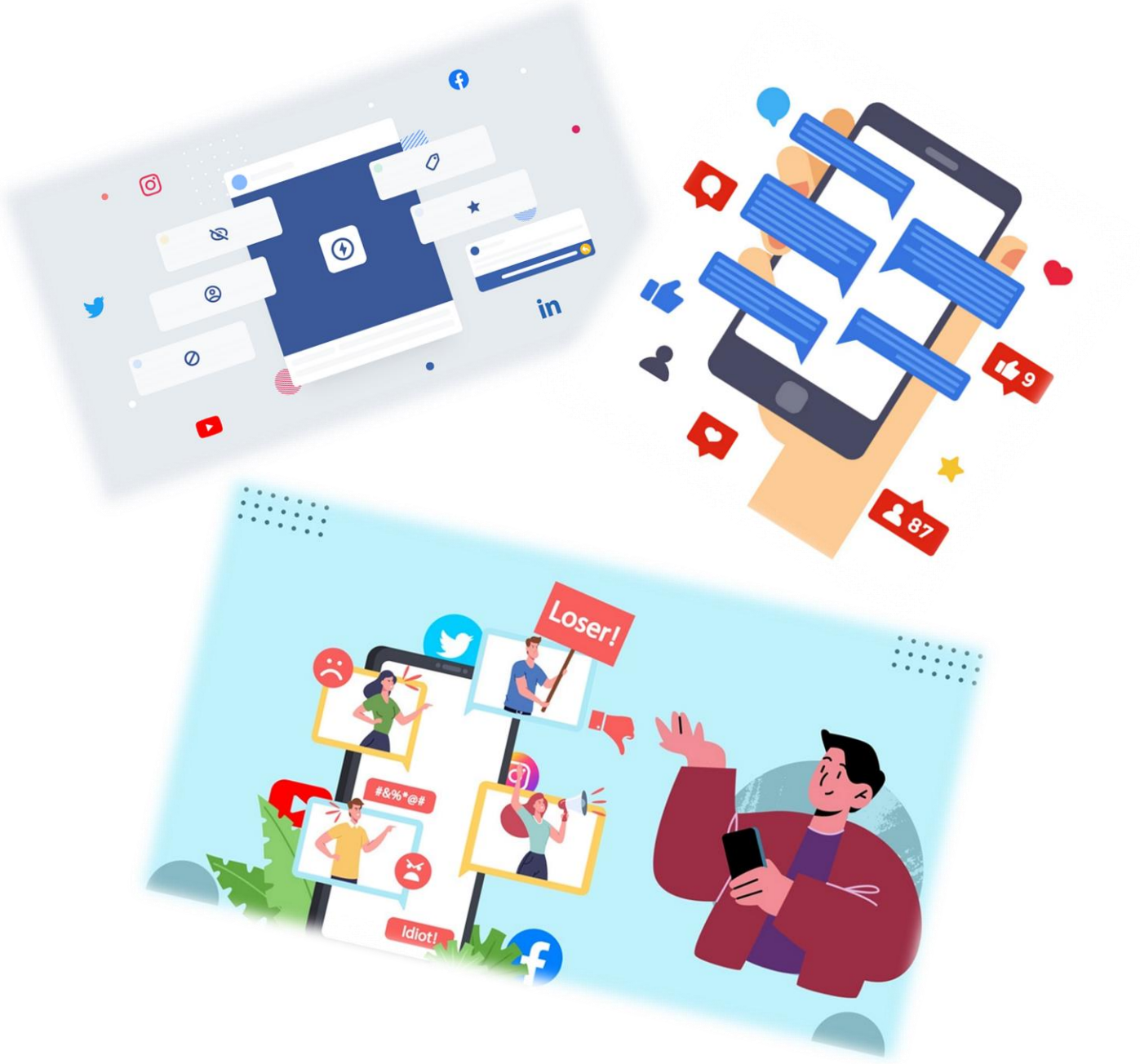
FLIP ROBO

Malignant Comments Classification



Submitted by:

SANTOSH H. HULBUTTI

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ACKNOWLEDGMENT

This project is completed using knowledge/information available on internet.

Following are the websites & YouTube Channels, which were used to scape data & understand concepts related to ML, AI & Data Visualization.

Websites:

1. towardsdatascience.com
2. medium.com
3. analyticsvidya.com
4. DataTrained LMS Platform
5. Carwale.com
6. Official documentation of ScikitLearn, Matplot library, AutoViz, Sweet Viz, Pandas Library & Seaborn library.
7. Kaggle.com
8. UCI ML Repository
9. Stackoverflow.com
10. YouTube Channels:
    a. Krish Naik
    b. Nicholas Renotte
    c. Sidhdhardan
    d. Keith Galli

I would like to thank FlipRobo Technologies, for giving an opportunity to work as an intern during this project period. And also like to thank mentor Ms. Gulshana Chaudhary for assigning the project.

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, cyber bullying, 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.

Conceptual Background of the Domain Problem

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.

So, we build a machine learning model that helps to understand which comment is malignant and which one is being based on the sample data. We do Exploratory Data Analysis to visualize the data graphically which is easy to understand. We also used some statistical techniques to see the insights of the data.

Review of Literature

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. First, we do all the data pre-processing steps and do EDA to visualize the data graphically and after that we make a machine learning model in order to improve.

Motivation for the Problem Undertaken

Every investigation begins with ideas that are further developed and inspired to address a variety of situations and circumstances. The client wants some predictions that could help them in further investment and improvement in selection of comments. So, to help them we make this project. My motivation behind this project is to do the proper research because research as a process for finding a solution to a problem after making a deep analysis and conducting studies of relevant factors. In general, research is a method designed to ensure that the information obtained is reasonable and supported by the quantitative and qualitative data, and that involves a systematic process. It includes the process of designing research methods, collecting and describing.

ANALYTICAL PROBLEM FRAMING

Mathematical/ Analytical Modeling of the Problem

- First, we check the basic information of the dataset that is its shape and its information using pandas library. The basic information tells the data type of our column and number of data present.
- Then we check the unique information of our data columns.
- After that we check for null values, if it present then we remove it because our data is text data and we cannot fill it.
- After that we check the summary statistics of our dataset. This part talks about the statistics of our dataset i.e., mean, median, max value, min values and also it tells whether outliers are present in our dataset or not.
- We check the length of data to understand the distribution of data.
- We use seaborn library to plot the target data and using word cloud for getting the sense of loud words in Malignant and Benign comments.
- Similarly, we can also make word cloud for separate columns where you can check the loud words for particular features because there are six target features.
- Before making the model, we convert our text into vectors so for that we use technique known as TF-IDF Vectorizer

Data Sources and their formats

- In this project the sample data is provided to us from our client database. The dataset is in csv (comma separated values) format.
- 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 0denotes 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:
    - **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 Pre-processing Done

1. First, we check the information of the given dataset because it tells that how many rows and columns are present in our dataset and data type of the columns whether they are object, integer or float.
2. Dropping duplicates rows if present in dataset.
3. Then we check for the null values present in our dataset. If null values are present then drop it because we cannot able to fill the text data.
4. After that we check the summary statistics of our dataset. This part talks about the statistics of our dataset i.e., mean, median, max value, in values and also it tells whether outliers are present in our dataset or not.
5. We also check the correlation of our target features with each other. If columns are highly correlated with each other let's say 90% or above then remove those columns to avoid multicollinearity problem.
6. There are six features in this dataset so we combined them and make one target feature giving the name as label and also, we do scale for that feature.
7. In data cleaning we use mainly five steps using function:
    a. Removing HTML tags
    b. Removing special characters
    c. Converting everything to lowercase
    d. Removing stop words
    e. Using WordNet Lemmatization for lemmatization
8. We create new column (clean text) after removing punctuations, stop words from input feature to check how much data is cleaned.

Data Inputs- Logic- Output Relationships

If the input has a particular word or relational words then, the value of the label's changes into 1, otherwise 0.

State the set of assumptions (if any) related to the problem under Consideration

- All stop words are present inside the stop words library
- The offensive words are always explicit and sarcasms are not considered

Hardware and Software Requirements and Tools Used

a. Software

i. ➔ Jupyter Notebook (Python 3.9)
ii. ➔ Microsoft Office

b. Hardware

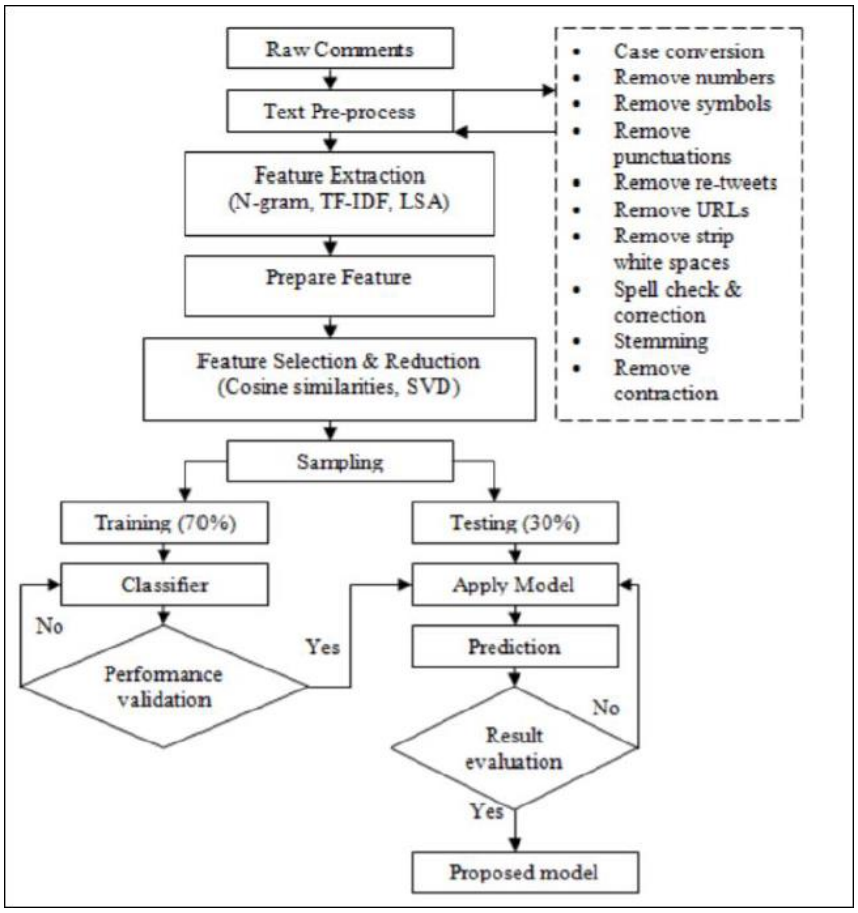
i. ➔ Processor – AMD Ryzen 5
ii. ➔ RAM - 8 GB
iii. ➔ Graphic Memory - 4Gb, Nvidia GEFORCE RTX1650

c. Python Libraries

i. ➔ Pandas
ii. ➔ Numpy
iii. ➔ Selenium
iv. ➔ Matplotlib
v. ➔ Seaborn
vi. ➔ Scipy
vii. ➔ Sklearn & skmultilearn
viii. ➔ NLTK
ix. ➔ re
x. ➔ Gradio

MODEL DEVELOPMENT AND EVALUATION

Identification of possible problem-solving approaches (methods)



Testing of Identified Approaches (Algorithms)

```
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from xgboost import XGBClassifier
from sklearn.svm import LinearSVC
from lightgbm import LGBMClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.multiclass import OneVsRestClassifier
```

	models_name	accuracies_train	accuracies_test	precision_scores	f1_scores	hamming_losses
5	KNeighbors Classifier	91.27	89.19	67.42	48.65	2.94
1	Multinomial Naive Bayes	91.55	91.26	87.56	60.47	2.21
6	Random Forest Classifier	99.10	91.29	80.18	67.88	2.04
7	StochasticGB Classifier	91.67	91.47	88.73	62.85	2.10
4	LightGBM Classifier	93.10	91.60	81.86	68.20	1.99
2	XGB Classifier	93.54	91.65	83.84	67.12	2.01
3	Linear SVC	92.28	91.74	84.71	67.89	1.96
0	Logistic Regression	92.12	91.76	86.02	66.65	1.99

Run and evaluate selected models

```
lgr = LogisticRegression(solver='lbfgs')
mnb = MultinomialNB()
xgb = XGBClassifier()
lsvc = LinearSVC(max_iter = 3000)
lgbm = LGBMClassifier()
knc = KNeighborsClassifier()
rfc = RandomForestClassifier()
sgdc = SGDClassifier()
```

```
models = [lgr,mnb,xgb,lsvc,lgbm,knc,rfc,sgdc]
models_name = ['Logistic Regression','Multinomial Naive Bayes',
               'XGB Classifier','Linear SVC','LightGBM Classifier',
               'KNeighbors Classifier','Random Forest Classifier','StochasticGB Classifier']
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size = 0.25, random_state = 42)
```

```
for Logistic Regression model..

Accuracy score for Train : 92.12%
Accuracy score for Test : 91.76%
F1 score for Test : 66.65%
Precision for Test : 86.02%
Hamming Loss : 1.99%


Confusion Matrix:

[[[35791   247]
  [ 1609  2218]]

 [[39424    52]
  [  306    83]]

 [[37593   149]
  [  776  1347]]

 [[39723    15]
  [  113    14]]

 [[37663   270]
  [  922  1010]]

 [[39470    41]
  [  265    89]]]
```

Test Classification report:

	precision	recall	f1-score	support
0	0.90	0.58	0.71	3827
1	0.61	0.21	0.32	389
2	0.90	0.63	0.74	2123
3	0.48	0.11	0.18	127
4	0.79	0.52	0.63	1932
5	0.68	0.25	0.37	354
micro avg	0.86	0.54	0.67	8752
macro avg	0.73	0.39	0.49	8752
weighted avg	0.85	0.54	0.66	8752
samples avg	0.05	0.05	0.05	8752

```
for Multinomial Naive Bayes model..

Accuracy score for Train : 91.55%
Accuracy score for Test : 91.26%
F1 score for Test : 60.47%
Precision for Test : 87.56%
Hamming Loss : 2.21%
```

```
Confusion Matrix:

[[[35914   124]
  [ 1976  1851]]

 [[39401    75]
  [  287   102]]

 [[37618   124]
  [  977  1146]]

 [[39738     0]
  [  127     0]]

 [[37702   231]
  [ 1037   895]]

 [[39491    20]
  [  306    48]]]
```

```
Test Classification report:

              precision    recall  f1-score   support

           0       0.94      0.48      0.64      3827
           1       0.58      0.26      0.36       389
           2       0.90      0.54      0.68      2123
           3       0.00      0.00      0.00       127
           4       0.79      0.46      0.59      1932
           5       0.71      0.14      0.23       354

   micro avg       0.88      0.46      0.60      8752
   macro avg       0.65      0.31      0.41      8752
weighted avg       0.86      0.46      0.60      8752
 samples avg       0.04      0.04      0.04      8752
```

```
for XGB Classifier model..

Accuracy score for Train : 93.54%
Accuracy score for Test : 91.65%
F1 score for Test : 67.12%
Precision for Test : 83.84%
Hamming Loss : 2.01%
```

```
Confusion Matrix:

[[[35748   290]
  [ 1636  2191]]

 [[39391    85]
  [  308    81]]

 [[37557   185]
  [  701  1422]]

 [[39718    20]
  [  106    21]]

 [[37612   321]
  [  852  1080]]

 [[39468    43]
  [  251   103]]]
```

```
Test Classification report:

              precision    recall  f1-score   support

           0       0.88      0.57      0.69      3827
           1       0.49      0.21      0.29       389
           2       0.88      0.67      0.76      2123
           3       0.51      0.17      0.25       127
           4       0.77      0.56      0.65      1932
           5       0.71      0.29      0.41       354

   micro avg       0.84      0.56      0.67      8752
   macro avg       0.71      0.41      0.51      8752
weighted avg       0.83      0.56      0.67      8752
 samples avg       0.05      0.05      0.05      8752
```

```
for Linear SVC model..

Accuracy score for Train : 92.28%
Accuracy score for Test : 91.74%
F1 score for Test : 67.89%
Precision for Test : 84.71%
Hamming Loss : 1.96%

Confusion Matrix:

[[[35728   310]
  [ 1519  2308]]

 [[39439    37]
  [  320    69]]

 [[37571   171]
  [  723  1400]]

 [[39722    16]
  [  100    27]]

 [[37626   307]
  [  872  1060]]

 [[39457    54]
  [  261    93]]]
```

Test Classification report:

	precision	recall	f1-score	support
0	0.88	0.60	0.72	3827
1	0.65	0.18	0.28	389
2	0.89	0.66	0.76	2123
3	0.63	0.21	0.32	127
4	0.78	0.55	0.64	1932
5	0.63	0.26	0.37	354
micro avg	0.85	0.57	0.68	8752
macro avg	0.74	0.41	0.51	8752
weighted avg	0.84	0.57	0.67	8752
samples avg	0.05	0.05	0.05	8752

```
for LightGBM Classifier model..

Accuracy score for Train : 93.10%
Accuracy score for Test : 91.60%
F1 score for Test : 68.20%
Precision for Test : 81.86%
Hamming Loss : 1.99%

Confusion Matrix:

[[[35699   339]
  [ 1573  2254]]

 [[39398    78]
  [  301    88]]

 [[37529   213]
  [  653  1470]]

 [[39699    39]
  [   98    29]]

 [[37516   417]
  [  757  1175]]

 [[39463    48]
  [  254   100]]]
```

Test Classification report:

	precision	recall	f1-score	support
0	0.87	0.59	0.70	3827
1	0.53	0.23	0.32	389
2	0.87	0.69	0.77	2123
3	0.43	0.23	0.30	127
4	0.74	0.61	0.67	1932
5	0.68	0.28	0.40	354
micro avg	0.82	0.58	0.68	8752
macro avg	0.69	0.44	0.53	8752
weighted avg	0.81	0.58	0.68	8752
samples avg	0.05	0.05	0.05	8752

```
for KNeighbors Classifier model..

Accuracy score for Train : 91.27%
Accuracy score for Test : 89.19%
F1 score for Test : 48.65%
Precision for Test : 67.42%
Hamming Loss : 2.94%
```

Confusion Matrix:

```
[[[35241   797]
  [ 2306  1521]]

 [[39360   116]
  [  300    89]]

 [[37480   262]
  [ 1198   925]]

 [[39711    27]
  [  105    22]]

 [[37581   352]
  [ 1218   714]]

 [[39456    55]
  [  295    59]]]
```

Test Classification report:

	precision	recall	f1-score	support
0	0.66	0.40	0.50	3827
1	0.43	0.23	0.30	389
2	0.78	0.44	0.56	2123
3	0.45	0.17	0.25	127
4	0.67	0.37	0.48	1932
5	0.52	0.17	0.25	354
micro avg	0.67	0.38	0.49	8752
macro avg	0.58	0.30	0.39	8752
weighted avg	0.67	0.38	0.48	8752
samples avg	0.03	0.03	0.03	8752

```
for Random Forest Classifier model..

Accuracy score for Train : 99.10%
Accuracy score for Test : 91.29%
F1 score for Test : 67.88%
Precision for Test : 80.18%
Hamming Loss : 2.04%
```

Confusion Matrix:

```
[[[35520   518]
  [ 1446  2381]]

 [[39441    35]
  [  348    41]]

 [[37464   278]
  [  610  1513]]

 [[39727    11]
  [  116    11]]

 [[37532   401]
  [  792  1140]]

 [[39481    30]
  [  289    65]]]
```

Test Classification report:

	precision	recall	f1-score	support
0	0.82	0.62	0.71	3827
1	0.54	0.11	0.18	389
2	0.84	0.71	0.77	2123
3	0.50	0.09	0.15	127
4	0.74	0.59	0.66	1932
5	0.68	0.18	0.29	354
micro avg	0.80	0.59	0.68	8752
macro avg	0.69	0.38	0.46	8752
weighted avg	0.79	0.59	0.66	8752
samples avg	0.06	0.05	0.05	8752

```
for StochasticGB Classifier model..

Accuracy score for Train : 91.67%
Accuracy score for Test : 91.47%
F1 score for Test : 62.85%
Precision for Test : 88.73%
Hamming Loss : 2.10%
```

```
Confusion Matrix:

[[[35891   147]
  [ 1877  1950]]

 [[39476     0]
  [  389     0]]

 [[37615   127]
  [  815  1308]]

 [[39738     0]
  [  127     0]]

 [[37675   258]
  [  967   965]]

 [[39502     9]
  [  318    36]]]
```

```
Test Classification report:

              precision    recall  f1-score   support

           0       0.93      0.51      0.66      3827
           1       0.00      0.00      0.00       389
           2       0.91      0.62      0.74      2123
           3       0.00      0.00      0.00       127
           4       0.79      0.50      0.61      1932
           5       0.80      0.10      0.18       354

   micro avg       0.89      0.49      0.63      8752
   macro avg       0.57      0.29      0.36      8752
weighted avg       0.83      0.49      0.61      8752
 samples avg       0.05      0.04      0.04      8752
```

	models_name	accuracies_train	accuracies_test	precision_scores	f1_scores	hamming_losses
5	KNeighbors Classifier	91.27	89.19	67.42	48.65	2.94
1	Multinomial Naive Bayes	91.55	91.26	87.56	60.47	2.21
6	Random Forest Classifier	99.10	91.29	80.18	67.88	2.04
7	StochasticGB Classifier	91.67	91.47	88.73	62.85	2.10
4	LightGBM Classifier	93.10	91.60	81.86	68.20	1.99
2	XGB Classifier	93.54	91.65	83.84	67.12	2.01
3	Linear SVC	92.28	91.74	84.71	67.89	1.96
0	Logistic Regression	92.12	91.76	86.02	66.65	1.99

We selected ***Logistic Regressor*** for the following reasons:

- Maximum ACCURACY with high Precision value.
- minimum hamming loss.

Key Metrics for success in solving problem under consideration

Following metrics used for evaluation:

```
from sklearn.model_selection import train_test_split,cross_val_score, GridSearchCV

from sklearn.metrics import confusion_matrix,multilabel_confusion_matrix,classification_report,accuracy_score
from sklearn.metrics import roc_auc_score, roc_curve, auc, precision_score,f1_score
from sklearn.metrics import hamming_loss, log_loss
```

Hyperparameter Tuning:

```
param = {'estimator__penalty' : ['l1', 'l2', 'elasticnet', 'none'],
         'estimator__max_iter' : [100, 200, 300, 400],
         'estimator__multi_class' : ['ovr', 'auto']}

lgr_ovr = OneVsRestClassifier(lgr)
lgr_grid = GridSearchCV(lgr_ovr, param, cv=5,verbose = 2)
x_train,x_test,y_train,y_test = train_test_split(X, Y, test_size=0.25, random_state=42)
lgr_grid.fit(x_train,y_train)
lgr_grid.best_params_
```

```
{'estimator__max_iter': 100,
 'estimator__multi_class': 'ovr',
 'estimator__penalty': 'l2'}
```

```
lgr_grid.best_score_
```

```
0.9182658137882018
```

```
lgr_tune = LogisticRegression(solver='lbfgs', max_iter= 100,penalty= 'l2',multi_class= 'ovr')
```

```
lgr_tune_final = OneVsRestClassifier(lgr_tune)
lgr_tune_final.fit(x_train,y_train)
pred_train = lgr_tune_final.predict(x_train)
pred_test = lgr_tune_final.predict(x_test)
print('::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::::')
print(' ')
print(' ')
print('for '+ models_name[0] + ' model..')
print(' ')
print(f"Accuracy score for Train : {accuracy_score(y_train,pred_train) * 100:.2f}%")
# accuracies_train.append(round(accuracy_score(y_train,pred_train)* 100,2))

print(f"Accuracy score for Test : {accuracy_score(y_test,pred_test) * 100:.2f}%")
# accuracies_test.append(round(accuracy_score(y_test,pred_test)* 100,2))

print(f"F1 score for Test : {f1_score(y_test,pred_test,average='micro') * 100:.2f}%")
# f1_scores.append(round(f1_score(y_test,pred_test,average='micro')* 100,2))

print(f"Precision for Test : {precision_score(y_test,pred_test,average='micro') * 100:.2f}%")
# precision_scores.append(round(precision_score(y_test,pred_test,average='micro')* 100,2))

print(f"Hamming Loss : {hamming_loss(y_test,pred_test) * 100:.2f}%")
# hamming_losses.append(round(hamming_loss(y_test,pred_test)* 100,2))

print(' ')
print(' ')
print('Confusion Matrix: ')
print(' ')
print(multilabel_confusion_matrix(y_test, pred_test))
print(' ')
print(' ')
print('Test Classification report: ')
print(' ')
print(classification_report(y_test, pred_test))
```

```
for Logistic Regression model..

Accuracy score for Train : 92.12%
Accuracy score for Test : 91.76%
F1 score for Test : 66.65%
Precision for Test : 86.02%
Hamming Loss : 1.99%
```

```
Confusion Matrix:

[[[35791   247]
  [ 1609  2218]]

 [[39424    52]
  [  306    83]]

 [[37593   149]
  [  776  1347]]

 [[39723    15]
  [  113    14]]

 [[37663   270]
  [  922  1010]]

 [[39470    41]
  [  265    89]]]
```

Test Classification report:

	precision	recall	f1-score	support
0	0.90	0.58	0.71	3827
1	0.61	0.21	0.32	389
2	0.90	0.63	0.74	2123
3	0.48	0.11	0.18	127
4	0.79	0.52	0.63	1932
5	0.68	0.25	0.37	354
micro avg	0.86	0.54	0.67	8752
macro avg	0.73	0.39	0.49	8752
weighted avg	0.85	0.54	0.66	8752
samples avg	0.05	0.05	0.05	8752

Saving & predictions of the model on Test data provided

```
filename='Malignant_commnet_classifier.pkl'
pickle.dump(lgr_tune_final,open(filename,'wb'))
```

```
model =pickle.load(open('Malignant_commnet_classifier.pkl','rb'))
pred =model.predict(fin_test)
pred
```

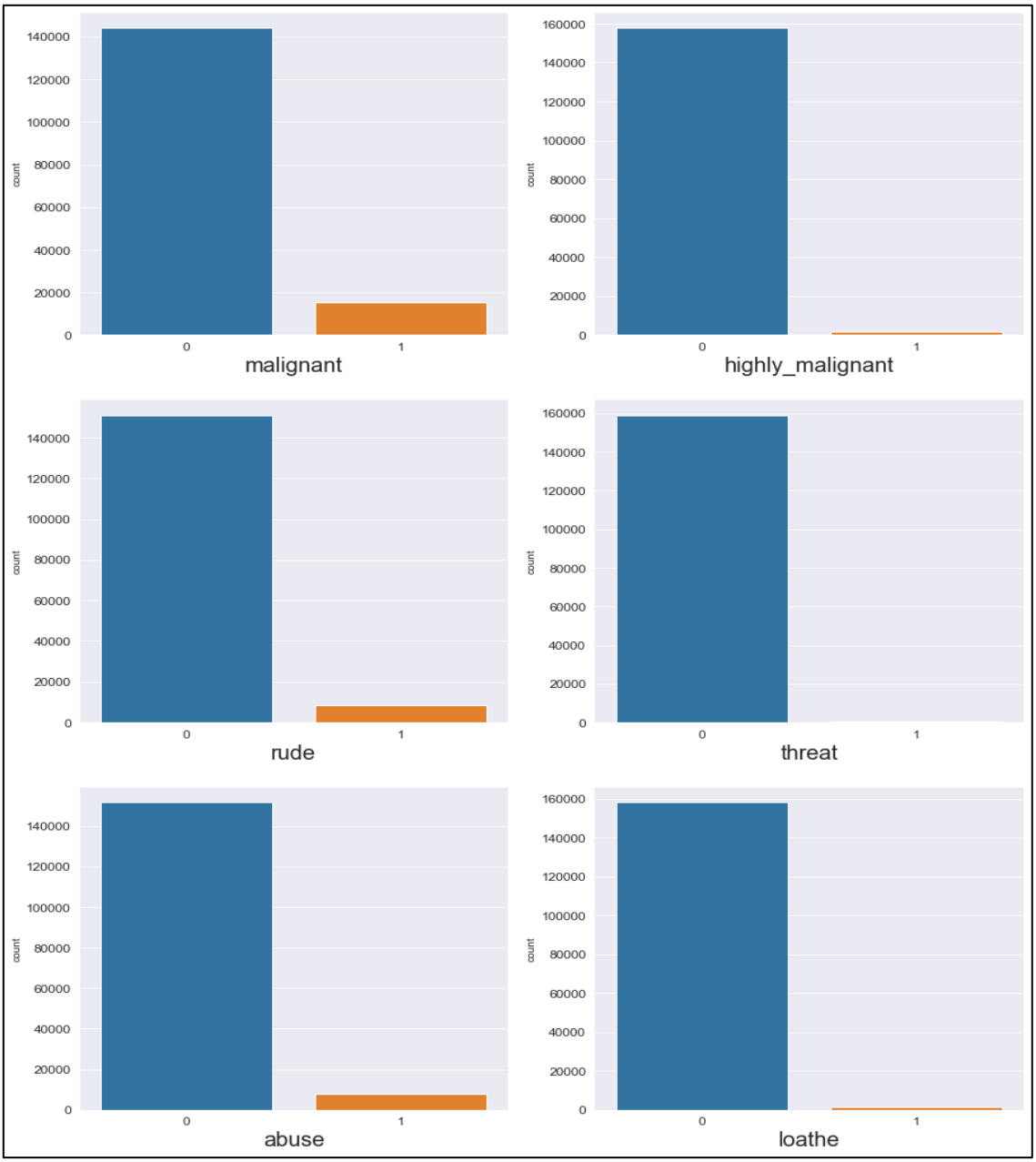
```
array([[0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0],
       ...,
       [0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0]])
```

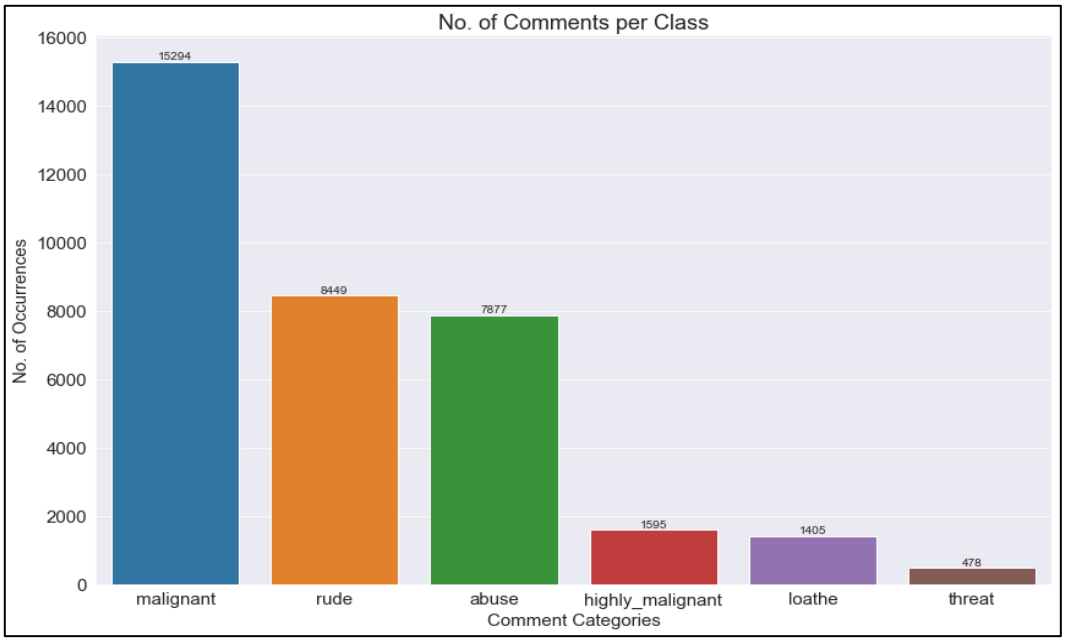
```
test_predictions_cleaned = pd.concat([test2['text_lemmatize'],
                                      pd.DataFrame(pred, columns= ['malignant','highly_malignant','rude',
                                                                   'threat','abuse','loathe'])], axis=1)
```

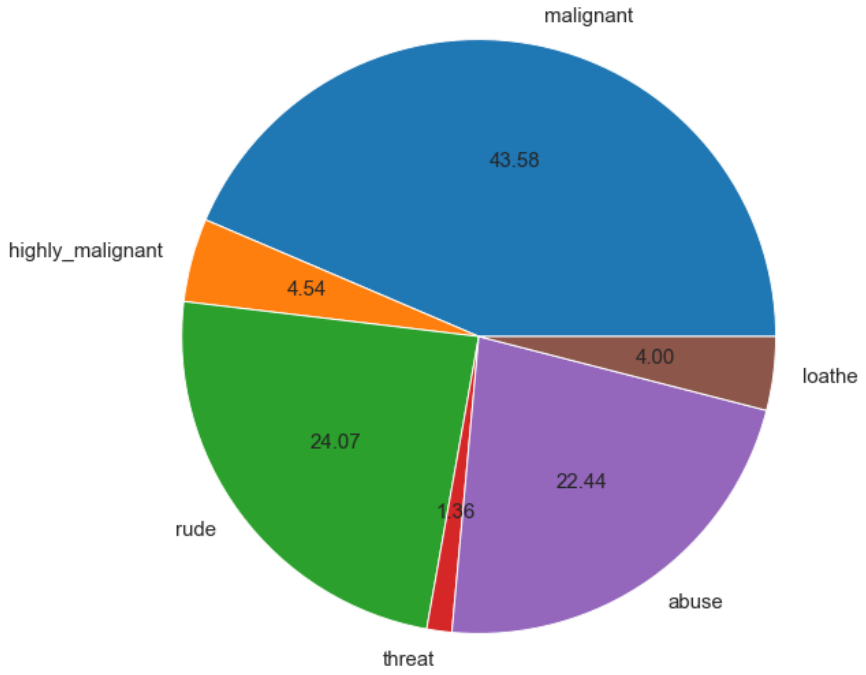
```
test_predictions_cleaned.head(5)
```

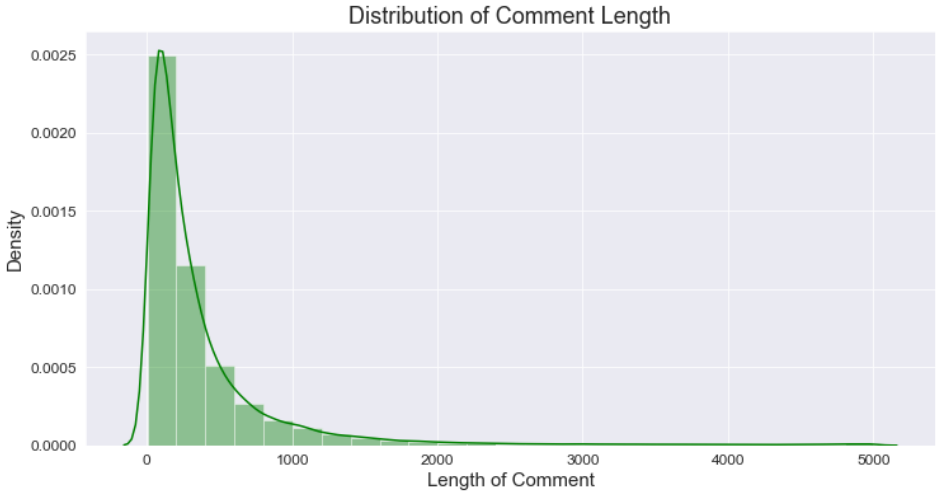
	text_lemmatize	malignant	highly_malignant	rude	threat	abuse	loathe
0	yo bitch ja rule succesful ever whats hating s...	0.0	0.0	0.0	0.0	0.0	0.0
1	rfc title fine imo	0.0	0.0	0.0	0.0	0.0	0.0
2	source zawe ashton lapland	0.0	0.0	0.0	0.0	0.0	0.0
3	look back source information updated correct f...	0.0	0.0	0.0	0.0	0.0	0.0
4	anonymously edit article	0.0	0.0	0.0	0.0	0.0	0.0
5	thank understanding think highly would revert ...	0.0	0.0	0.0	0.0	0.0	0.0
6	please add nonsense wikipedia edits considered...	0.0	0.0	0.0	0.0	0.0	0.0
7	dear god site horrible	0.0	0.0	0.0	0.0	0.0	0.0
8	fool believe number correct number lie ponder ...	0.0	0.0	0.0	0.0	0.0	0.0
9	double redirects fixing double redirects blank...	0.0	0.0	0.0	0.0	0.0	0.0

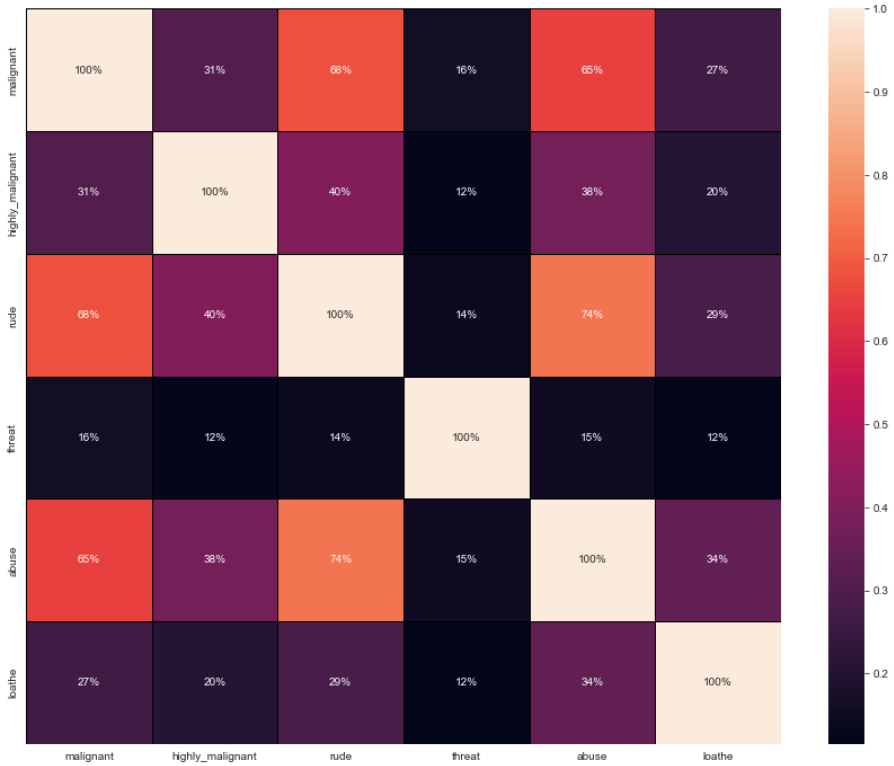
VISUALIZATIONS & EDA

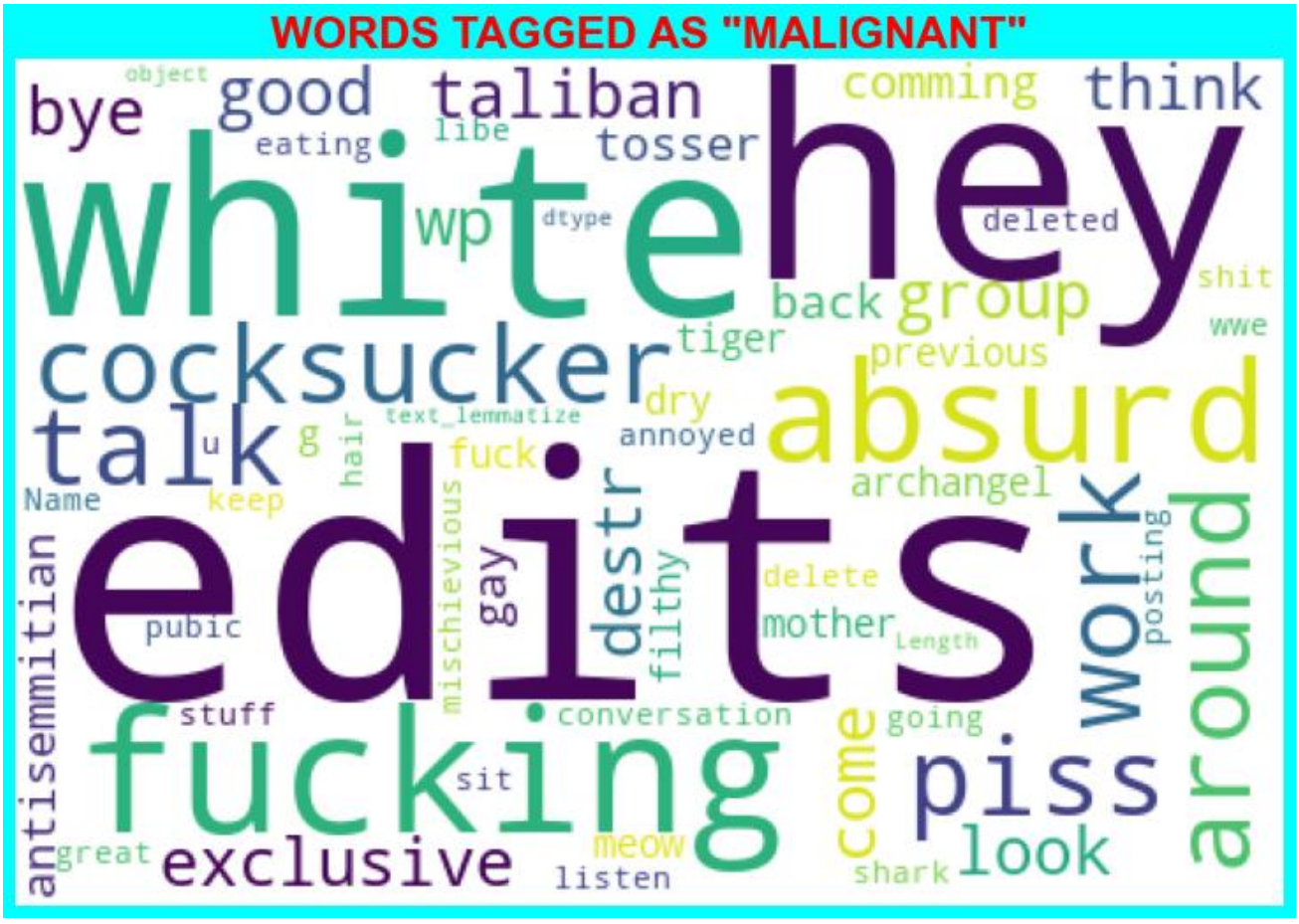





malignant
43.58
highly_malignant
4.54
4.00
loathe
24.07
22.44
1.36
rude
abuse
threat


Distribution of Comment Length
Density
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
0
1000
2000
3000
4000
5000
Length of Comment


malignant
highly_malignant
rude
threat
abuse
loathe
100% 31% 68% 16% 65% 27%
31% 100% 40% 12% 38% 20%
68% 40% 100% 14% 74% 29%
16% 12% 14% 100% 15% 12%
65% 38% 74% 15% 100% 34%
27% 20% 29% 12% 34% 100%
malignant
highly_malignant
rude
threat
abuse
loathe
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2


WORDS TAGGED AS "MALIGNANT"
bye
good
taliban
comming
think
white
hey
eating
libe
tosser
wp
dtype
deleted
shit
back
group
wwe
cocksucker
tiger
previous
talk
dry
absurd
text_lemmatize
annoyed
fuck
archangel
Name
keep
edits
destr
work
around
pubic
gay
filthy
delete
mother
Length
posting
stuff
conversation
going
fucking
piss
sit
come
great
exclusive
meow
look
listen
shark


WORDS TAGGED AS "HIGHLY_MALIGNANT"
crow
antonio
leave
text_lemmatize
fucking
wi
peace
mother
better
hi
stuff
fuckhead
gay
back
shit
jimbo
pathetic
quite
piss
filthy
fuck
cunt
u
frankly
fucker
shalom
semite
wale
know
stop
dirty
rootmyass
blocking
work
deleting
piece
stinking
lol
object
moron
mercado
woman
walter
im
de
son
co
Name
kill
stupid
bitch
stink
feel
cocksucker
good
around
cc
motherfucking
asshole
crap
dtype
never
Length


WORDS TAGGED AS "RUDE"
shit
fucking
white
edits
absurd
piss
mother
around
stuff
cocksuckerantisemmitian
gay
cant
fuckeeed
archangel
meow
asshole
put
naked
filthy
lolwat
tiger
got
posting
libe
conversation
fucked
gg
dry
fuck
peace
work
stupid
Length
great
keep
drink
deleting
stop
obese
shark
Name
previous
deleted
thought
sit
faggot
text_lemmatize
going
object
dtype


WORDS TAGGED AS "THREAT"
die
fuck
bitch
suck
hi
stop
hey
last
think
back
burn
hell
stupid
undoing
sorry
warning
hate
fagget
account
puppet
sock
edits
dance
wife
live
hore
grave
dead
first
time
son
gay
smith
butt
semite
find
oife
death
shalom
getting
go
wi
man
dick
dumb
big
yet
leave
Name
hole
want
fucking
watching
surprise
kill
head
faggot
dtype
Length
text_lemmatize
object
sodomize
please
sincerely
notified
mom
musulmans


WORDS TAGGED AS "ABUSE"
tony
great
eating
wwe
shit
stuff
Name
hey
pubic
tiger
sit
fistfuckee
stupid
meow
arm
peace
dtype
delete
edits
absurd
archangel
filthy
mischievious
deleted
asshole
mother
going
g
hair
dry
u
antisemmitian
piss
Length
keep
obviously
stop
white
around
annoyed
sidaway
object
text_lemmatize
deleting
libe
gay
work
posting
previous
shark
listen
fucking
fuck
cocksucker
conversation
love


WORDS TAGGED AS "LOATHE"
gay
leave
bitch
know
hating
son
nazi
sorry
smelly
Name
p
burn
mum
good
hell
jew
fag
woman
oife
pair
said
racist
antisemmitian
boy
meow
u
hard
fucking
feel
ur
archangel
object
schmuck
beat
nigger
pansy
hate
Length
others
s
tw
fagget
fuck
shit
b
dtype
brith
included
whine
semite
lol
tiger
nai
previous
never
shalom
oh
g
think
kill
white
eating
weiner
wi
conversation
text_lemmatize
libe

Observations from Exploratory Data Analysis:

1. Out of total Negative comments the maximum negative comments come with Malignant in nature followed by rude categories.
2. Around 90% comments are Good/Neutral in nature while rest 10% comments are Negative in nature.
3. Very few comments come with threatening nature.
4. Most of the comments are short with only a few comments longer than 1000 words.
5. Majority of the comments are of length 500, where maximum length is 5000 and minimum is 5.
6. From word cloud, it is clear that negative comments include words like edits, hey,die, bitch, suck, white, crow, absurd, Taliban, fuck/fucking, gay, cocksucker, jew, kill, hate, fagget, piss & shit.

CONCLUSION

Key Findings and Conclusions of the Study

- Most of the comments which are offensive in nature are malignant & these can be classified as having only one label
- Logistic Regressor was best performing model, with accuracy above 90%.

Learning Outcomes of the Study in respect of Data Science

- In this project we learn how to build a machine learning model for classification-based problem.
- The goal of any machine learning problem is to find a single model that will best predict our wanted outcome. Rather than making one model and hoping this model is the best/most accurate predictor we can make, ensemble methods take a myriad of models into account, and average those models to produce one final model.
- So based on all the learning and outcomes our Logistic Regression Model gives the best result so we save this model as our final model for future data/comments predictions.

Limitations of this work and Scope for Future Work

- The Maximum feature used while vectorization is 2000. Employing more feature in vectorization lead to more accurate model which I not able to employed due computational resources.
- Data is imbalanced in nature but due to computational limitation we have not employed balancing techniques here.
- Deep learning CNN, ANN can be employed to create more accurate model.