MALIGNANT COMMENTS CLASSIFICATION

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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.

Conceptual Background

- 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 un offensive, but "u are an idiot" is clearly offensive.

Objective-

✓ 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 Modelling of the Problem-

- 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 o or 1, where o 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:
- Malignant: It is the Label column, which includes values o 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 Sources and their formats

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	id	comment text	malignant	highly malignant	rude	threat	abuse	loathe
0		Explanation\nWhy the edits made under my usern	0	0	0	0	0	0
1	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
5	00025465d4725e87	"\n\nCongratulations from me as well, use the	0	0	0	0	0	0
6	0002bcb3da6cb337	COCKSUCKER BEFORE YOU PISS AROUND ON MY WORK	1	1	1	0	1	0
7	00031b1e95af7921	Your vandalism to the Matt Shirvington article	0	0	0	0	0	0
8	00037261f536c51d	Sorry if the word 'nonsense' was offensive to	0	0	0	0	0	0
9	00040093b2687caa	alignment on this subject and which are contra	0	0	0	0	0	0
10	0005300084f90edc	"\nFair use rationale for Image:\Wonju.jpg\n\nT	0	0	0	0	0	0
11	00054a5e18b50dd4	bbq \n\nbe a man and lets discuss it-maybe ove	0	0	0	0	0	0
12	0005c987bdfc9d4b	Hey what is it\n@ talk .\nWhat is it	1	0	0	0	0	0
13	0006f16e4e9f292e	Before you start throwing accusations and warn	0	0	0	0	0	0
14	00070ef96486d6f9	Oh, and the girl above started her arguments w	0	0	0	0	0	0
15	00078f8ce7eb276d	"\n\nJuelz Santanas Age\n\nIn 2002, Juelz Sant	0	0	0	0	0	0
16	0007e25b2121310b	Bye! \n\nDon't look, come or think of comming	1	0	0	0	0	0
17	000897889268bc93	REDIRECT Talk:Voydan Pop Georgiev- Chernodrinski	0	0	0	0	0	0
18	0009801bd85e5806	The Mitsurugi point made no sense - why not ar	0	0	0	0	0	0
19	0009eaea3325de8c	Don't mean to bother you \n\nI see that you're	0	0	0	0	0	0

Data Sources and their formats

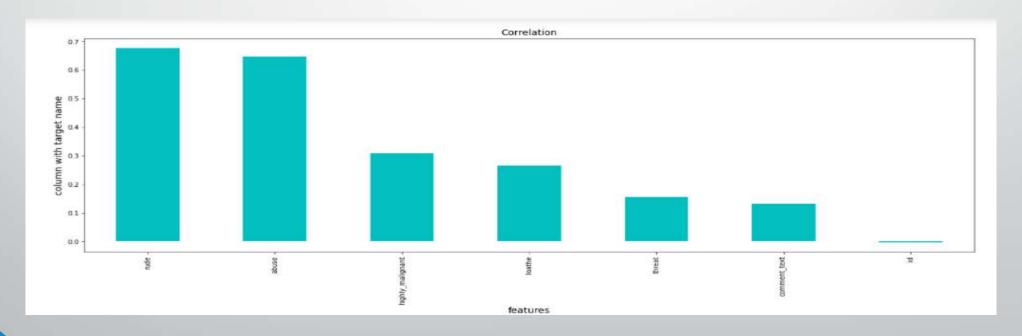
- Their are 159571 rows and 8 columns in dataset.
- Two types of data type present in dataset. 1. object, 2. integer
- No null values has been observed in dataset

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159571 entries, 0 to 159570
Data columns (total 8 columns):
    Column
                      Non-Null Count
                                      Dtype
    id
                      159571 non-null
                                      object
    comment text
                      159571 non-null
                                      object
    malignant
                      159571 non-null int64
    highly malignant 159571 non-null int64
    rude
                      159571 non-null int64
    threat
                      159571 non-null int64
    abuse
                      159571 non-null int64
    loathe
                      159571 non-null int64
dtypes: int64(6), object(2)
```

```
id
                     object
                     object
comment text
malignant
                      int64
highly malignant
                      int64
rude
                      int64
threat
                      int64
abuse
                      int64
loathe
                      int64
dtype: object
```

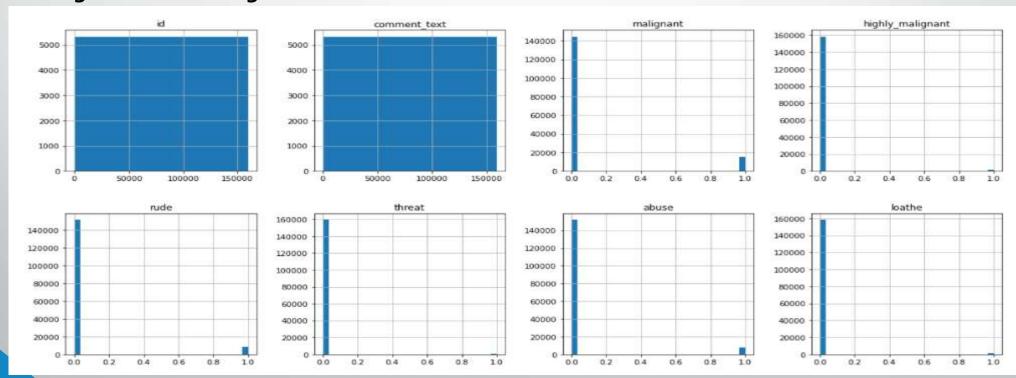
Data Sources and their formats

- It has been observed that two columns have object type data, converted them to interger datatype.
- Correlation matrix has been checked with target variable, 6 columns shown +ve correlation with label. 1 column shown -ve correlation with label. Highest correlation is observed with rude col- 0.676515



	id	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
id	1.000000	0.002812	-0.003263	-0.001403	-0.002188	-0.001165	-0.002086	-0.000844
comment_text	0.002812	1.000000	0.132016	0.057627	0.104020	0.026093	0.111724	0.046234
malignant	-0.003263	0.132016	1.000000	0.308619	0.676515	0.157058	0.647518	0.266009
highly_malignant	-0.001403	0.057627	0.308619	1.000000	0.403014	0.123601	0.375807	0.201600
rude	-0.002188	0.104020	0.676515	0.403014	1.000000	0.141179	0.741272	0.286867
threat	-0.001165	0.026093	0.157058	0.123601	0.141179	1.000000	0.150022	0.115128
abuse	-0.002086	0.111724	0.647518	0.375807	0.741272	0.150022	1.000000	0.337736
loathe	-0.000844	0.046234	0.266009	0.201600	0.286867	0.115128	0.337736	1.000000

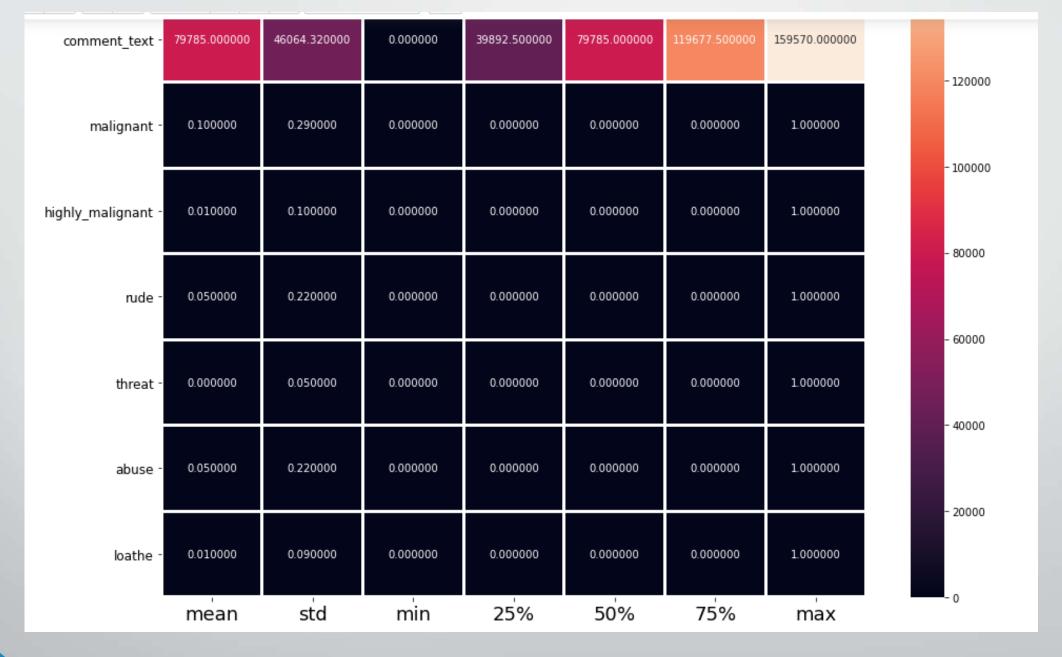
Histogram for checking distribution



More analysing data for better understanding

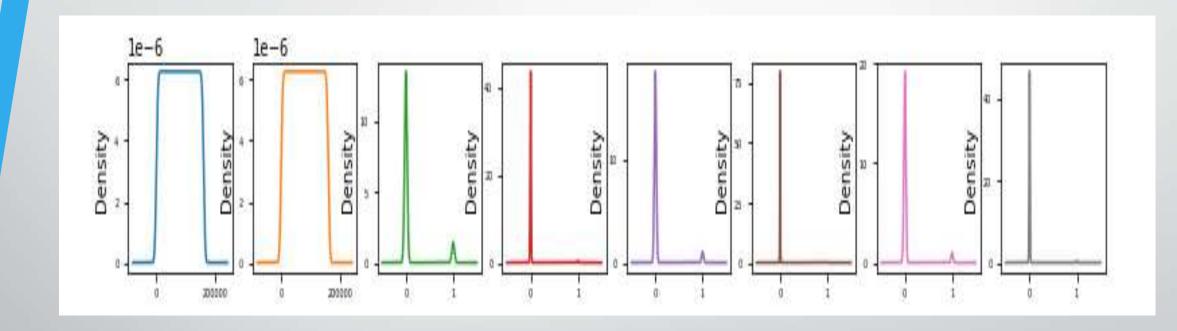
Statistical summary for describing dataset

	id	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
count	159571.00000	159571.00000	159571.000000	159571.000000	159571.000000	159571.000000	159571.000000	159571.000000
mean	79785.00000	79785.00000	0.095844	0.009996	0.052948	0.002996	0.049364	0.008805
std	46064.32424	46064.32424	0.294379	0.099477	0.223931	0.054650	0.216627	0.093420
min	0.00000	0.00000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	39892.50000	39892.50000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	79785.00000	79785.00000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	119677.50000	119677.50000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
max	159570.00000	159570.00000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

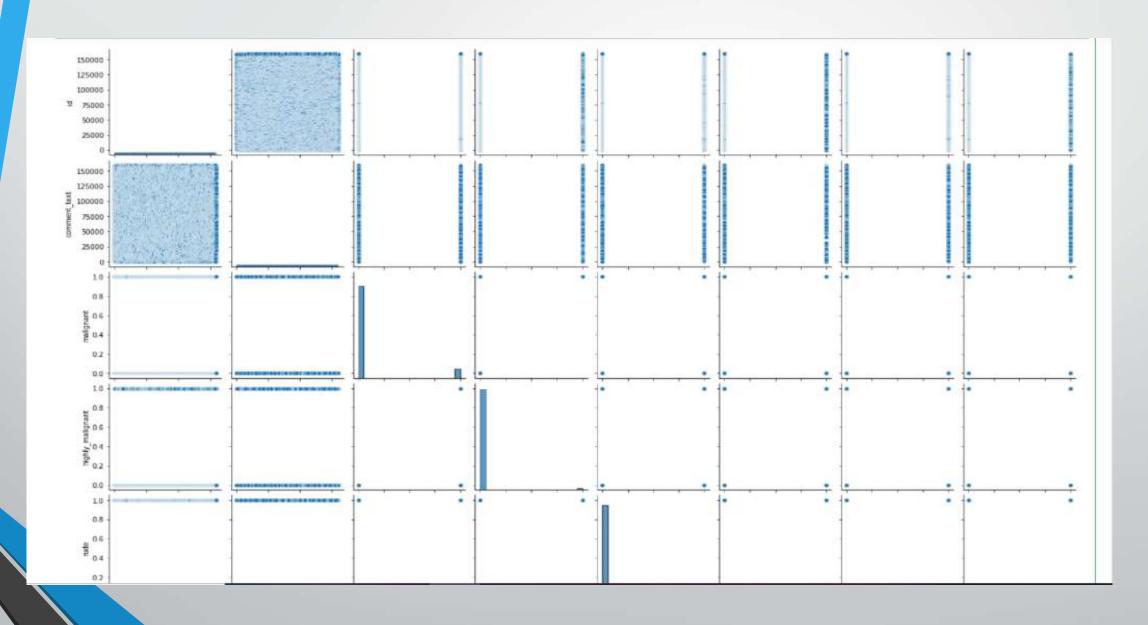


Variable summary related to target variable is shown in above heatmap

Dataset also checked for skewness in columns, and treated for skewness



Plot for seeing relation between columns-using pairplot



Their is imbalance in classes of target variable/label, decided to treat them with sampling technique(SMOTE function for over sampling)

Before

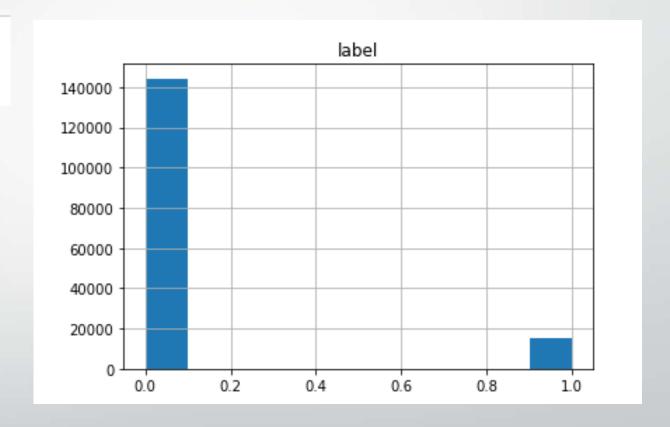
0 144277 1 15294

Name: malignant, dtype: int64

After oversampling

0 144277 1 144277

Name: malignant, dtype: int64



Model/s Building and Evaluation

Five different classification model has been build for micro-credit loan prediction

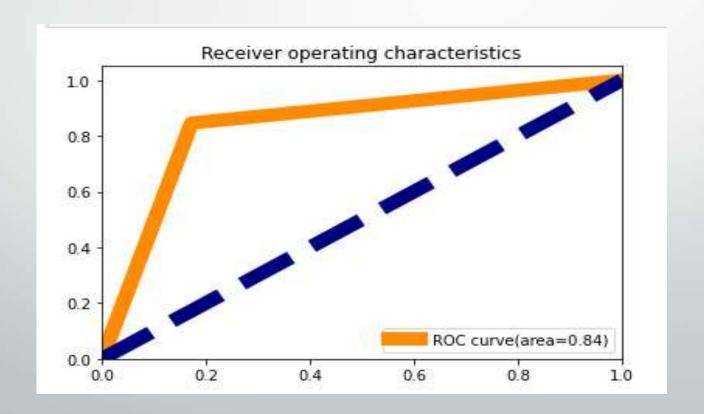
- 1. Linear Regression
- 2. Decision Tree Classifier
- 3. Random Forest Classifier
- 4. SVC model
- 5. KNN Classifier
- ✓ Model is selected on the basis of accuracy and cross-validation report
- ✓ Best Accuracy % obtained in Decision Tree Classifier

0.8381831413818198 [[35994 7392] [6616 36565]]									
	precision	recall	f1-score	support					
0	0.84	0.83	0.84	43386					
1	0.83	0.85	0.84	43181					
-	0.05	0.03	0.04	45101					
accuracy			0.84	86567					
macro avg	0.84	0.84	0.84	86567					
weighted avg	0.84	0.84	0.84	86567					
	3.5.	3.0.	0.0.	2220,					

Followed by best model hypertunning-using Grid search CV

Checking Accuracy-AUC_ROC Curve

- ✓ getting ROC curve area 0.84, AUC score is 84%
- ✓ Model performance is good(84%) for predicting comments, hence saving a model



TEST DATASET

- Their are 153164 rows and 2 columns
- only one type of dataset is observed in test dataset i.e. object
- No null values has been observed in test dataset

comment_text	id	
Yo bitch Ja Rule is more succesful then you'll	00001cee341fdb12	0
== From RfC == \n\n The title is fine as it is	0000247867823ef7	1
" \n\n == Sources == \n\n * Zawe Ashton on Lap	00013b17ad220c46	2
:If you have a look back at the source, the in	00017563c3f7919a	3
I don't anonymously edit articles at all.	00017695ad8997eb	4
Thank you for understanding. I think very high	0001ea8717f6de06	5
Please do not add nonsense to Wikipedia. Such	00024115d4cbde0f	6
:Dear god this site is horrible.	000247e83dcc1211	7
" \n Only a fool can believe in such numbers	00025358d4737918	8
== Double Redirects == \n\n When fixing double	00026d1092fe71cc	9
I think its crap that the link to roggenbier i	0002eadc3b301559	10
"::: Somebody will invariably try to add Relig	0002f87b16116a7f	11
, 25 February 2010 (UTC) \n\n :::Looking it ov	0003806b11932181	12

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

Conclusion

- ✓ The data set contains the training set, which has approximately 1,59,000 samples
- ✓ Malignant comment classifier-- Model performance is good(84%) for predicting comments.
- ✓ Test Dataset-containing 153164 rows and 2 columns

Thank you