Mini Project Report

on

Hate Speech Data Analytics

Submitted by

Makam Sujith 21BCS061
Ruthvik Jangam 21BCS047
Amballa V. Sriram 21BCS008

Under the guidance of

Anil Kumar 21BEC056

Dr. Animesh Chaturvedi Designation



DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING INDIAN INSTITUTE OF INFORMATION TECHNOLOGY DHARWAD 29/04/2024

Certificate

This is to certify that the project, entitled **Hate Speech Data Analytics**, is a bonafide record of the Mini Project coursework presented by the students whose names are given below during 2023-24 in partial fulfilment of the requirements of the degree of Bachelor of Technology in Computer Science and Engineering, Electronics and Communication Engineering.

Roll No	Names of Students
<21BCS061>	<makam sujith=""></makam>
<21BCS047 $>$	<ruthvik jangam=""></ruthvik>
<21BCS008>	<amballa sriram="" v.=""></amballa>
<21BEC056>	<anil kumar=""></anil>

Animesh Chaturvedi (Project Supervisor)

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1 Introduction

Hate speech, defined as any speech, gesture, conduct, writing, or display that may incite violence or prejudicial action against or by a particular individual or group, has become a pervasive issue in the digital age. With the rise of social media platforms and online forums, the dissemination of hate speech has reached unprecedented levels, posing significant challenges to societies worldwide.

In response to this growing concern, researchers and practitioners have increasingly turned to data analytics techniques to understand, identify, and combat hate speech online. By leveraging large datasets extracted from various online platforms, researchers can analyze patterns, trends, and linguistic features associated with hate speech. This analytical approach offers valuable insights into the dynamics of hate speech propagation, its underlying motivations, and its impact on targeted communities.

In this paper, we delve into the realm of hate speech data analytics, exploring the methodologies, challenges, and implications of leveraging data-driven approaches to address this pressing societal issue. We examine the role of language processing, string matching, and computational linguistics in detecting and categorizing hate speech, as well as the ethical considerations and limitations inherent in such endeavors. Furthermore, we discuss the potential applications of hate speech data analytics in informing policy decisions, fostering online safety measures, and promoting inclusive online environments.

Furthermore, ethical considerations are paramount. Striking a balance between protecting free speech and safeguarding individuals from harm is crucial. Automated content moderation systems can inadvertently silence legitimate dissent, while failing to catch all instances of hate speech. Additionally, the potential for data breaches and the misuse of hate speech data for targeted harassment raise significant privacy concerns.

Despite these challenges, hate speech data analytics holds immense potential. Insights gleaned from data analysis can inform policy decisions by providing a deeper understanding of the sources and pervasiveness of hate speech. Additionally, these analyses can be used to develop more effective detection and mitigation tools, fostering safer online environments for all.

By harnessing the power of data and approaching the issue with a nuanced understanding of language and ethics, researchers and practitioners can play a critical role in turning the tide against hate speech. This ongoing battle requires collaboration between researchers, policymakers, technology companies, and civil society to ensure that the digital world becomes a space for inclusive and respectful communication.

2 Related Work

The paper introduces two approaches to quantitatively measure and qualitatively visualize the relationship between co-occurring Hate Terms (HTs). It discusses generating an Inter-agreement HTs list that includes offensive metric values and the HTs lists containing these HTs, aiming to improve hate speech classification efficiency. The paper proposes generating Stable Hate Rules (SHRs) based on frequently co-occurring HTs among multiple hate speech (HS) datasets. It uses metrics like Hatefulness, Relativeness, and Offensiveness to gauge HT severity and presents results using a confusion matrix to show Inter-Agreement between HS data and HTs-lists. Examples of SHRs, concepts, transitivities, and lattices are provided, along with comparisons and analysis of HS data.

Caselli et al., described abuse and offense by studying Inter-Agreement. We have also analyzed Inter-agreement between HTs-list and HS-data Classes, such that, this process generates a Severe HTs-list. Pedersen presented lists of HTs, whereas we have retrieved Severe HTs-list. Liu et al., presented a Multi-Task Deep Neural Network (MT-DNN) for learning text representations for multiple natural language understanding (NLU). Zampieri et al., annotated the datasets for abusive messages named Offensive Language Identification Dataset (OLID), which they further used for Offensive Language in Social Media (Offens Eval), Devlin et al., presented a popular language representation model named Bidirectional Encoder Representations from Transformers (BERT) for tasks like question answering and language inference. al., measured hate and toxicity Recently, Mitos toxicity with the percentage of hate words, and the level of toxicity/inflammatory.

They used HTs available on hatebase.org. which were previously worked out by Hine et al., and Vidgen et al. presented dynamic human and model-based four rounds of hate speech training. Ball et al., studied racial dialect using neural networks' harmful tweet detection. Vidgen et al., described a contextual abuse dataset with six taxonomies for abusive, non-abusive, and neutral speech.

3 Data and Methods

The study collected and analysed two types of data: hate phrase lists and hate speech data. Hate phrase lists were taken from t-davidson's GitHub repository, while hate speech data included offensive remarks sourced from Twitter, notably the Hugging Face dataset. The use of this dataset was approved by the respective user. The hate phrase lists were divided into six categories, while the hate speech data was divided into three sections for study. Using this dataset, analytics were performed to identify patterns and trends in the data. The data appears like this:

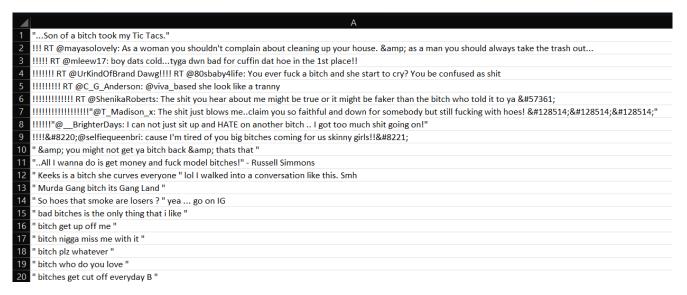


Figure 1. dataset containing sentences



Figure 2. List of hate terms

Methods used in the code:

These are the core functions of our project which will contribute more in the project.

MakeListHateTermFrequencies: The makeListHateTermFrequencies method, encapsulated within a class named BasicUtilities, serves the purpose of extracting hate term frequencies from a set of CSV files. These files are named based on different databases and reside within a specified directory. The method iterates through each database file, reads its content, and extracts hate terms along with their frequencies. These terms are then added to a list for further processing.

MakeListHateTermPercentLine: As shown in the above function here we will store the percentage of hate-terms.

IntraHTsListMatrix: This method essentially processes term occurrences, calculates relevant metrics, and writes them to a file, enabling further analysis of hate speech-related data.

InterAgreementTerms: This method calculates and writes inter-agreement terms data to a CSV file based on specified hate term files.

InterAgreementConfusionMatrix: This method calculates various metrics for a confusion matrix, such as counts, percentages, accuracy, recall, precision, and F-measure, based on the provided Hate Term file name (HTFileName). It then writes these metrics to a CSV file representing the confusion matrix for inter-agreement analysis.

SummaryTermConfusionMatrix4Cases: The summaryTermConfusion-Matrix4Cases method, declared as private and residing within an undisclosed class, is responsible for generating a summary of confusion matrix statistics for four different cases related to terms. It computes various metrics such as recall and precision for each case and writes the results to a CSV file named "TermConfusionMatrix.csv".

SummaryConfusionMatrix4Cases: The summaryConfusionMatrix4Cases method declared as private and residing within an undisclosed class, is responsible for summarizing confusion matrix statistics for four different cases related to hate, offensive, and non-offensive content classification. It computes various metrics such as recall, precision, accuracy, and F-measure for each case and writes the results to a CSV file named "ConfusionMatrix.csv".

MakeOuterJoinHateTermFrequencies: The makeOuterJoinFrequenciesFile method, declared private and residing within a class, is designed to create a string representing the frequencies of a specific term across multiple databases. This method processes CSV files containing hate term frequencies for different databases, extracts the frequency corresponding to the provided term from each file, and constructs a comma-separated string containing these frequencies.

4 Results and Discussions

Output Generated after running the code:

The processing of the hate term file named list1.csv entails iterating through multiple datasets (dataset1.csv, dataset2.csv, dataset3.csv) alongside the same hate term file. For each dataset, the software calculates and records the occurrence frequency of hate terms in corresponding output files. Moreover, it computes aggregate metrics related to hate for each dataset.

```
Make Sum HateLine with dataset2

Processing the DBFile and HTFile:
   D\mini\Batasets\dataset3.csv,
   D\mini\Batasets\dataset3.csv,
   Write Top Frequency Hate Forms: D\mini\list2\dataset3\AllHateTermFrequencies.csv
   Write Top Frequency Hate Forms
   Write Top Frequency Hate Hateleast
   Write Top Frequency Hateleast
   Write Top Frequency
   Write All F
```

```
Frocessing the DBFile and HTFile:
D:\mini\Datasets\datasetl.csv
Write All Frequency Mate Terms: D:\mini\list3\dataset!\AllHateTermFrequencies.csv
Write Top Frequency Mate Terms
Make sum of MateTermLines with dataset!
Make Sum HateLine with dataset!
Make Sum HateLine with dataset!
Processing the DBFile and HTFile:
D:\mini\Datasets\datasets\datasetz.csv
D:\mini\Datasets\datasets\datasetz.csv
D:\mini\Datasets\datasets\datasetz.csv
Write All Frequency Mate Terms: D:\mini\list3\dataset2\AllHateTermFrequencies.csv
Write Top Frequency Mate Terms:
Make sum of HateTermLines with dataset2
Make Sum HateLine with dataset2
Make Sum HateLine with dataset3
D:\mini\Datasets\dataset3.csv,
D
```

```
list3, --, --, --, -, ., .,
list3, --, --, --, --, .,
list3, --, --, --, --, .,
list3, --, --, --, --, .,
list3, --, --, --, --, --, .,
list3, --, --, --, --, --, --, --,
list3, --, --, --, --, --, --, --,
list3, --, --, --, --, --, --,
list3, --, --, --, --, --, --,
list3,
```

```
Write Top Prequency Nate Terms
Make sum of HateTermEines with dataset3
Make Sum fateLenie with dataset3
offensiveNonOffensive: 218
onlyOffensive: 218
hateNonOffensive: 394
hateNonOffensive: 376
onlyNonOffensive: 376
offensiveNonOffensive: 376
offensiveNonOffensive: 776
offensiveNonOffensive: 776
offensiveNonOffensive: 776
hateNonOffensive: 383
hateNonOffensive: 383
hateNonOffensive: 400
list4, --, --, --, , , ,
list4, --, --, --, , , ,
list4, --, --, --, , , ,

**Make Summary Confundatrix for Term list4
Make List HateTermErequencies with list4
OuterJoinTerms OuterJoinTsFrequencies.csv
Make List HateTermErectLines with list4
OuterJoinTerms OuterJoinTsFrequencies.csv

Hate Term File Name: list5.csv

Processing the DBFile and HTFile:
D:\unini\Natasets\Natasetsl.csv.
D:\unini\Natasets\Natasetsl.csv.
Frite Top Frequency Nate Terms: D'\unini\listS\Natasetsl\AllHateTermFrequencies.csv

Make Sum of NateTermLines with datasetl
Make Sum fateLine with datasetl
Make Sum fateLine with datasetl
Make Sum fateLine with datasetl
```

```
Make Sum Hateline with dataset1

Processing the DBFile and HTFile:
D'NainiNatasets/dataset2.csv,
D'NainiNatasets/dataset2.csv,
Write All Frequency Mate Terms: D'NainiNistS/dataset2/AllHateTermFrequencies.csv
Write Top Frequency Mate Terms
Make Sum Hateline with dataset2

HAMAD Sum Hateline with dataset2

Processing the DBFile and HTFile:
D'NainiNatasets/dataset3.csv,
D'NainiNatasets/dataset3.csv,
D'NainiNatasets/dataset3.csv,
D'NainiNatasets/dataset3.csv,
D'NainiNatasets/dataset3.csv,
D'NainiNatasets/dataset3.csv,
D'NainiNatasets/dataset3.csv,
D'NainiNateNiTVISTVISTC.csv
Write Top Frequency face Terms: D'NainiNistS/dataset3/AllHateTermFrequencies.csv
Write Top Frequency face Terms:
Write Top Frequency face Terms:
OffensiveNonOffensive: 33
Anake Sum RateLine with dataset3

Make Sum RateLine with dataset3

Anake Sum RateLine with dataset3

AnakeMonOffensive: 30

AnakeMonOffensive: 81

AnakeMonOffensive: 81

AnakeMonOffensive: 82

AnakeMonOffensive: 86

Inst. - , - , - , - , , , ,

IistS. - , - , - , - , , , ,

Make Summary ConfusionMatrix for Term listS

Make Summary ConfusionMatrix for Term listS
```

```
Processing the DBFile and HFFile:
D'AminiNastartixthisto.csv
Write Top Frequency Hate Terms: D'AminiNisto\datasetl\AllHateTermFrequencies.csv
Write Top Frequency Hate Terms: D'AminiNisto\datasetl
Make Sum of HateTermLines with datasetl
Make Sum HateLine with datasets:
D'AminiNastarets\dataset2.csv,
D'AminiNastarets\dataset2.csv,
D'AminiNastarets\dataset2.csv,
D'AminiNastarets\dataset3.csv,
D'Amini
```

```
hateNonOffensive: 67
list6, -- , -- , -- , -- , , , ,
list6, -- , -- , -- , -- , , , ,
list6, -- , -- , -- , -- , , , ,

Make Summary ConfusionMatrix for Term list6
Make List HateTermFrequencies with list6
OuterJoinTerms OuterJoinHTsFrequencies.csv
Make List HateTermPercentLines with list6
OuterJoinTerms OuterJoinHTsPercentLines.csv
OuterJoinTerms InterAgreementTerms.csv
OuterJoinTerms InterAgreementTerms.csv
OuterJoinTerms InterAgreementHTsPercentage.csv
```

Once all datasets are processed, the program generates a summary confusion matrix and various lists based on hate term frequencies and percentages specific to the term list1.

From here we will show the folder structure of our code before and after execution.

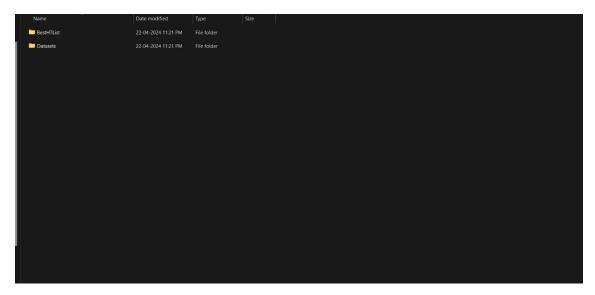


Figure 3. folders before code execution

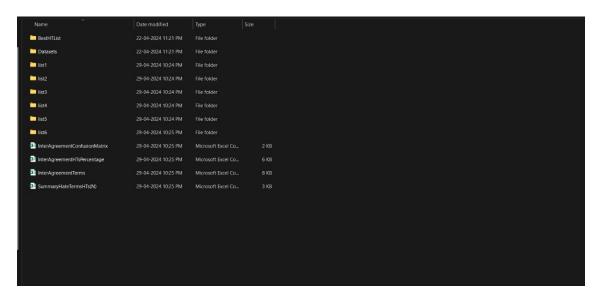


Figure 4. folders after execution

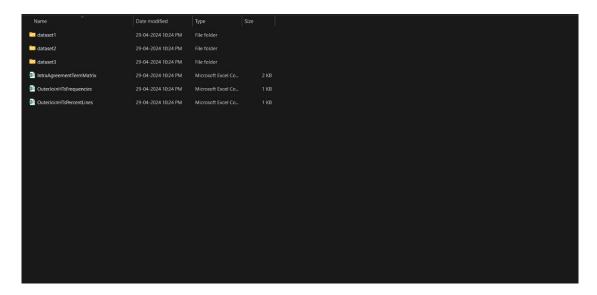


Figure 5. Files generated for each list

The output that we are focusing on the most is the **inter-agreement** confusion matrix. This provides details on the confusion matrix elements including True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) used to calculate accuracy, precision, recall, and f-measure for each hate term in the entire hate terms list within hate speech data.

A												M	0	Q
HateList N	Dataset N	HT Lines	#Lines	% HTs Line	%ТР	%TN	%FP	%FN	Accuracy	Recall	Precision	F-Measure		
list1_31	dataset1 (605	8664	0.07	0.07	0.955	0.045	0.93	0.512	0.07	0.607	0.125		
list2_31	dataset1 (75	8664	0.009	0.009	0.994	0.006	0.991	0.501	0.009	0.585	0.017		
list3_31	dataset1 (81	8664	0.009	0.009	0.994	0.006	0.991	0.502	0.009	0.621	0.018		
list4_31	dataset1 (218	8664	0.025	0.025	0.98	0.02	0.975	0.503	0.025	0.557	0.048		
0 list5_30	dataset1 (53	8664	0.006	0.006	0.997	0.003	0.994	0.501	0.006	0.657	0.012		
1														
2 list6_30	dataset1 (39	8664	0.005	0.005	0.997	0.003	0.995	0.501	0.005	0.612	0.009		
3														
4 Case: Clas:														
Case 1: Ha														
Case 2: Ha														
7 Case 3: Of														
TP True Po	= %HT Lin													
9 TN True No	= %(#Line:													
FP False Po	= %HT Lin													
1 FN False N	= %(#Line:													
Accuracy =														
Precision =														
4 Recall = TF														
F-Measure														

Figure 6. inter-agreement confusion matrix

For our hate speech dataset, we merged hate terms from various lists to establish consensus. We then evaluated each term's offensiveness based on its level of hatred and relevance. Some terms were found to be less offensive when used alone. We calculated corresponding percentages to reflect these findings.

_ A	В		D	E F
Hate Terms (HTs)	Percentage(Hate)	Percentange(Offensive)	Percentage(Non-Offensive)	
a bitch made	0.035	0.011	0.033	
a bitch made nigga	0.035	0.011	0.011	
a fag and	0.023	0.011		
a fag but	0.012	0.023		
a faggot and	0.035	0.011		
a faggot for	0.012	0.023	0.022	
a fucking queer	0.035		0.011	
a lame nigga you		0.011		
a nigga ask		0.011	0.011	
1 a nigger	1.235	1.504	1.182	
a white person	0.012	0.011	0.011	
a white trash	0.035	0.011		
4 all niggers	0.069	0.114	0.19	
all these fucking	0.023		0.033	
all white	0.035	0.034	0.033	
7 always fuck		0.011	0.022	
are all white	0.012	0.011	0.022	
ass white	0.058	0.011	0.011	
be killed		0.034	0.011	
be killed for		0.011		
beat him	0.012			
B biggest faggot	0.035		0.022	
bitch made nigga	0.058	0.023	0.022	
blacks	0.035	0.046	0.022	
blame the	0.012	0.011	0.022	
7 chink	0.127	0.091	0.056	
8 chinks in			0.022	
9 coon shit	0.035	0.011		

Figure 7. Inter agreement Hate Term matrix $\,$

5 Conclusion

Based on the comprehensive analysis conducted on hate speech data, several key findings have emerged. Through the examination of inter-agreement between hate terms (HTs) and hate speech data (HS-data), valuable insights into the frequency, offensiveness, and patterns of hate speech have been generated. The identification of Stable Hate Rules (SHRs) and associated concepts has allowed for the establishment of transitivity relationships among hate terms, facilitating a deeper understanding of context-specific hate speech dynamics.

Quantitative analysis, employing a proposed threshold for severe hate terms, has demonstrated the superior performance of the Severe HTs-list in capturing and categorizing hate speech. Meanwhile, qualitative analysis utilizing SHRs has provided visual representations of hate term co-occurrences, offering nuanced insights into the underlying dynamics of hate speech propagation. for all users.

These findings not only contribute to the body of knowledge on hate speech analytics but also offer practical implications for the development of more effective moderation strategies and intervention measures. By leveraging the insights gleaned from this analysis, stakeholders can better address the challenges posed by online hate speech, fostering a safer and more inclusive digital environment for all users.

quantitative analysis using a newly proposed threshold for classifying "severe" hate terms has demonstrated the effectiveness of a refined "Severe HTs-list" in capturing and categorizing the most egregious forms of hate speech. This refined list can be a powerful tool for identifying and filtering out the most harmful content.

By understanding the structure and patterns of hate speech, stakeholders like social media platforms and policymakers can create more targeted and efficient methods to combat online hate.

Ultimately, these insights pave the way for a safer and more inclusive digital environment. By leveraging the knowledge gleaned from this data analysis, we can work towards a future where online spaces foster respectful and constructive communication for all users.

References

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