

## Motivation & Problem Statement

In an era of ubiquitous online communication, hate speech and toxic remarks have attracted a lot of attention. Using data mining and machine learning algorithms, this project attempts to create a model that is able to recommend to the user to change/update their comments to reduce online negativity and promote a positive discussion, or discourse. The primary focus of this project is,

- To create a model to analyze the sentiment of user comments in an online setting to identify comments for – 'toxic', 'severe\_toxic', 'obscene', 'threat', 'insult', and, 'identity\_hate' classes.
- 2. To help users to choose a positive discourse in an effort to reduce online negativity in form of bullying, or abusing which can affect the mental and psychological health of the content creators.

Dataset Overview

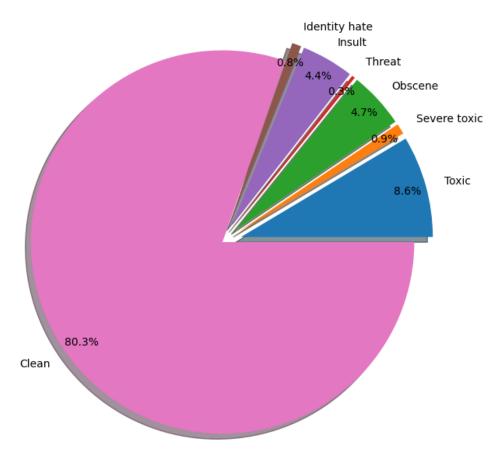
- The dataset is readily available on Kaggle with -
  - 159571 rows and 8 columns
- The dataset has a variety of comments classified into 6 different levels of toxicities.



#### EDA

- Data Composition -
- - The number of 'toxic' comments is, 10,652
- The number of 'severe\_toxic' comments is, 1091
- - The number of 'obscene' comments is, 5876
- - The number of 'threat' comments is, 338
- - The number of 'insult' comments is, 5474
- - The number of 'identity\_hate' comments is, 950
- - The number of 'clean' comments is, 99,384

#### Percentages of Types of comments



Disclaimer – The following slides may include explicit language, sensitive topics, or triggering themes that may be distressing to some users. Reader discretion is advised.

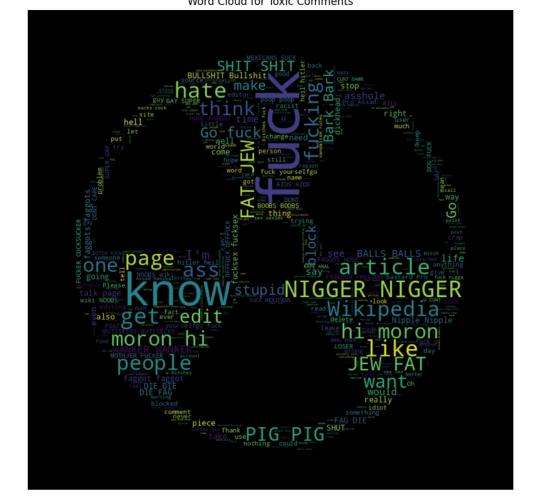
#### Wordclouds for 'toxic' and 'severe\_toxic' comments

Word Cloud for Severe Toxic Comments

yourselfgo fuck



Word Cloud for Toxic Comments

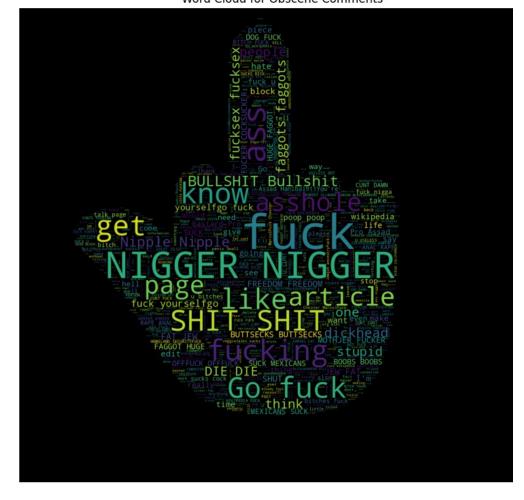


### Wordclouds for 'threat' and 'obscene' comments

Word Cloud for Threat Comments

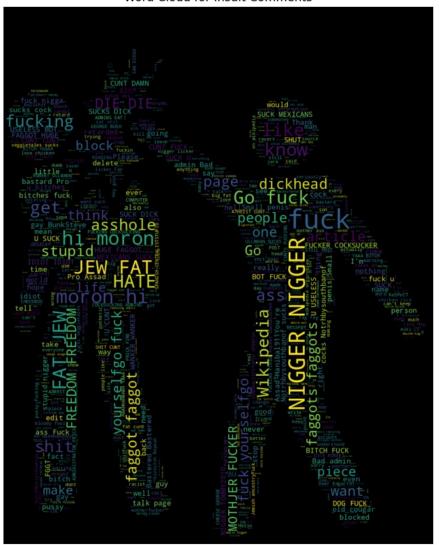


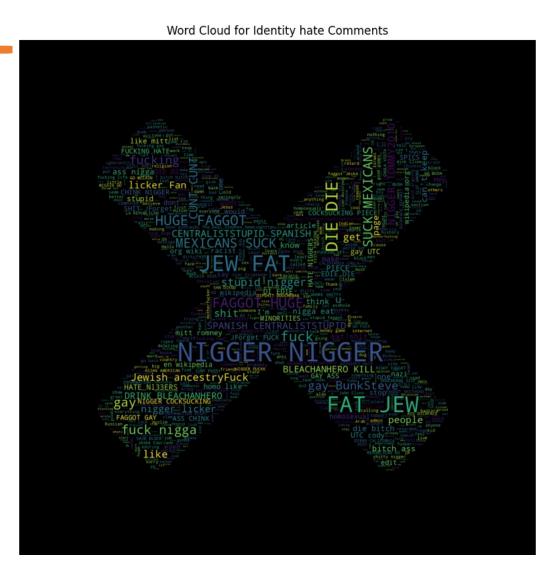
Word Cloud for Obscene Comments



## Wordclouds for 'insult' and 'identity\_hate' comments

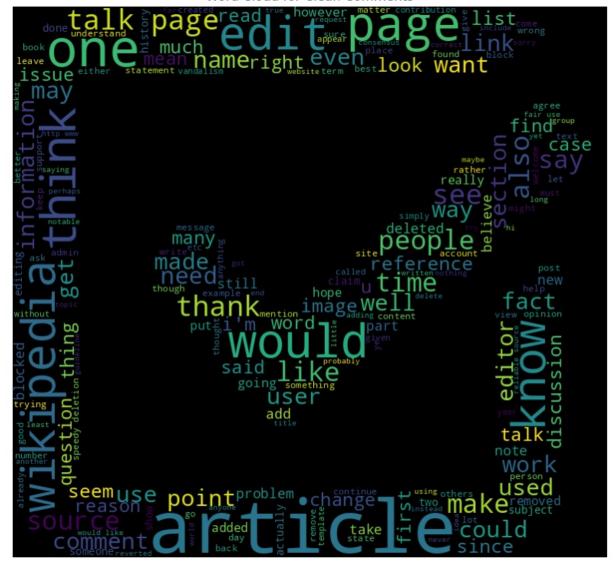
Word Cloud for Insult Comments





## Wordcloud for 'clean' comments

#### Word Cloud for Clean Comments



# Current Models & Observations

	Label	Accuracy	Precision	Recall	F1 Score
0	toxic	0.9569	0.9551	0.9569	0.9532
1	severe_toxic	0.9903	0.9879	0.9903	0.9885
2	obscene	0.9767	0.9756	0.9767	0.9746
3	threat	0.9978	0.9971	0.9978	0.9971
4	insult	0.9689	0.9657	0.9689	0.9653
5	identity_hate	0.9917	0.9897	0.9917	0.9890
6	Combined	0.9183	0.8928	0.9183	0.9022

Logistic Regression – 91.8% accuracy

	Label	Accuracy	Precision	Recall	F1 Score
0	toxic	0.9572	0.9548	0.9572	0.9548
1	severe_toxic	0.9898	0.9849	0.9898	0.9858
2	obscene	0.9778	0.9766	0.9778	0.9767
3	threat	0.9977	0.9969	0.9977	0.9969
4	insult	0.9687	0.9658	0.9687	0.9664
5	identity_hate	0.9915	0.9897	0.9915	0.9885
6	Combined	0.9172	0.8907	0.9172	0.8991

Random Forest – 91.7% accuracy

	Label	Accuracy	Precision	Recall	F1 Score
0	toxic	0.9600	0.9582	0.9600	0.9573
1	severe_toxic	0.9902	0.9879	0.9902	0.9858
2	obscene	0.9792	0.9781	0.9792	0.9779
3	threat	0.9978	0.9971	0.9978	0.9972
4	insult	0.9710	0.9683	0.9710	0.9685
5	identity_hate	0.9919	0.9905	0.9919	0.9891
6	Combined	0.9213	0.8974	0.9213	0.9061

SVM - 92.1% accuracy

Layer (type)	Output Shape ====================================	Param #			
input_3 (InputLayer)	[(None, 100)]	0			
embedding_1 (Embedding)	(None, 100, 300)	52248900			
<pre>spatial_dropout1d_1 (Spati alDropout1D)</pre>	(None, 100, 300)	0			
bidirectional (Bidirection al)	(None, 100, 256)	439296			
conv1d (Conv1D)	(None, 100, 64)	16448			
<pre>max_pooling1d (MaxPooling1 D)</pre>	(None, 50, 64)	0			
flatten (Flatten)	(None, 3200)	0			
dense (Dense)	(None, 128)	409728			
dropout (Dropout)	(None, 128)	0			
batch_normalization (Batch Normalization)	(None, 128)	512			
dense_1 (Dense)	(None, 6)	774			

**LSTM Neural Net** 

Non-trainable params: 52249156 (199.31 MB)

(Please note, the project is still being optimized, we are still trying to improve the recall and reduce computational time.)

#### Expected Outcomes & Future Improvements

- We are still involved in optimizing the models further, to improve the recall for multiple labels.
- Multi language recognition
- Develop real-time monitoring capabilities to identify and address toxic comments as soon as they are posted.
- Integrate user feedback mechanisms to enhance the model's performance on real-world usage.



