage of good/neutral comments =  89.83211235124176
Percentage of negative comments =  10.167887648758239
```

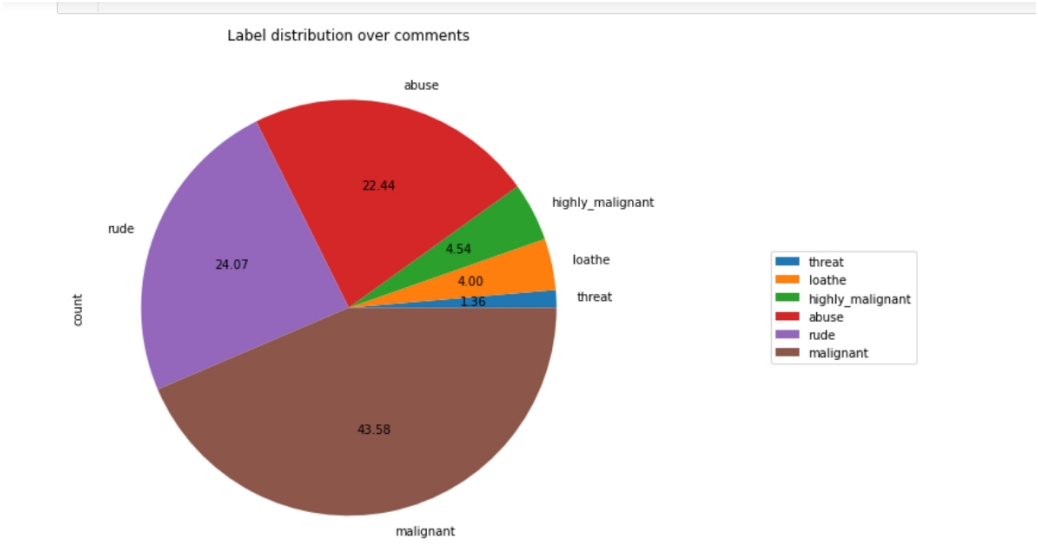
Around 90% of comments are Good/Neutral in nature. Around 10% of comments are negative comments

So, only 10% of the data is getting classified as malignant comments data is unbalanced.



Key observation:

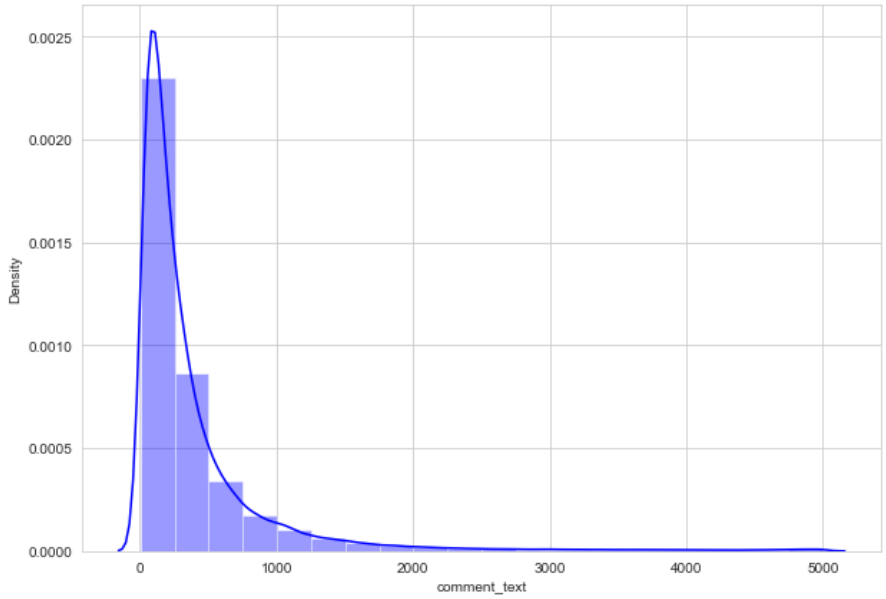
1. We can see malignant and rude are high categorised sentences in the data.



Observation : Out of total negative comments around 43.58% are malignant in nature followed by 24.07% are rude comments.

Key observation:

1. As we see above malignant, and rude sentence are high classified and threat, loathe are least classified.



Key observation:

1. We can see that few sentences are really long but most of the sentence are small.

Key Observations:

1. We can see more corelations in the variables, Abuse have more corelation with malignant and rude.
2. Rude has more positive corelation with malignant
3. we don't have any negative corelations in the data.

Data Sources and their formats

The data set contains the training set, which has approximately 1,59,000 samples and the test set which contains nearly 1,53,000 samples. All the data samples contain 8 fields which includes 'Id', 'Comments', 'Malignant', 'Highly malignant', 'Rude', 'Threat', 'Abuse' and 'Loathe'.

The label can be either 0 or 1, where 0 denotes a NO while 1 denotes a YES. There are various comments which have multiple labels. The first attribute is a unique ID associated with each comment.

The data set includes:

1. Malignant: It is the Label column, which includes values 0 and 1, denoting if the comment is malignant or not.

2. Highly Malignant: It denotes comments that are highly malignant and hurtful.
3. Rude: It denotes comments that are very rude and offensive.
4. Threat: It contains indication of the comments that are giving any threat to someone.
5. Abuse: It is for comments that are abusive in nature.
6. Loathe: It describes the comments which are hateful and loathing in nature.
7. ID: It includes unique Ids associated with each comment text given.
8. Comment text: This column contains the comments extracted from various social media platforms.

This project is more about exploration, feature engineering and classification that can be done on this data. Since the data set is huge and includes many categories of comments, we can do good amount of data exploration and derive some interesting features using the comments text column available.

Data Pre-processing Done

```
#Importing Required libraries
import nltk
import re
import string
from nltk.corpus import stopwords
from wordcloud import WordCloud
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from sklearn.feature_extraction.text import TfidfVectorizer

```

I imported all the required libraries for cleansing the data.

After importing all the required libraries, I have defined Stopwords and lemmatize to a variable.

```
#Defining the stop words
stop_words = stopwords.words('english')

#Defining the lemmatizer
lemmatizer = WordNetLemmatizer()

```

Post which I have defined a function for cleaning the data.

```
def format_comments(text):

    #convert to lower case
    lowered_text = text.lower()

    #Replacing email addresses with 'emailaddress'
    text = re.sub(r'^[a-z0-9]+[\._]?[ a-z0-9]+[@]\w+[. ]\w{2,3}$', 'emailaddress', lowered_text)

    #Replace URLs with 'webaddress'
    text = re.sub(r'http\S+', 'webaddress', text)

    #Removing numbers
    text = re.sub(r'[0-9]', " ", text)

    #Removing the HTML tags
    text = re.sub(r"<.*?>", " ", text)

    #Removing Punctuations
    text = re.sub(r'[^\w\s]', ' ', text)
    text = re.sub(r'\_',' ',text)

    #Removing all the non-ascii characters
    clean_words = re.sub(r'[^\x00-\x7f]',r'', text)

    #Removing the unwanted white spaces
    text = " ".join(text.split())

    #Splitting data into words
    tokenized_text = word_tokenize(text)

    #Removing remaining tokens that are not alphabetic, Removing stop words and Lemmatizing the text
    removed_stop_text = [lemmatizer.lemmatize(word) for word in tokenized_text if word not in stop_words if word.isalpha()]
```

Post on creating a function I have passed my data into the same to clean it.

```
# Apply above function for the column comment_text in training dataset to replace original with cleaned text
df['comment_text'] = df['comment_text'].apply(format_comments)
df['comment_text'].head()
```

```
0    explanation edits made username hardcore metal...
1    aww match background colour seemingly stuck th...
2    hey man really trying edit war guy constantly ...
3    make real suggestion improvement wondered sect...
4                       sir hero chance remember page
Name: comment_text, dtype: object
```

```
In [27]: print("Total Words Removed:", (df.length_before_cleaning.sum()) - (df.length_after_cleaning.sum()))

Total Words Removed: 24416722
```

The total amount of data that is cleansed from the original data is 24416722. Now the data is cleansed and ready for training but before which I converted the data into vectors for the machine learning models to understand the data, so I imported TFIDF vectorizer and I have made the max feature as 2000.

1. Vectorizer & Spliting Train dataset

```
# Converting the features into number vectors
tf_vec = TfidfVectorizer(max_features = 2000, stop_words='english')

```

```
# Let's Separate the input and output variables represented by X and y respectively in train data and convert them
X = tf_vec.fit_transform(df['comment_text']).toarray()

```

```
df.head()
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe	label	length_before_cleaning	length_after_cleaning
0	explanation edits made username hardcore metal...	0	0	0	0	0	0	0	264	156
1	aww match background colour seemingly stuck th...	0	0	0	0	0	0	0	112	67
2	hey man really trying edit war guy constantly ...	0	0	0	0	0	0	0	233	141
3	make real suggestion improvement wondered sect...	0	0	0	0	0	0	0	622	364
4	sir hero chance remember page	0	0	0	0	0	0	0	67	29

```
output_labels= df.columns[1:7]
```

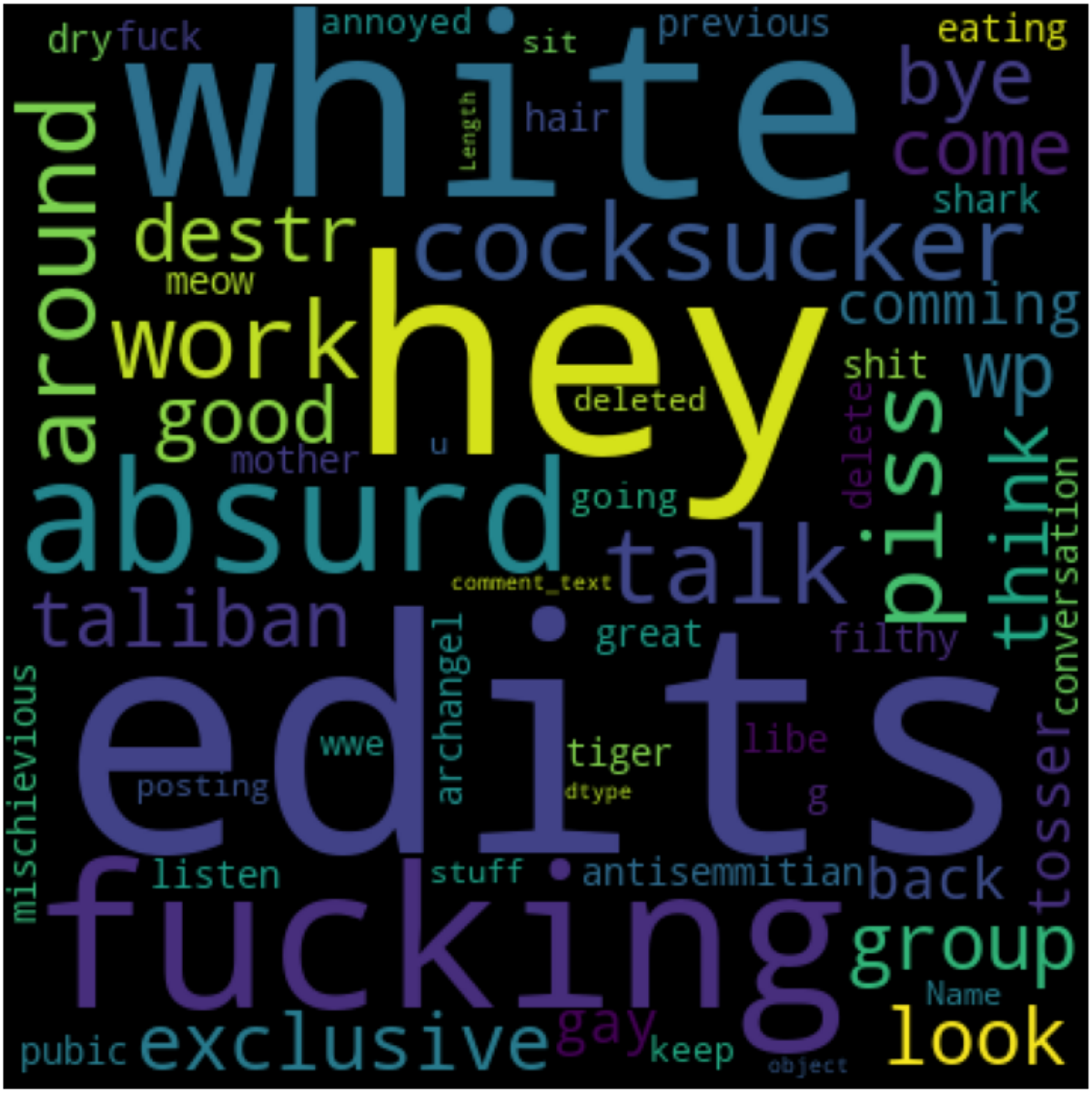
```
# output variables
from scipy.sparse import csr_matrix
Y = csr_matrix(df[output_labels]).toarray()
```

And I have split the data into two parts X and y and made them ready for training. I have created a new feature name label and summed all the other numerical column and changed the output as binary i.e., if the sentence is categorised as malignant it will be 1 or else it will be 0.

Data Inputs- Logic- Output Relationships

I have analysed the input output logic with word cloud and I have word clouded the sentenced that as classified as foul language in every category.

WORDS TAGGED AS MALIGNANT



Key observation.

We can see the foul words that are mostly used in malignant classified sentences we are seeing top 300 words the words which are bigger in size are mostly used.

WORDS TAGGED AS HIGHLY MALIGNANT

Key observation.

We can see the foul words that are mostly used in highly_malignant classified sentences we are seeing top 300 words the words which are bigger in size are mostly used.

WORDS TAGGED AS RUDE

Key observation.

We can see the foul words that are mostly used in rude classified sentences we are seeing top 300 words the words which are bigger in size are mostly used.

WORDS TAGGED AS ABUSE

Key observation.

We can see the foul words that are mostly used in abuse classified sentences we are seeing top 200 words the words which are bigger in size are mostly used.

WORDS TAGGED AS LOATHE

Key observation.

We can see the foul words that are mostly used in loathe classified sentences we are seeing top 500 words the words which are bigger in size are mostly used.

Hardware and Software Requirements and Tools Used

1. Python 3.8.
2. NumPy.
3. Pandas.
4. Matplotlib.
5. Seaborn. 6. Data science.
6. SciPy
7. Sklearn.
8. Anaconda Environment, Jupyter Notebook.

Model/s Development and Evaluation

Testing of Identified Approaches (Algorithms)

I have started the training in selecting the best random state parameter for the model as follows.

```
#Importing Machine learning Model library
from sklearn.linear_model import LogisticRegression
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 AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from skmultilearn.problem_transform import BinaryRelevance
from sklearn.svm import SVC, LinearSVC
#from sklearn.multiclass import OneVsRestClassifier
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn.metrics import hamming_loss, log_loss

```

```
import timeit, sys
import tqdm.notebook as tqdm
```

```
# Creating a function to train and test model
def build_models(models,x,y,test_size=0.33,random_state=13):
    # spliting train test data using train_test_split
    x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=test_size,random_state=random_state)

    # training models using BinaryRelevance of problem transform
    for i in tqdm.tqdm(models,desc="Building Models"):
        start_time = timeit.default_timer()

        sys.stdout.write("\n=================================================================================\n")
        sys.stdout.write(f"Current Model in Progress: {i} ")
        sys.stdout.write("\n=================================================================================\n")

        br_clf = BinaryRelevance(classifier=models[i]["name"],require_dense=[True,True])
        print("Training: ",br_clf)
        br_clf.fit(x_train,y_train)

        print("Testing: ")
        y_pred = br_clf.predict(x_test)

        ham_loss = hamming_loss(y_test,y_pred)
        sys.stdout.write(f"\n\tHamming Loss  : {ham_loss}")

        ac_score = accuracy_score(y_test,y_pred)
        sys.stdout.write(f"\n\tAccuracy Score: {ac_score}")

        cl_report = classification_report(y_test,y_pred)
        sys.stdout.write(f"\n{cl_report}")

        end_time = timeit.default_timer()
        sys.stdout.write(f"Completed in [{end_time-start_time} sec.]")
```

After selecting the best random state parameter, I have splitted the data into test and train with test size as 33 %. Again, I have imported the required libraries to import my ML algorithms.

Run and evaluate selected models

In [53]:
```
# Preparing the list of models for classification purpose
models = {
          "Logistic Regression": {"name": LogisticRegression()},
          "Random Forest Classifier": {"name": RandomForestClassifier()},
          "Support Vector Classifier": {"name": LinearSVC(max_iter = 3000)},
          "Ada Boost Classifier": {"name": AdaBoostClassifier()},
          "Decision Tree Classifier": {"name":DecisionTreeClassifier()},
          "KNeighbors Classifier" :{"name":KNeighborsClassifier()},
          "Random Forest Classifier" :{"name":RandomForestClassifier()},
          "Gradient Boosting Classifier" : {"name":GradientBoostingClassifier()},
          "XGBClassifier": {"name":XGBClassifier()},
          "MultinomialNB": {"name":MultinomialNB()},
         }

# Taking one forth of the total data for training and testing purpose
half = len(df)//4
trained_models = build_models(models,X[:half,:],Y[:half,:])

```

As we can see above, I have imported 10 classification algorithms and I am going to shortlist the best amongst these in basis of accuracy precision recall and F1 scores.

So, like above I have run all the algorithms with the data.

Key-Metrics for success in solving problem under consideration.

I have taken key metrics as Accuracy, Precision, Recall and F1 scores to analysis the best model.

```
================================================================================
Training:  BinaryRelevance(classifier=RandomForestClassifier(), require_dense=[True, True])
Testing:

        Hamming Loss  : 0.022015444993037092
        Accuracy Score: 0.906950246866692
              precision    recall  f1-score   support

           0       0.83      0.61      0.70      1314
           1       0.55      0.07      0.13       151
           2       0.84      0.71      0.77       710
           3       0.00      0.00      0.00        41
           4       0.72      0.55      0.62       680
           5       0.83      0.15      0.25       128

   micro avg       0.80      0.57      0.66      3024
   macro avg       0.63      0.35      0.41      3024
weighted avg       0.78      0.57      0.64      3024
 samples avg       0.06      0.05      0.05      3024
Completed in [592.8934651 sec.]
```

As we can see above Support Vector Classifier tops the chart, I have selected Support Vector Classifier as my final model and I have saved the same for the further usage. Further I have imported the test data and have done prediction on the same.

CONCLUSION

Key Findings and Conclusions of the Study

The finding of the study is that only few users over online use

```
# Make predictions and view the results
predict_test = best_model.predict(test_vec.toarray())

# Saving predicted values into a CSV file
pd.DataFrame(predict_test).to_csv('Predicted_test_output.csv')
```

```
df1 = pd.read_csv('Predicted_test_output.csv')
df1.drop("Unnamed: 0", axis=1, inplace=True)
df1.rename({'0':'malignant', '1':'highly_malignant', '2':'rude', '3':'threat', '4':'abuse', '5':'loathe'},
           axis='columns', inplace=True)
df2=df_test.copy()
df = pd.concat([df2, df1], axis=1)
df
```

	id	comment_text	length_before_cleaning	length_after_cleaning	malignant
0	00001cee341fdb12	yo bitch ja rule succesful ever whats hating s...	367	235	NaN
1	0000247867823ef7	rfc title fine imo	50	18	NaN
2	00013b17ad220c46	source zawe ashton lapland	54	26	NaN
3	00017563c3f7919a	look back source information updated correct f...	205	109	NaN
4	00017695ad8997eb	anonymously edit article	41	24	NaN
...	...	...	...	...	...
153159	fffcd0960ee309b5	totally agree stuff nothing long crap	60	37	NaN
153160	fffd7a9a6eb32c16	throw field home plate get faster throwing cut...	198	107	NaN
153161	fffda9e8d6fafa9e	okinotorishima category see change agree corre...	423	238	NaN
153162	fffe8f1340a79fc2	one founding nation eu germany law return quit...	502	319	NaN
153163	ffffce3fb183ee80	stop already bullshit welcome fool think kind ...	141	74	NaN

153164 rows × 5 columns

```
df.to_csv('test_dataset_predictions2.csv', index=False)
```

unparliamentary language. And most of these sentences have more stop words, and are being long. As discussed before few motivated disrespectful crowds uses these foul languages in the online forum to bully the people around and to stop them from doing the things that they are supposed to do. Our Study helps the online forms and social media to induce a ban to profanity or usage of profanity over these forms.

Learning Outcomes of the Study in respect of Data Science

The use of social media is the most common trend among the activities of today's people. Social networking sites offer today's teenagers a platform for communication and entertainment. They use social media to collect more information from their friends and followers. The vastness of social media sites ensures that not all of them provide a decent environment for children. In such cases, the impact of the negative influences of social media on teenage users increases with an increase in the use of **offensive language** in social conversations. This increase could lead to **frustration**, **depression** and a large change in their behaviour. Hence, I propose a novel approach to classify bad language usage in text conversations. I have considered the English medium for textual conversation. I have developed our system based on a foul language classification approach; it is based on an improved version of a Support Vector Classification Algorithm that detects offensive language usage in a conversation. As per our evaluation, we found that lesser number of users conversation is not decent all the time. We trained 159571 observations for eight context categories using a Support Vector Classification algorithm for context detection. Then, the system classifies the use of foul language in one of the trained contexts in the text conversation. In our testbed, we observed 10% of participants used foul language during their text conversation. Hence, our proposed approach can identify the impact

of foul language in text conversations using a classification technique and emotion detection to identify the foul language usage

Limitations of this work and Scope for Future Work

The limitation of the study is that we have a imbalanced data so our model learnt more about the non-abusive sentence more than the abusive sentence. Which makes our model act like a overfit model when tested with live data. And also, model tend to not identify a foul or a sarcastically foul language.