Malignant-Comments-Classifier

Submitted by:

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ACKNOWLEDGMENT

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I am making this project to increase my knowledge.

INTRODUCTION

Problem Statement:

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.

Objective:

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.

Analytical Problem Framing

Firstly, we will start by importing required libraries and databases.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier, RandomForestClassifier

from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score

from nltk.stem import WordNetLemmatizer
import nltk
from nltk.corpus import  stopwords
import string

import joblib
import warnings
warnings.filterwarnings('ignore')
```

```
train=pd.read_csv(r"C:\Users\SAGAR KADAM\Downloads\Malignant-Comments-Classifier-Project--1-\Malignant Comments Classifier P
train=pd.DataFrame(data=train)
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 is the list of all columns and size of dataset:

```
train.columns
```

```
Index(['id', 'comment_text', 'malignant', 'highly_malignant', 'rude', 'threat',
       'abuse', 'loathe'],
      dtype='object')
```

```
train.shape
```

```
(159571, 8)
```

Let’s check the datatype of all columns:

```
1 train.dtypes
```

```
id                   object
comment_text         object
malignant             int64
highly_malignant      int64
rude                  int64
threat                int64
abuse                 int64
loathe                int64
dtype: object
```

We can see both type of columns numerical and object type.

Then with the help of describe we will take a glimpse of data:

```
1 train.describe(include='all').T
```

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
id	159571	159571	a2ae72dce45c1d4b	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
comment_text	159571	159571	"destroy me"" but will"	1	NaN	NaN	NaN	NaN	NaN	NaN	NaN
malignant	159571	NaN	NaN	NaN	0.0958445	0.294379	0	0	0	0	1
highly_malignant	159571	NaN	NaN	NaN	0.00999555	0.0994771	0	0	0	0	1
rude	159571	NaN	NaN	NaN	0.0529482	0.223931	0	0	0	0	1
threat	159571	NaN	NaN	NaN	0.00299553	0.0546496	0	0	0	0	1
abuse	159571	NaN	NaN	NaN	0.0493636	0.216627	0	0	0	0	1
loathe	159571	NaN	NaN	NaN	0.00880486	0.0934205	0	0	0	0	1

We can see in feature Id and comment_text all values are unique. Andd for all other features named malignant, highly_malignant, rude, threat, abuse and loathe we can see only 2 unique values 0 and 1 hence we getting 0 as min and 1 as max for these features.

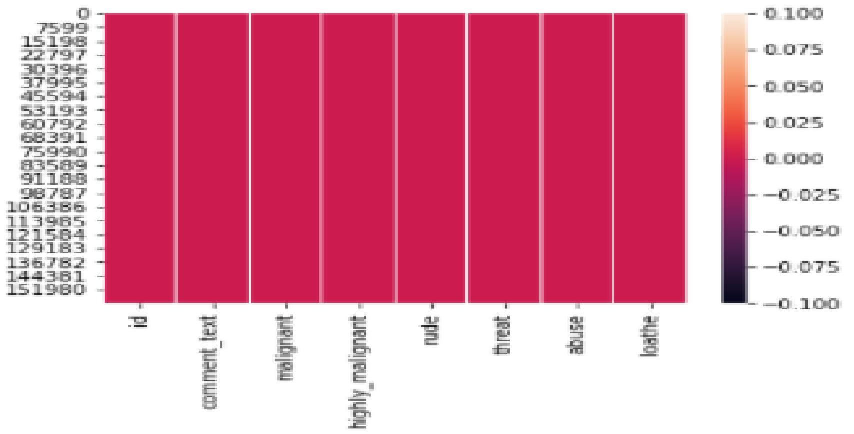
We can see count is all same for all variable, let's check for null values now:

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

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

```
1 #visual reprentation with the help of heatmap
2 sns.heatmap(train.isnull())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d91126c6d0>
```

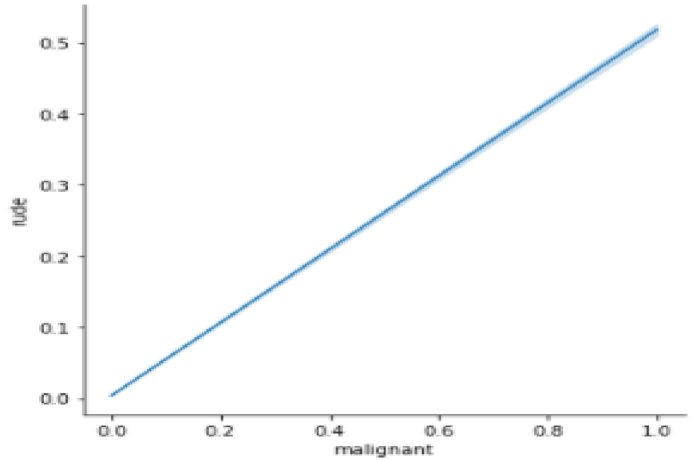


We can see id feature also has all uninque values like serial number hence we dont require feature for future analysis

```
train.drop('id', axis=1, inplace= True)
```

```
1 sns.relplot(x='malignant',y='rude',data=train,kind='line')
```

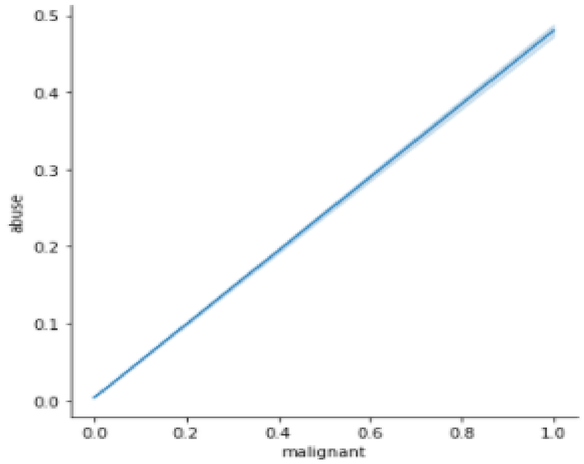
```
<seaborn.axisgrid.FacetGrid at 0x1d9112b16d0>
```



We can see positive relation in features malignant and rude.

```
1 sns.relplot(x='malignant',y='abuse',data=train,kind='line')
```

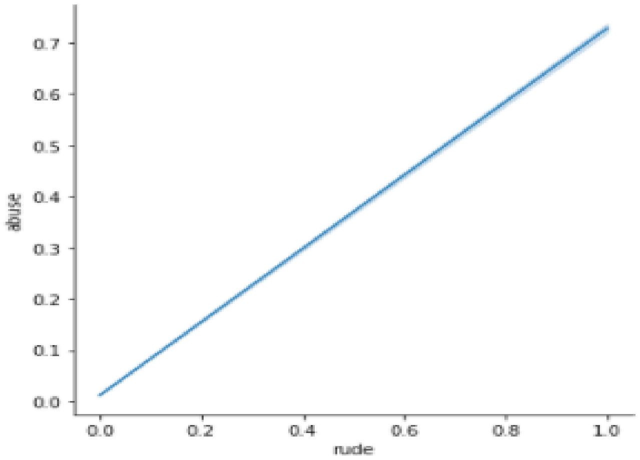
```
<seaborn.axisgrid.FacetGrid at 0x1d9116a5220>
```



We can see positive relation in features malignant and abuse.

```
sns.relplot(x='rude',y='abuse',data=train,kind='line')
```

```
<seaborn.axisgrid.FacetGrid at 0x1d917354940>
```

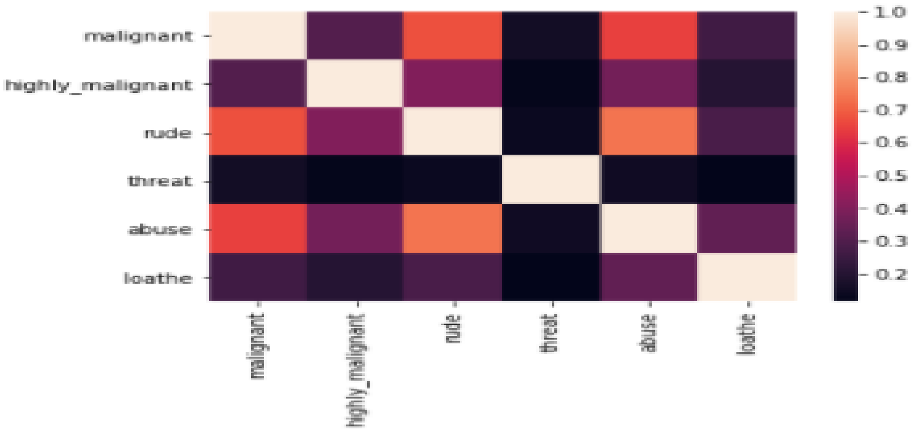


We can see positive relation in features rude and abuse.

Checking correlation in dataset:

```
print(train.corr())
print(sns.heatmap(train.corr()))
```

```
                   malignant  highly_malignant      rude    threat     abuse  \
malignant           1.000000          0.308619  0.676515  0.157058  0.647518
highly_malignant    0.308619          1.000000  0.403014  0.123601  0.375807
rude                0.676515          0.403014  1.000000  0.141179  0.741272
threat              0.157058          0.123601  0.141179  1.000000  0.150022
abuse               0.647518          0.375807  0.741272  0.150022  1.000000
loathe              0.266009          0.201600  0.286867  0.115128  0.337736

                    loathe
malignant         0.266009
highly_malignant  0.201600
rude              0.286867
threat            0.115128
abuse             0.337736
loathe            1.000000
AxesSubplot(0.125,0.125;0.62x0.755)
```



In the above representation we can see dark or purple color which says low positive relationship of features and where we have orange going towards white is symbol of good positive relationship.

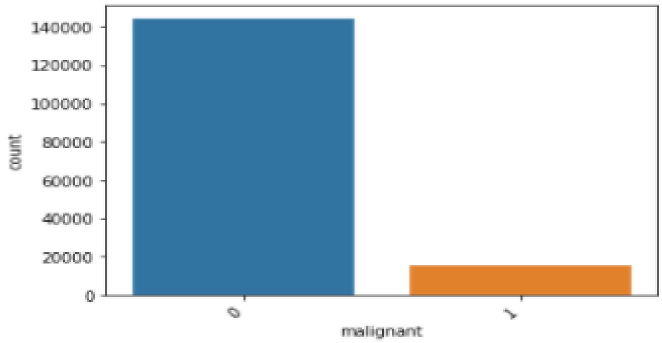
```
cat_col=[]
for i in train:
    if train[i].nunique() <= 2:
        cat_col.append(i)

print(cat_col)
```

```
['malignant', 'highly_malignant', 'rude', 'threat', 'abuse', 'loathe']
```

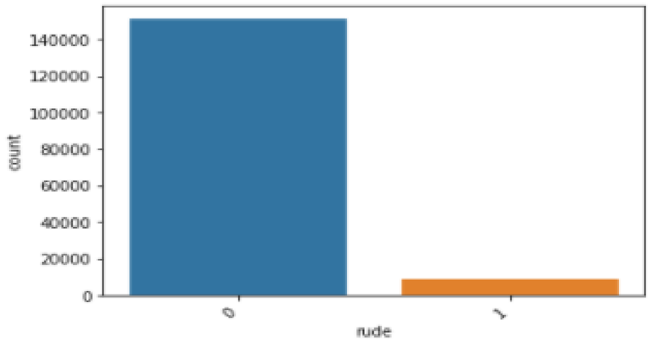
Though all the above features is on numeric type but it has only unique values in it. 0 represents 'No' and 1 represents 'Yes'.

```python
for i in cat_col:
    plt.figure()
    a=sns.countplot(train[i])
    print(train[i].value_counts())
    a.set_xticklabels(a.get_xticklabels(), rotation=40, ha="right")
    plt.show()
```

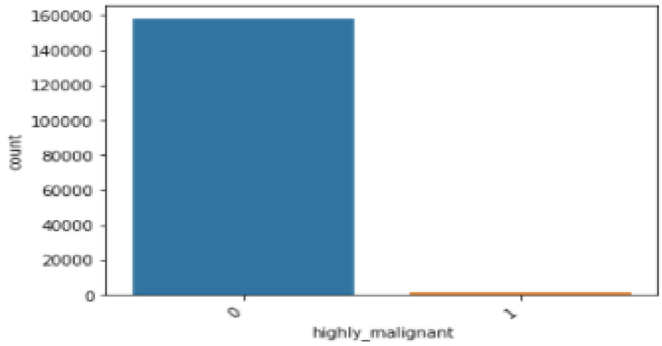
```
0    144277
1     15294
Name: malignant, dtype: int64
```



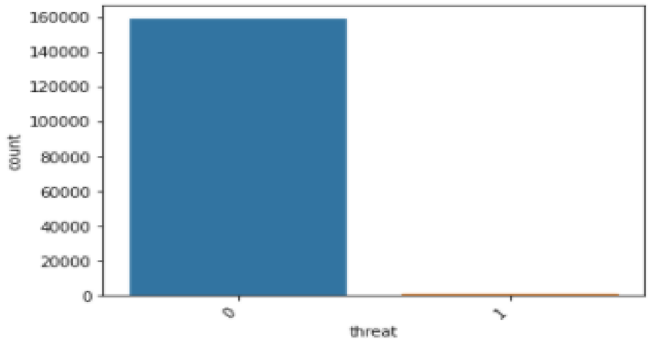

```
0    151122
1      8449
Name: rude, dtype: int64
```



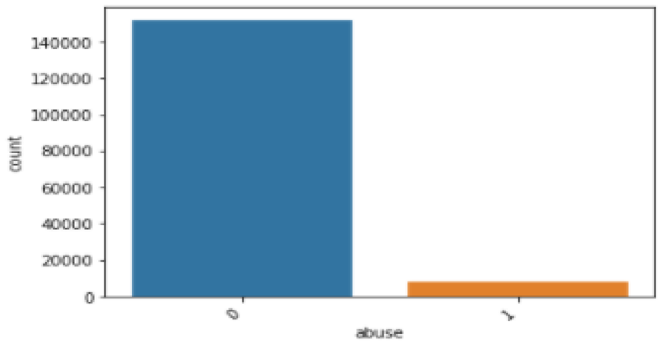

```
0    157976
1      1595
Name: highly_malignant, dtype: int64
```



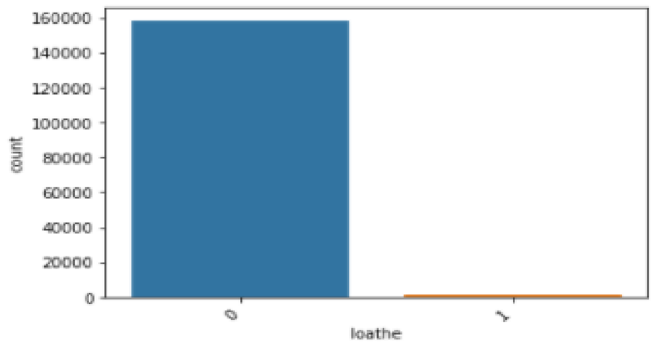

```
0    159093
1       478
Name: threat, dtype: int64
```




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




```
0    158166
1      1405
Name: loathe, dtype: int64
```

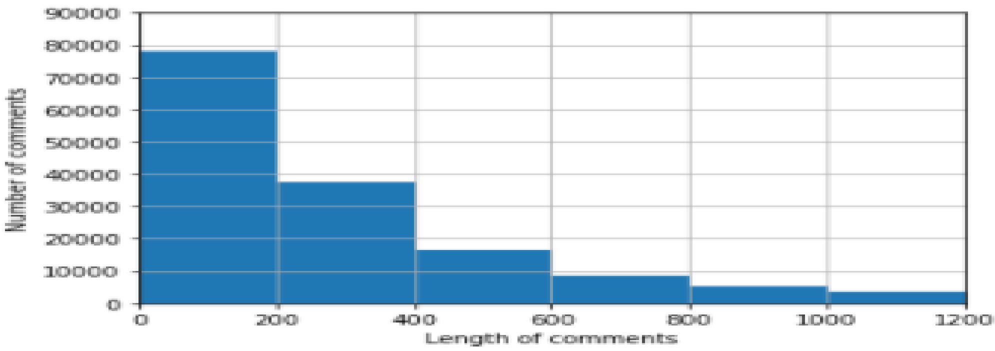


Below are the observations we can find from the above graph:

1. For feature malignant, we have 0 value 144277 times and 1 for 15294 times.
2. For feature highly_malignant, we have 0 value 157976 times and 1 for 1595 times.
3. For feature rude, we have 0 value 151122 times and 1 for 8449 times.
4. For feature threat, we have 0 value 159093 times and 1 for 478 times.
5. For feature abuse, we have 0 value 151694 times and 1 for 7877 times.
6. For feature loathe, we have 0 value 158166 times and 1 for 1405 times.

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

print('average length of comment: {:.3f}'.format(sum(x)/len(x)) )
bins = [1,200,400,600,800,1000,1200]
plt.hist(x, bins=bins)
plt.xlabel('Length of comments')
plt.ylabel('Number of comments')
plt.axis([0, 1200, 0, 90000])
plt.grid(True)
plt.show()
```

```
average length of comment: 394.139
```



Above graph shows us the length of comments vs the number of comments. Maximum comments are with length 200 and very less comments are with length 1200.

```python
train['length'] = train['comment_text'].str.len()
train.head(2)
```

	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

Added a new feature where we can see length of the particular comment.

```python
# Convert all messages to lower case
train['comment_text'] = train['comment_text'].str.lower()

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

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

# Replace money symbols with 'moneysymb' (£ can by typed with ALT key + 156)
train['comment_text'] = train['comment_text'].str.replace(r'£|\$', 'dollers')

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


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

# Remove punctuations
train['comment_text'] = train['comment_text'].apply(lambda x: ' '.join(
    term for term in x.split() if term not in string.punctuation))

# Remove 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))

# Lemmetize words
lem=WordNetLemmatizer()
train['comment_text'] = train['comment_text'].apply(lambda x: ' '.join(
 lem.lemmatize(t) for t in x.split()))
```

After cleaning the comment text, let’s have a look at comment length now.

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

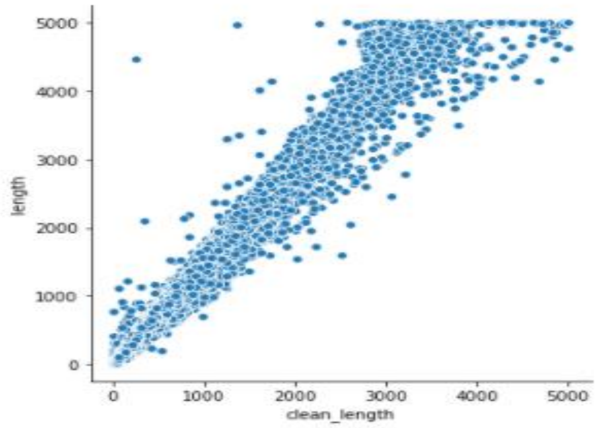
	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe	length	clean_length
0	explanation edits made username hardcore metal...	0	0	0	0	0	0	264	180
1	d'aww! match background colour i'm seemingly s...	0	0	0	0	0	0	112	111
2	hey man, i'm really trying edit war. guy const...	0	0	0	0	0	0	233	149
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

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

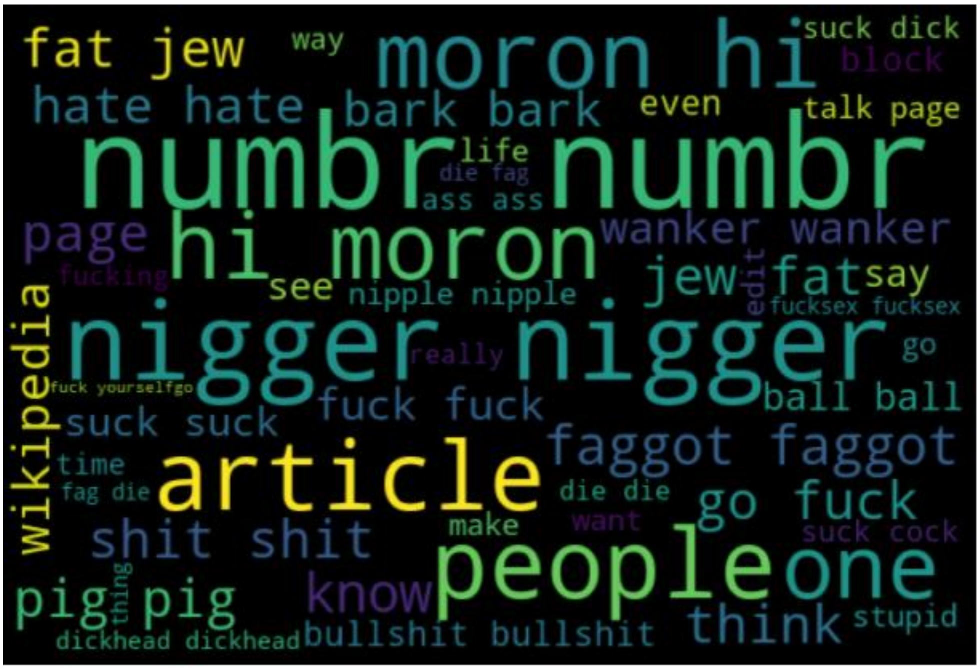
```
Origian Length 62893130
Clean Length 43575187
```

```
sns.relplot(x='clean_length',y='length',data=train,kind='scatter')
```

```
<seaborn.axisgrid.FacetGrid at 0x1d919ec3b50>
```




```
#Getting sense of Loud words which are malignant
from wordcloud import WordCloud
hams = train['comment_text'][train['malignant']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

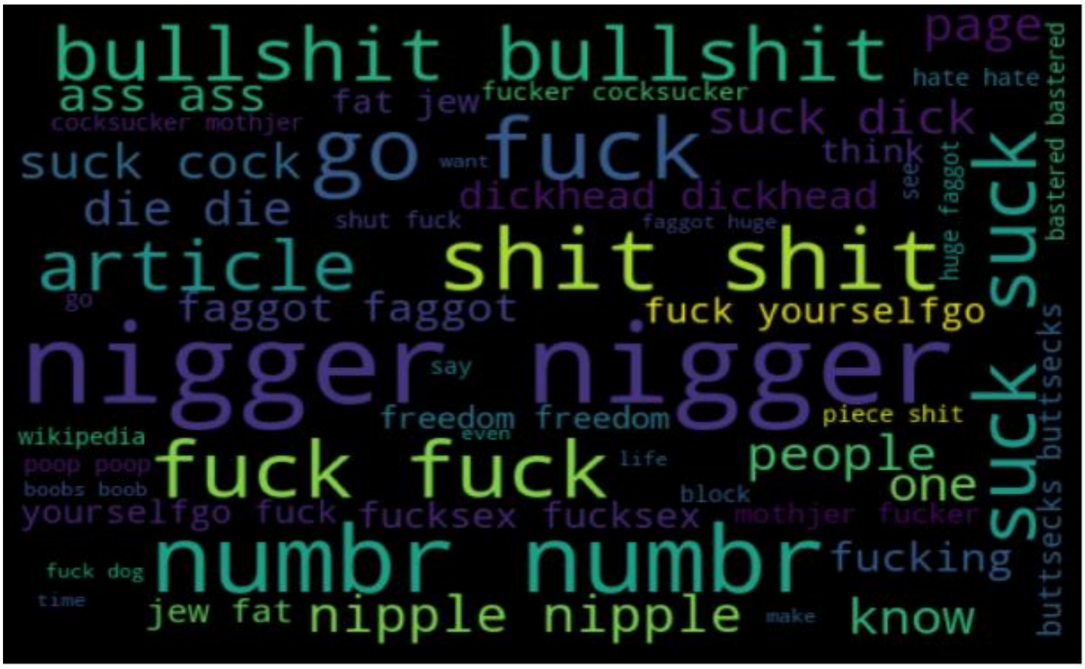


With respect to malignant feature the loud words are article, hi moron, moron hi, numbr, people and nigger.

```
#Getting sense of loud words which are highly_malignant
from wordcloud import WordCloud
hams = train['comment_text'][train['highly_malignant']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

With respect to highly_malignant feature the loud words are fuck, shit, suck, go fuck etc.

```
#Getting sense of loud words which are rude
from wordcloud import WordCloud
hams = train['comment_text'][train['rude']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



With respect to rude feature the loud words are nigger, suck, people, fuck, bullshit, shit and numbr.

```python
#Getting sense of loud words which are threat
from wordcloud import WordCloud
hams = train['comment_text'][train['threat']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

With respect to threat feature the loud words are ass, kill, must die, jim wale, block, die die.

```python
#Getting sense of loud words which are abuse
from wordcloud import WordCloud
hams = train['comment_text'][train['abuse']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

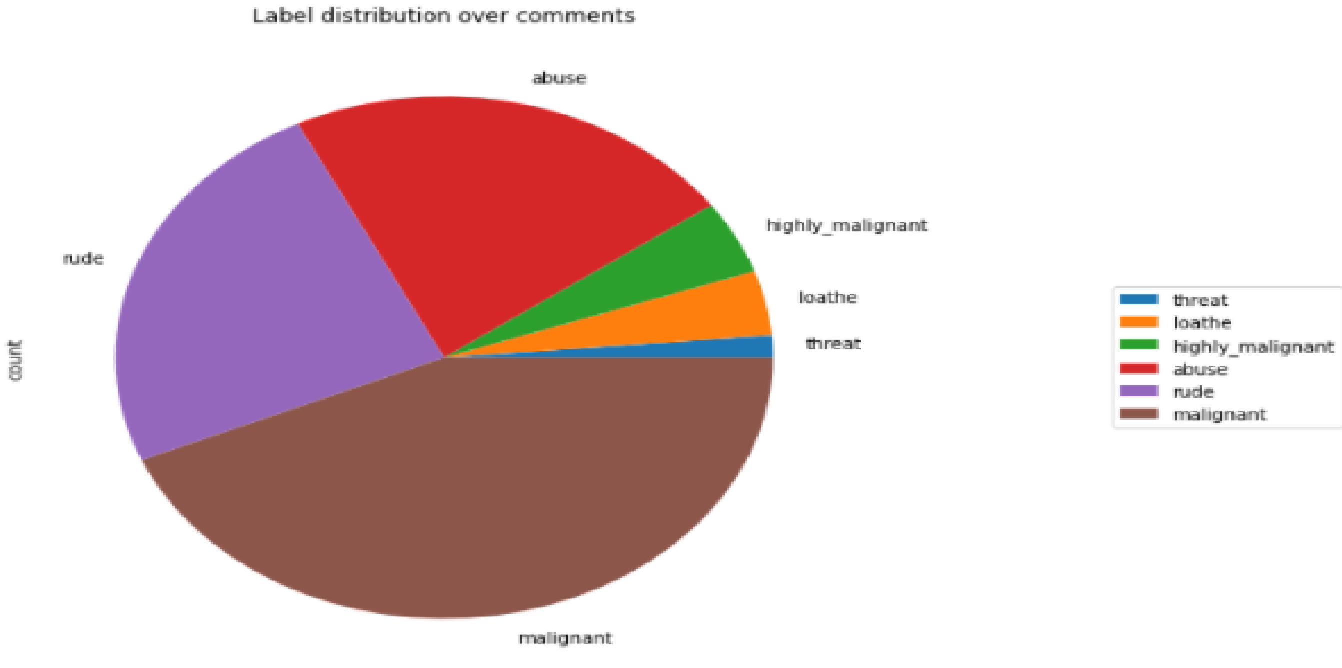
With respect to abuse feature the loud words are mororn hi, fat jew, hi mororn, nigger, faggot.

```python
#Getting sense of Loud words which are Loathe
from wordcloud import WordCloud
hams = train['comment_text'][train['loathe']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```

With respect to loathe feature the loud words are nigger, fat jew, die die, jew fat.

```python
cols_target = ['malignant','highly_malignant','rude','threat','abuse','loathe']
df_distribution = train[cols_target].sum()\
                            .to_frame()\
                            .rename(columns={0: 'count'})\
                            .sort_values('count')

df_distribution.plot.pie(y='count',
                                      title='Label distribution over comments',
                                      figsize=(8, 8))\
                            .legend(loc='center left', bbox_to_anchor=(1.3, 0.5))
```

```
<matplotlib.legend.Legend at 0x1d9112e80d0>
```



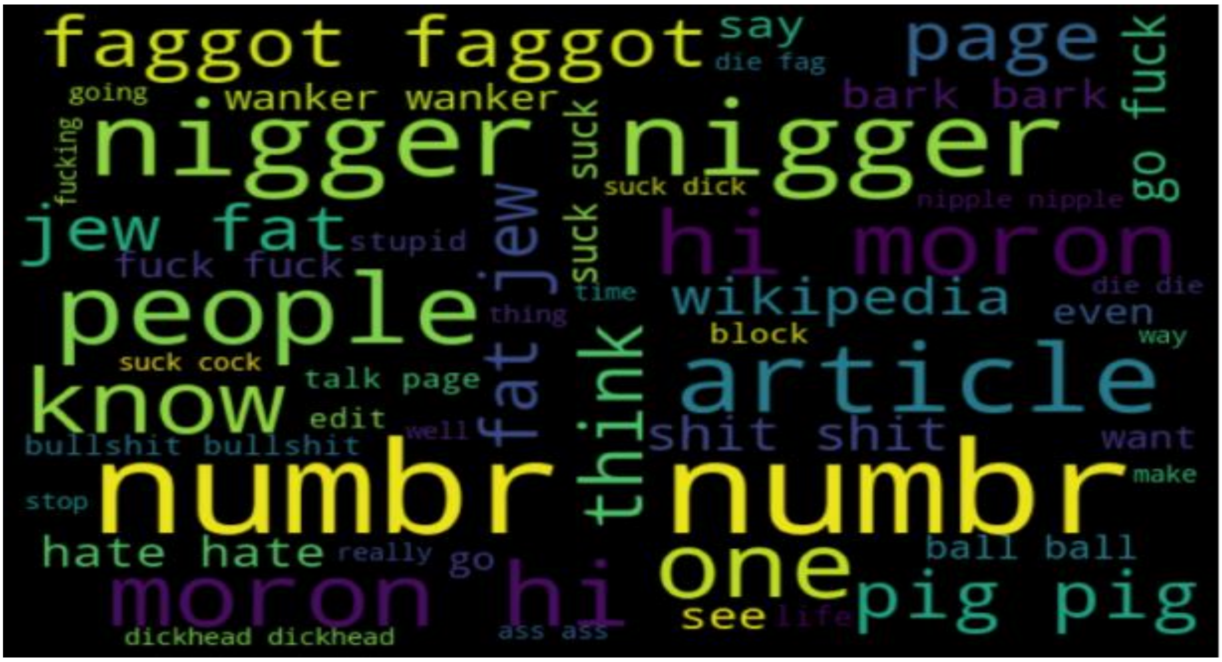
In the above pie chart, we can see very high number for malignant then rude and abuse are almost with same numbers. Then highly_malignant and loathe are almost with same numbers. Lastly, we can see very less numbers for feature threat.

```
target_data = train[cols_target]

train['bad'] =train[cols_target].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
```

I have created a new feature name bad and it is the combination of features malignant, highly_malignant, rude, threat, abuse, loathe where the where value is 1.

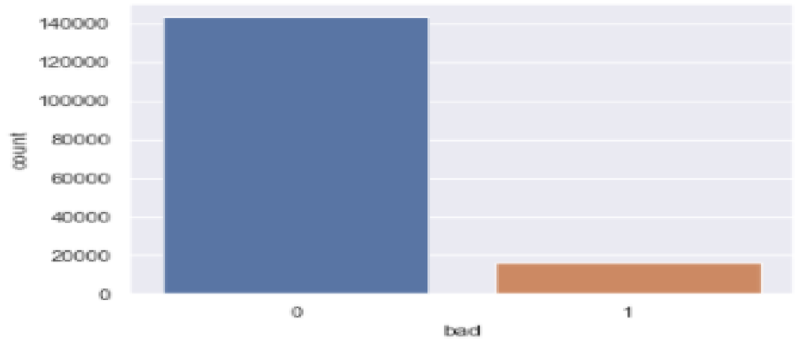
```
#Getting sense of loud words which are loathe
from wordcloud import WordCloud
hams = train['comment_text'][train['bad']==1]
spam_cloud = WordCloud(width=600,height=400,background_color='black',max_words=50).generate(' '.join(hams))
plt.figure(figsize=(10,8),facecolor='k')
plt.imshow(spam_cloud)
plt.axis('off')
plt.tight_layout(pad=0)
plt.show()
```



Now with respect to bad feature the loud words are nigger, numbr, artivle, peoplr, hi moron one.

```
sns.set()
print(train['bad'].value_counts())
sns.countplot(x="bad" , data = train)
plt.show()
```

```
0    143346
1     16225
Name: bad, dtype: int64
```



We can see value count of target column is not same. We will work on this now.

Let's use TFidf method to transform data into vectors:

```
#  Convert text into vectors using TF-IDF
from sklearn.feature_extraction.text import TfidfVectorizer
tf_vec = TfidfVectorizer(max_features = 30000, stop_words='english')
features = tf_vec.fit_transform(train['comment_text'])
x = features
```

```
train.shape
```

```
(159571, 10)
```

```
y=train['bad']
```

```
print(x.shape,y.shape)
```

```
(159571, 30000) (159571,)
```

We will use under sampling method to balance the target column value counts:

```
from imblearn import under_sampling
from collections import Counter
```

```
from imblearn.under_sampling import RandomUnderSampler

rus=RandomUnderSampler(random_state=0)
x_resample,y_resampled=rus.fit_resample(x,y)
print(sorted(Counter(y_resampled)),y_resampled.shape)
```

```
[0, 1] (32450,)
```

```
y_resampled.value_counts()
```

```
1    16225
0    16225
Name: bad, dtype: int64
```

```
x_resample.shape, y_resampled.shape
```

```
((32450, 30000), (32450,))
```

```
x=x_resample
y=y_resampled
```

Let's split data into train and test set:

```
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=56,test_size=.30)
```

```
x_train.shape,x_test.shape, y_train.shape,y_test.shape
```

```
((22715, 30000), (9735, 30000), (22715,), (9735,))
```

Model/s Development and Evaluation

Finding best random state:

```
maxAccu=0
maxRS=0
for i in range(1,200):
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.20,random_state=i)
    LR=LogisticRegression()
    LR.fit(x_train,y_train)
    pred=LR.predict(x_test)
    acc=accuracy_score(y_test,pred)
    if acc>maxAccu:
        maxAccu=acc
        maxRS=i
print("Best accuracy is ",maxAccu, " on Random State ",maxRS)
```

```
Best accuracy is  0.9061633281972264  on Random State  55
```

```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.20,random_state=maxRS)
```

```
model=[LogisticRegression(),DecisionTreeClassifier(),KNeighborsClassifier(),AdaBoostClassifier(),RandomForestClassifier()]

for m in model:
    m.fit(x_train,y_train)
    #m.score(x_train,y_train)
    pred=m.predict(x_test)
    acc=accuracy_score(y_test,pred)
    print('Accuracy Score of',m,'is:', acc)
    print(confusion_matrix(y_test,pred))
    print(classification_report(y_test,pred))
    print('\n')
```

```
Accuracy Score of LogisticRegression() is: 0.9061633281972264
[[3107  205]
 [ 404 2774]]
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      3312
           1       0.93      0.87      0.90      3178

    accuracy                           0.91      6490
   macro avg       0.91      0.91      0.91      6490
weighted avg       0.91      0.91      0.91      6490
```

```
Accuracy Score of KNeighborsClassifier() is: 0.6063174114021571
[[1964 1348]
 [1207 1971]]
              precision    recall  f1-score   support

           0       0.62      0.59      0.61      3312
           1       0.59      0.62      0.61      3178

    accuracy                           0.61      6490
   macro avg       0.61      0.61      0.61      6490
weighted avg       0.61      0.61      0.61      6490
```

```
Accuracy Score of DecisionTreeClassifier() is: 0.8469953775038521
[[2835  477]
 [ 516 2662]]
              precision    recall  f1-score   support

           0       0.85      0.86      0.85      3312
           1       0.85      0.84      0.84      3178

    accuracy                           0.85      6490
   macro avg       0.85      0.85      0.85      6490
weighted avg       0.85      0.85      0.85      6490
```

```
Accuracy Score of AdaBoostClassifier() is: 0.8305084745762712
[[3174  138]
 [ 962 2216]]
              precision    recall  f1-score   support

           0       0.77      0.96      0.85      3312
           1       0.94      0.70      0.80      3178

    accuracy                           0.83      6490
   macro avg       0.85      0.83      0.83      6490
weighted avg       0.85      0.83      0.83      6490
```

```
Accuracy Score of RandomForestClassifier() is: 0.8790446841294299
[[3084  228]
 [ 557 2621]]
              precision    recall  f1-score   support

           0       0.85      0.93      0.89      3312
           1       0.92      0.82      0.87      3178

    accuracy                           0.88      6490
   macro avg       0.88      0.88      0.88      6490
weighted avg       0.88      0.88      0.88      6490
```

- Accuracy for LogisticRegression model is 90.62%
- Accuracy for DecisionTreeClassifier model is 84.70%
- Accuracy for SVC model is 60.63%
- Accuracy for AdaBoostClassifier is 83.05%
- Accuracy for RandomForestClassifier is 87.90%

Hyper parameter tunning:

```
from sklearn.model_selection import RandomizedSearchCV
#creating  parameter list to pass in RandomizedSearchCV
```

1. LogisticRegression:

```
#LogisticRegression parameters
parameters1={'penalty':['l2','l1','elasticnet', 'none'], 'dual':[True,False],'tol':[0.0001],'C':[1.0],
            'fit_intercept':[True,False],'intercept_scaling':[1], 'class_weight':[None], 'random_state':range(0,20),
            'solver':['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'], 'max_iter':[100],
            'multi_class':['auto', 'ovr', 'multinomial'], 'verbose':[0],'warm_start':[True,False],
            'n_jobs':[None], 'l1_ratio':[None]}
```

```
RSV1=RandomizedSearchCV(LogisticRegression(),parameters1,cv=5)
```

```
RSV1.fit(x_train,y_train)
```

```
RandomizedSearchCV(cv=5, estimator=LogisticRegression(),
                   param_distributions={'C': [1.0], 'class_weight': [None],
                                        'dual': [True, False],
                                        'fit_intercept': [True, False],
                                        'intercept_scaling': [1],
                                        'l1_ratio': [None], 'max_iter': [100],
                                        'multi_class': ['auto', 'ovr',
                                                        'multinomial'],
                                        'n_jobs': [None],
                                        'penalty': ['l2', 'l1', 'elasticnet',
                                                    'none'],
                                        'random_state': range(0, 20),
                                        'solver': ['newton-cg', 'lbfgs',
                                                   'liblinear', 'sag', 'saga'],
                                        'tol': [0.0001], 'verbose': [0],
                                        'warm_start': [True, False]})
```

```
RSV1.best_params_
```

```
{'warm_start': False,
 'verbose': 0,
 'tol': 0.0001,
 'solver': 'lbfgs',
 'random_state': 11,
 'penalty': 'l2',
 'n_jobs': None,
 'multi_class': 'multinomial',
 'max_iter': 100,
 'l1_ratio': None,
 'intercept_scaling': 1,
 'fit_intercept': False,
 'dual': False,
 'class_weight': None,
 'C': 1.0}
```

```
RSV_pred1=RSV1.best_estimator_.predict(x_test)
```

```
RSV_pred1
```

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

```
score1=RSV1.score(x_train,y_train)
```

2. DecisionTreeClassifier

```
#DecisionTreeClassifier parameters
parameters2={'criterion':["gini", "entropy"],'splitter':["best", "random"],
             'max_depth':[None],'random_state':range(0,20),
             'max_leaf_nodes':[None],'class_weight':[None], 'min_samples_split':[1,2,3],
             'min_samples_leaf':[1,2,3],'max_features':[None],'min_impurity_decrease':[0.0,1.0,2.0],
             'min_weight_fraction_leaf':[0.0,1.0,2.0]}
```

```
RSV2=RandomizedSearchCV(DecisionTreeClassifier(),parameters2,cv=5)
```

```
RSV2.fit(x_train,y_train)
```

```
RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(),
                   param_distributions={'class_weight': [None],
                                        'criterion': ['gini', 'entropy'],
                                        'max_depth': [None],
                                        'max_features': [None],
                                        'max_leaf_nodes': [None],
                                        'min_impurity_decrease': [0.0, 1.0,
                                                                  2.0],
                                        'min_samples_leaf': [1, 2, 3],
                                        'min_samples_split': [1, 2, 3],
                                        'min_weight_fraction_leaf': [0.0, 1.0,
                                                                     2.0],
                                        'random_state': range(0, 20),
                                        'splitter': ['best', 'random']})
```

```
RSV2.best_params_
```

```
{'splitter': 'random',
 'random_state': 2,
 'min_weight_fraction_leaf': 0.0,
 'min_samples_split': 3,
 'min_samples_leaf': 2,
 'min_impurity_decrease': 0.0,
 'max_leaf_nodes': None,
 'max_features': None,
 'max_depth': None,
 'criterion': 'gini',
 'class_weight': None}
```

```
RSV_pred2=RSV2.best_estimator_.predict(x_test)
```

```
RSV_pred2
```

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

```
score2=RSV2.score(x_train,y_train)
```

3. KNeighborsClassifier

```
#KNeighborsClassifier parameters
parameters3={'n_neighbors':[4,5,6],'weights':['uniform','distance'],'algorithm':['auto','ball_tree','kd_tree','brute'],
             'n_jobs':range(0,20)}

```

```
RSV3=RandomizedSearchCV(KNeighborsClassifier(),parameters3,cv=5)
```

```
RSV3.fit(x_train,y_train)
```

```
RandomizedSearchCV(cv=5, estimator=KNeighborsClassifier(),
                   param_distributions={'algorithm': ['auto', 'ball_tree',
                                                      'kd_tree', 'brute'],
                                        'n_jobs': range(0, 20),
                                        'n_neighbors': [4, 5, 6],
                                        'weights': ['uniform', 'distance']})
```

```
RSV3.best_params_
```

```
{'weights': 'distance', 'n_neighbors': 4, 'n_jobs': 18, 'algorithm': 'kd_tree'}
```

```
RSV_pred3=RSV3.best_estimator_.predict(x_test)
```

```
RSV_pred3
```

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

```
score3=RSV3.score(x_train,y_train)
```

4. AdaBoostClassifier

```
parameters4={'base_estimator':[None],'n_estimators':[20,40, 50,75,100],
            'learning_rate':[0.1,0.01,1.0,2.0],'algorithm':['SAMME.R','SAMME'],
            'random_state':range(0,20)}
```

```
RSV4=RandomizedSearchCV(AdaBoostClassifier(),parameters4,cv=5)
```

```
RSV4.fit(x_train,y_train)
```

```
RandomizedSearchCV(cv=5, estimator=AdaBoostClassifier(),
                   param_distributions={'algorithm': ['SAMME.R', 'SAMME'],
                                        'base_estimator': [None],
                                        'learning_rate': [0.1, 0.01, 1.0, 2.0],
                                        'n_estimators': [20, 40, 50, 75, 100],
                                        'random_state': range(0, 20)})
```

```
RSV4.best_params_
```

```
{'random_state': 10,
 'n_estimators': 20,
 'learning_rate': 1.0,
 'base_estimator': None,
 'algorithm': 'SAMME.R'}
```

```
RSV_pred4=RSV4.best_estimator_.predict(x_test)
```

```
RSV_pred4
```

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

```
score4=RSV4.score(x_train,y_train)
```

5. RandomForestClassifier

```
parameters5={'n_estimators':[100],'criterion':['gini','entropy'],'max_depth':[None],
            'min_samples_split':[2],'min_samples_leaf':[1],'min_weight_fraction_leaf':[0.0],
            'max_features':['auto'],'max_leaf_nodes':[None],'min_impurity_decrease':[0.0],
            'min_impurity_split':[None],'bootstrap':[True,False],'oob_score':[True,False],'n_jobs':[None],
            'random_state':range(0,20),'verbose':[0],'warm_start':[True,False],'class_weight':[None],
            'ccp_alpha':[0.0],'max_samples':[None]}
```

```
RSV5=RandomizedSearchCV(RandomForestClassifier(),parameters5,cv=5)
```

```
RSV5.fit(x_train,y_train)
```

```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(),
                   param_distributions={'bootstrap': [True, False],
                                        'ccp_alpha': [0.0],
                                        'class_weight': [None],
                                        'criterion': ['gini', 'entropy'],
                                        'max_depth': [None],
                                        'max_features': ['auto'],
                                        'max_leaf_nodes': [None],
                                        'max_samples': [None],
                                        'min_impurity_decrease': [0.0],
                                        'min_impurity_split': [None],
                                        'min_samples_leaf': [1],
                                        'min_samples_split': [2],
                                        'min_weight_fraction_leaf': [0.0],
                                        'n_estimators': [100], 'n_jobs': [None],
                                        'oob_score': [True, False],
                                        'random_state': range(0, 20),
                                        'verbose': [0],
                                        'warm_start': [True, False]})
```

```
RSV5.best_params_
```

```
{'warm_start': True,
 'verbose': 0,
 'random_state': 6,
 'oob_score': False,
 'n_jobs': None,
 'n_estimators': 100,
 'min_weight_fraction_leaf': 0.0,
 'min_samples_split': 2,
 'min_samples_leaf': 1,
 'min_impurity_split': None,
 'min_impurity_decrease': 0.0,
 'max_samples': None,
 'max_leaf_nodes': None,
 'max_features': 'auto',
 'max_depth': None,
 'criterion': 'entropy',
 'class_weight': None,
 'ccp_alpha': 0.0,
 'bootstrap': False}
```

```
RSV_pred5=RSV5.best_estimator_.predict(x_test)
```

```
RSV_pred5
```

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

```
score5=RSV5.score(x_train,y_train)
```

```
print("Accuracy for LogisticRegression is ",score1*100,"%\n")
print("Accuracy for DecisionTreeClassifier is ",score2*100,"%\n")
print("Accuracy for KNeighborsClassifier is ",score3*100,"%\n")
print("Accuracy for AdaBoostClassifier is ",score4*100,"%\n")
print("Accuracy for RandomForestClassifier is ",score5*100,"%\n")
```

```
Accuracy for LogisticRegression is  94.79583975346686 %

Accuracy for DecisionTreeClassifier is  94.59167950693374 %

Accuracy for KNeighborsClassifier is  99.89214175654854 %

Accuracy for AdaBoostClassifier is  75.38135593220339 %

Accuracy for RandomForestClassifier is  99.8959938366718 %
```

AUC_ROC:

```
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
```

```
#RandomizedSearchCV - LogisticRegression
fpr,tpr,thresholds=roc_curve(y_test,RSV_pred1)
```

```
plt.plot([0.1],[0.1],'k--')
plt.plot(fpr,tpr,label=' LogisticRegression - RandomizedSearchCV')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('RandomizedSearchCV')
plt.show()
```


```
#RandomizedSearchCV - DecisionTreeClassifier
fpr,tpr,thresholds=roc_curve(y_test,RSV_pred2)
```

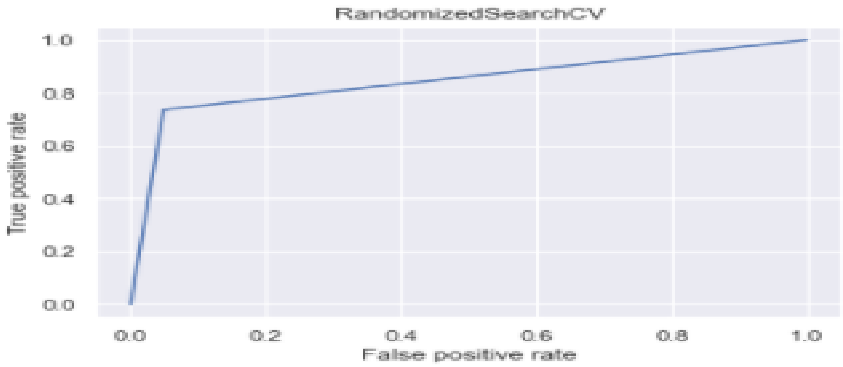
```
#RandomizedSearchCV - DecisionTreeClassifier
fpr,tpr,thresholds=roc_curve(y_test,RSV_pred2)
```

```
plt.plot([0.1],[0.1],'k--')
plt.plot(fpr,tpr,label=' DecisionTreeClassifier  - RandomizedSearchCV')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('RandomizedSearchCV')
plt.show()
```

```
#RandomizedSearchCV - KNeighborsClassifier
fpr,tpr,thresholds=roc_curve(y_test,RSV_pred3)
```

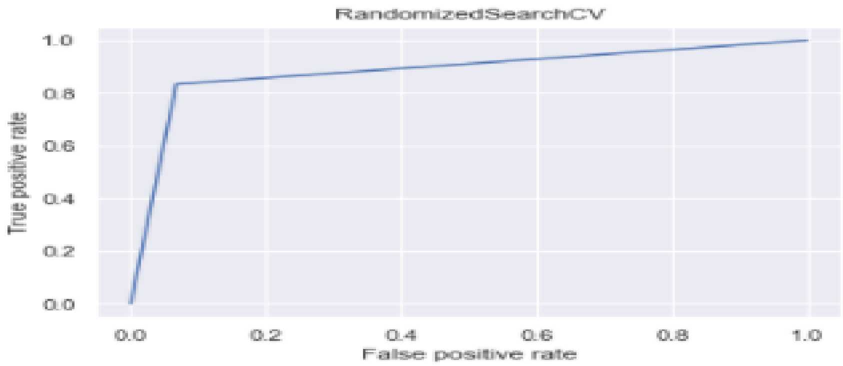
```
plt.plot([0.1],[0.1],'k--')
plt.plot(fpr,tpr,label=' KNeighborsClassifier - RandomizedSearchCV')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('RandomizedSearchCV')
plt.show()
```


```
plt.plot([0.1],[0.1],'k--')
plt.plot(fpr,tpr,label=' AdaBoostClassifier - RandomizedSearchCV')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('RandomizedSearchCV')
plt.show()
```




```
#RandomizedSearchCV - RandomForestClassifier
fpr,tpr,thresholds=roc_curve(y_test,RSV_pred5)
```

```
plt.plot([0.1],[0.1],'k--')
plt.plot(fpr,tpr,label=' RandomForestClassifier  - RandomizedSearchCV')
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('RandomizedSearchCV')
plt.show()
```



Considering LogisticRegression with RandomizedSearchCV as final model for saving model as we have got best accuaracy score with RandomForestClassifier - logistic regression and AUC_roc score is graph also is better than other models.

Saving the model:

```
#saving the model
import pickle
filename='RSVMalignant.pkl'
pickle.dump(RSV1,open(filename,'wb'))
```

We will import the test file now:

```
test=pd.read_csv(r"C:\Users\SAGAR KADAM\Downloads\Malignant-Comments-Classifier-Project--1-\Malignant Comments Classifier Pr
test=pd.DataFrame(data=test)
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.
...	...	...
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	NaN	bad

153165 rows × 2 columns

```
test.columns #list of columns
```

```
Index(['id', 'comment_text'], dtype='object')
```

```
test.shape
```

```
(153165, 2)
```

Test dataset consists of 153164 rows and 2 columns.

```
test.dtypes
```

```
id              object
comment_text    object
dtype: object
```

We can see both type of columns object type.

```
test.describe(include='all').T
```

	count	unique	top	freq
id	153164	153164	c3efd845b70c67d3	1
comment_text	153165	153165	" \n ***So images of ass and shit are okay, bu...	1

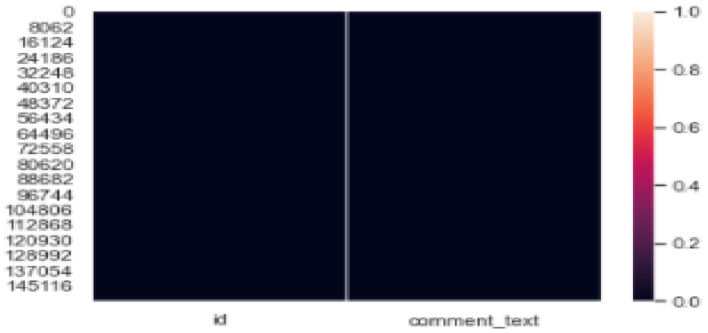
We can see count is all same for all variable, let's check for null values now:

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

```
id              1
comment_text    0
dtype: int64
```

```
#visual reprentation with the help of heatmap
sns.heatmap(test.isnull())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d911ac8e20>
```

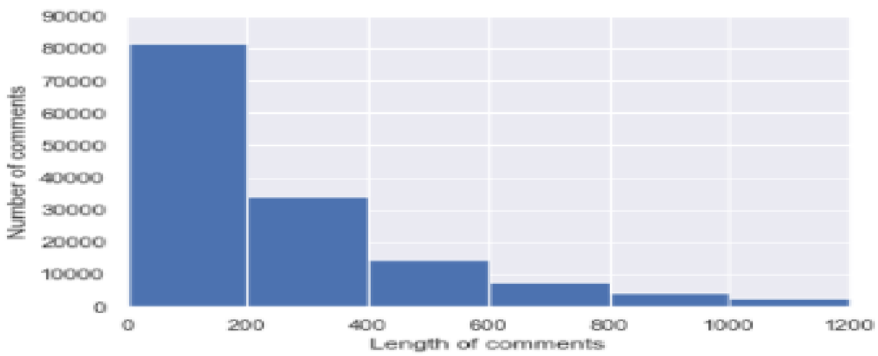


Id feature also has all unique values like serial number hence we dont require feature for future analysis

```
test.drop('id', axis=1, inplace= True)
```

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

print('average length of comment: {:.3f}'.format(sum(x)/len(x)) )
bins = [1,200,400,600,800,1000,1200]
plt.hist(x, bins=bins)
plt.xlabel('Length of comments')
plt.ylabel('Number of comments')
plt.axis([0, 1200, 0, 90000])
plt.grid(True)
plt.show()
```

```
average length of comment: 364.873
```



Above graph shows us the length of comments vs the number of comments. Maximum comments are with length 200 and very less comments are with length 1200.

```
test['length'] = test['comment_text'].str.len()
test.head(2)
```

	comment_text	length
0	Yo bitch Ja Rule is more succesful then you'll...	367
1	== From RfC == \n\n The title is fine as it is...	50

Added a new feature where we can see length of the particular comment.

```
# Convert all messages to lower case
test['comment_text'] = test['comment_text'].str.lower()

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

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

# Replace money symbols with 'moneysymb' (£ can by typed with ALT key + 156)
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')


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

# Remove punctuations
test['comment_text'] = test['comment_text'].apply(lambda x: ' '.join(
    term for term in x.split() if term not in string.punctuation))

# Remove 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))

# Lemmetize words
lem=WordNetLemmatizer()
test['comment_text'] = test['comment_text'].apply(lambda x: ' '.join(
 lem.lemmatize(t) for t in x.split()))
```

After cleaning the comment text, let's have a look at comment length now.

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

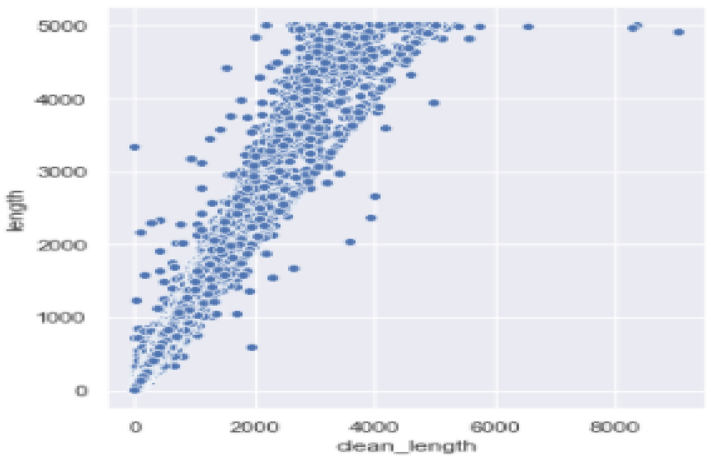
	comment_text	length	clean_length
0	yo bitch ja rule succesful ever whats hating s...	367	249
1	== rfc == title fine is, imo.	50	29
2	== source == zawe ashton lapland —	54	34
3	:if look back source, information updated corr...	205	117
4	anonymously edit article all.	41	29

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

```
Origian Length 55885736
Clean Length 39400455
```

```
sns.relplot(x='clean_length',y='length',data=test,kind='scatter')
```

```
<seaborn.axisgrid.FacetGrid at 0x1d919ecd040>
```



Dropping newly created columns because it's not required for further analysis:

```
test.drop('length', axis=1, inplace= True)
```

```
test.drop('clean_length', axis=1, inplace= True)
```

Let's use TFidf method to transform data into vectors:

```
#  Convert text into vectors using TF-IDF
from sklearn.feature_extraction.text import TfidfVectorizer
tf_vec = TfidfVectorizer(max_features = 30000, stop_words='english')
features = tf_vec.fit_transform(test['comment_text'])
x = features
```

```
x.shape
```

```
(153165, 30000)
```

load the model

```
fitted_model=pickle.load(open("RSVMalignant.pkl","rb"))
```

```
fitted_model
```

```
RandomizedSearchCV(cv=5, estimator=LogisticRegression(),
                   param_distributions={'C': [1.0], 'class_weight': [None],
                                        'dual': [True, False],
                                        'fit_intercept': [True, False],
                                        'intercept_scaling': [1],
                                        'l1_ratio': [None], 'max_iter': [100],
                                        'multi_class': ['auto', 'ovr',
                                                        'multinomial'],
                                        'n_jobs': [None],
                                        'penalty': ['l2', 'l1', 'elasticnet',
                                                    'none'],
                                        'random_state': range(0, 20),
                                        'solver': ['newton-cg', 'lbfgs',
                                                   'liblinear', 'sag', 'saga'],
                                        'tol': [0.0001], 'verbose': [0],
                                        'warm_start': [True, False]})
```

prediction over test dataset

```
prediction=fitted_model.predict(x)
```

```
prediction=fitted_model.best_estimator_.predict(x)
```

```
prediction
```

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

```
test['bad'] = prediction
test.to_csv('test.csv')
```

CONCLUSION

In Malignant Comments Classifier project our goal was 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. Our database consists of 159571 rows and 8 columns in which we have 2 object type columns and all other columns are numeric. First, I have dropped some columns which are not required also I have dropped id column has all unique values like serial number hence we don’t require feature for future analysis

I have performed some visualization showing relations between some features. Then I have checked correlation of data. With the help of countplot tried to show numbers with all features. And with help of NLP methods, I cleaned comments text feature. Wordcloud helped in showing allowed word with respect to all feature. Used pie chart to show contribution of all features. Then created a new feature combining all features.

With the help of TFidf method to transform data into vectors. Our target column does not contain equal number of data hence I performed under sampling method to equalized. Used 5 methods for model building. With the help of RandomizedSearchCV I have tried to improve accuracy. I decided to go ahead with Logistic Regression and saved model.

Performed similar operations on test dataset as well according to the requirement. After that loaded the model and performed prediction over test dataset and then saved the predictions in the test file.