Sentiment Analysis of Dota 2 videogame chat in context of Cyber-bullying

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Sentiment Analysis of Dota 2 videogame chat in context of Cyber-bullying

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Abstract

In video gaming, emotion analysis can be used to better understand players and how they interact with the game. The focus of this suggestion is on the in-game conversation of Defense of the Ancient 2 (DOTA2), a multiplayer online battle arena (MOBA) video game aimed at combating cyberbullying. Positive and negative interaction is always present, but excessive negativity causes players to leave the game permanently. Sentiment Analysis when performed on the chat data can identify any instances of cyberbullying in DOTA 2. Normal sentimental analysis methods are inappropriate for the task due to the absence of specific words used primarily in the game to showcase negative emotions. Henceforth, an updated dictionary in line with DOTA 2 specific words is used for more accurate representation of the chat. A rating system is used as compared to a classifier to flag a chat as a negative or positive. The updated lexicon dictionary showed slight rise in performance across the evaluation parameters spectrum with 82% Accuracy, 0.73 Precision and 0.72 Recall. Highly negative logs can be reviewed by a human invigilator afterwards.

Keywords— Sentiment analysis, valence aware dictionary and sentiment reasoner, lexicon, machine learning

1 Introduction

In terms of entertainment, the emergence of the video game industry has become the hallmark of the twenty-first century [1]. The main driver of the rise in video games is the digitalization of the entertainment industry. The changing public perception of video games as an alternative source of entertainment has accelerated the development of video games. There are millions of people throughout the industry, with thousands of people working specifically on graphic design and game creation. The development can also be attributed to a pandemic, as a result of which people, locked at home, consume multiple sources of digital entertainment . For this growth to continue, more video game research is needed to generate additional wealth.

There had been a significant increase in social media games as showed in Business Wire. Whether it's co-op play in multiplayer online games / online role-playing games (MMOG / MMORPG) like World of Warcraft or World of Tanks, or just social play on traditional social media like Facebook, social interaction with other players has become a

[1] https://www.vuelio.com/uk/resources/white-papers/pr-media-travel-trends-2021/

reality. Gaming has traditionally been more popular among men, but research shows that gender inequalities are fading in this area, and gaming has become a popular pastime for both boys and girls.

MOBA belongs to the subgenre of online strategy games. The category was created in the 2000s and has grown a lot since then. Valve made and dispersed Dota 2, a multiplayer online fight field (MOBA) computer amusement. Defense of the People of old (DotA), a community-created mod for Tempest Entertainment's Warcraft III: Rule of Chaos, is the game's spin-off. Dota 2 could be a amusement in which two groups of five players compete against each other, each guarding and possessing their claim base on the outline. Each of the ten players is in charge of a capable character known as a "Hero" who all have diverse aptitudes and play styles. Amid a coordinated play, players accumulate involvement focuses and gear for their heroes in arrange to defeat the heroes of the other group in player versus player combat. The first group to annihilate the contradicting side's "Ancient" a gigantic structure housed inside their base, wins.

Chat data is rich in important player interactions that can be used to map the overall user experience and find out what the player likes and dislikes. It also reflects the overall mood of the community, whether positive or malicious. It's to some degree obvious that, in couple with the rise in social movement in gaming, there has moreover been a rise in anti-social behaviour. Griefing, chat spamming, bug abuse, and cyberbullying are illustrations of anti-social or troublesome behaviour (commonly alluded to as "toxic" inside the gaming community) (counting racial or minority badgering). In spite of the fact that these concepts are particular, there's some cover within the definitions for a few of these behaviours, for illustration, a griefer has been characterized as a player who infers satisfaction from diminishing the satisfaction of other players. Chat spamming could be a troublesome procedure that surges the in-game chat with content, frequently the same content, rehashed over and over, successfully blocking the communication channel and diverting players. Negativity adversely affects the mental health of players, especially young people. Cyberbullying spreads and has a major impact through negative abuse and exports of blasphemous language. Sentiment analysis is a convenient way to determine the emotions of a community. While videogame developers have put up toxic counters in place, there is a still lack of implementation on controlling player behaviour on chat. Chat bans and account bans are primarily based on user remarks and hence is very heavily manpower intensive which all developer cannot afford.

1.1 Research Question

In light of this, the research question is to determine the effectiveness of sentiment analysis in DOTA 2 videogame and how it can be used to identify cyberbullying after incorporating specific word and nuances common to the game.

2 Related Work

Sentiment Analysis research is an ever-evolving field for machine learning analysts that has seen broad appropriation. In spite of the fact that there's a parcel of writing on the subject, videogames require more investigation. Whereas opinion examination has been utilized in an assortment of spaces and applications, videogaming is still a generally modern field for Sentiment Analysis, especially during active gaming sessions. The writing

(Thompson et al.; 2017) was found too be the closest to the current research in scope and application but on different game.

2.1 Cyberbullying in games

In spite of the fact that a few have comparable or common characteristics, there has however to be a ruling single definition of cyberbullying. By one standard cyberbullying centers exclusively on the behavior, such as being extremely rude to others socially and bring forceful utilizing modern services like the Web (Hinduja and Patchin; 2008), which is the definition utilized here since this work is additionally centered on the same topic.

Other definitions, in difference to the broader context of online hostility, put stricter prerequisites some time recently an action which can be considered cyberbullying: rehashed behavior over time, an lopsidedness of control between the culprit and the casualty, and at long last the aim to hurt (Gualdo et al.; 2015), in spite of the fact that the significance of a few or all of these perspectives is addressed (Cuadrado-Gordillo; 2012). Another fervently talked about address is how to recognize between typical bullying and online redundancy or indeed control freak nature (Slonje et al.; 2013).

Cyberbullying can have a assortment of negative repercussions, counting destitute scholastic performance, fear (Gualdo et al.; 2015), stretch, forlornness, and lose of hope (Ortega et al.; 2012). Cyberbullying isn't basically a issue for kids; it's too had hindering results within the work environment (Daniels and Bradley; 2011). Cyberbullying often results to suicide, injury, and acts of viciousness in extraordinary circumstances (Daniels and Bradley; 2011). In videogames, the negative impacts of cyberbullying is important for game publishers, who confront extreme monetary results as a result of cyberbullying (Mulligan and Patrovsky; 2003).

Concurring to another overview, 38% of players skipped multiplayer recreations due to stresses by cyberbullying, 54% stopped a since somebody online was locked in in this sort of behavior, and over 63% concurred or unequivocally concurred that cyberbullying could be a extreme issue within the online videogame community (Fryling et al.; 2015). This becomes a huge issue for the gaming industry, which is worth more than a hundred billion dollars and for which finding solution to this problem is doubtlessly significant (Balci and Salah; 2015). The preferences of the machine learning technique are only feasible when a given dataset, has been labelled on the basis of sentiment being negative or positive.

For case, a set of 2000 motion picture surveys were utilized to make a set of classifiers, each of which was labelled concurring to whether the commentator thought the motion picture was great or awful. In most circumstances, their execution is almost 80% or higher. In other words, the resultant classifiers can precisely foresee the extremity of novel information 80% of the time. These strategies have appeared to be valuable in an assortment of areas. On a individual level, there are more results for players. Cyberbullying is connected to forceful behaviour in genuine life (Yang; 2012), as well as expanded separation and lower self-esteem (Fryling et al.; 2015). Undoubtedly, there are reported cases of a few occurrences where negative behavior in an online environment has brought about in real-life savagery and dangers (Parkin; 2015).

Within the setting of cyberbullying, emotive examination for bad human behaviour interferences could be a significant element for the proposed investigetive agencies. (Ahmad et al.; 2019) is an internet content investigation of groups taking part in radical social media exercises. The paper centres on recognizing terrorist groups in society. To raise the precision to 94.8 percent, the (Shaukat Dar et al.; 2020) vocabulary procedure is utilized to develop an unused word reference. After adding psychological militant words, a part of negative input is created, which is inspected utilizing assumption investigation. Another of research analysis is centered on unfavourable assessments highlights the emotionalism of social media (Wang et al.; 2020). The study considers groups in China utilizing a fine-tuned BERT (Bi-directional Encoder Representations from Transformers) model to illustrate the issue. The demonstration was found to be satisfactory for distinguishing unfavourable audit traits. The utilize of wistful examination in pre-emptive forecast has vital results for government authorities (Cheng et al.; 2020).

2.2 Sentiment Analysis in video gaming

(Thompson et al.; 2017) conducted an in-game chat sentiment investigation of the StarCraft online amusement, which is one of the foremost important investigate on the issue. The analysts tended to the ponder by broadening the lexicon-based show to incorporate particular nuances and expressions related to the StarCraft amusement and video gaming in common dictionary. Destitute player involvement is regularly connected to poisonous quality in chat, which disheartens existing players from contributing within the diversion (Thompson et al.; 2017).

In-game communication can too be analyzed for an assortment of other purposes. (Obst et al.; 2018) looked at the execution of gendered personalities within the World of Warcraft online amusement by analyzing in-game communication. In-game communications might uncover the apparent contrasts between male and female gamer counterparts. Male-female interaction too uncovers a fundamental social issue that's reflected within the gaming industry. Females as often as possible depict themselves to real-world generalizations in avatars and intuitive, whereas males do the same (Obst et al.; 2018). This may be utilized within the extend to recognize any fundamental propensities in cyberbullying and create a preventative cure. The information from the game's chat has been truly valuable.

Opinion investigation in video diversions is a well-studied subject. Whereas (Zagal et al.; 2012) focuses on video diversion surveys, the thought centers on in-game communication. The paper centers on bits of knowledge instead of approaches in arrange to reveal imperative angles such as sexual orientation contrasts and age. The number of words and polished skill within the survey moreover uncover the reviewer's mental state at the time of giving feedback. Another interesting disclosure was the affect of more seasoned audits on more youthful audits when the writing period of the survey was taken into thought.

To move forward the effectiveness of sentiment analysis, a CNN (Convolutional Neural Networks) show is used. Social organizing destinations moreover serve as a stage for cyberbullying. Part of Speech (POS) labeling was recognized by (Fortunatus et al.; 2020) to classify things, intensifiers, descriptive words, and other linguistic use components. The objective of sentiment analysis is to supply a framework that can be utilized to decide whether a modern piece of substance, whether it's a tweet, a sentence, a headline, an extricate, or the complete content, incorporates positive or negative assumption. Machine learning and lexicon-based opinion classifiers are two essential approaches to the issue. A classifier is prepared on a set of already classified data of other things within the machine learning strategy (sentences, reports, etc.).

The classifier learns what recognizes a positive sentence from a negative one. Words or tokens that occur more frequently within the preparing dataset are the highlights that models are taught to do. Intemperate capitalization ought to be dodged when it comes to cyberbullying, swear words, and supremacist mishandle, agreeing to (Salawu et al.; 2017). The word reference must be overhauled with DOTA2-specific terms and nuances. Another issue emerged within the confirmation untrue positive propping up, which was afterward settled. This wrong positive issue was caused by the anonymity that online gamers appreciate.

By switching a few negative affecting words, parody can be successfully tended to. With reference to nostalgic examination in videogaming (Murnion; 2018) given valuable understanding on how to address the cyberbullying issue. The writing too highlighted a few of the conceivable exercises that could be performed to halt bullying after the examination. The extend was based on the World of Tanks amusement. The notoriety of video recreations has produced a modern kind of amusement known as e-sports. With players from an assortment of nations battling against one another, patriotism and ethnicity have risen to unmistakable quality and can be doubtlessly followed (Ismangil; 2019). It illustrated how national discussion can be protected online as well, utilizing memes and micro-expressions as illustrations.

Analysts begin with existing Natural Language Processing (NLP) techniques to translate demeanour in content (Qu; 2004). Study within this specific field has already developed in line with the rise of social media, where assumption examination is regarded as a basic commerce insights apparatus for customer-company relationship and public relative brand management. Permitting companies to study whether clients have affirmative or negative states of mind toward their items (Cambria et al.; 2017) is seen imporant. Models prepared on motion picture surveys will be one-sided toward that information, and they won't be able to get a handle on a few of the complexities and one-of-a-kind characteristics seen in unused spaces like in-game messages. Building a modern classifier would require the creation of extra preparing tests, which would incorporate impressive human coding of different comments. In any case, estimation investigation is much more than fair a procedure for identifying positive and negative extremity in conclusions (Cambria et al.; 2017).

Sentiment Analysis has been found to be successful in identifying incongruity and mockery in content (Farias and Rosso; 2017) as well as identifying conclusion points in discourse (Peleja and Magalhaes; 2015). An important point to in-game cyberbullying is group based focus on a single person that may often have heavy consequences which may not be visible that clearly. Semantic investigation approaches have now been started considered for utilization in gaming field, such as in online communication to channel out trolling chats and spam (Cambria et al.; 2017). An exertion was made in this work to utilize AI strategies to naturally classify communications by temperament in arrange to decide in the event that this may be valuable in recognizing cyberbullying.

2.3 Lexicon Based Approach to Sentimental Analysis

Whereas machine learning calculations are engaging due to their exactness, they habitually have a assortment of downsides (Sharma et al.; 2021). To start with, they are frequently not transferable to distinctive sorts of information since they are prepared on labelled data. To apply analysis on diverse opinions and datasets, new technique has to be rule based which requires significant human coding.

Sentiment lexicon is a set of language words or phrases that express specific emotions.

Each section within the estimation vocabulary includes an assumption introduction and quality related with it as stated in (Deng et al.; 2016). The opinion introductions of words within the vocabulary may be split into three categories: positive, negative, and impartial. Conclusion dictionary, SWN, General Inquirer, and Multi-Perspective Question Answering are a few of the foremost well-known general-purpose made Opinion Library (OL).

Lexicon Dictionary approaches check and weight sentiment-related words that have been evaluated and labelled, employing a vocabulary to do sentiment investigation. Three fundamental supposition ways have been inspected to accumulate the conclusion word list. The first one is a manual approach, the second is a lexicon-based approach, and the final is custom corpus-based approach. Since manpower based approach is inefficient, it is as often as possible utilized in conjunction with computerized ways as a final check, since programmed strategies make mistakes.

In recent sentimental investigation approaches, there's a part of assumption predisposition. In spite of the truth that opinion predisposition has been recognized, small investigation has been done. The article (Gonçalves et al.; 2013) presents a bias-aware thresholding (BAT) estimation examination approach, in which the aboce explained bias is diminished by deciding whether a survey is positive or negative employing a limit parameter (in the event that the sentiment result of a audit is bigger than the threshold esteem, the audit is classified as positive, anything else, it is classified opposite). A little preliminary set is utilized to decide the threshold esteem. The effect of the weights of positive and negative sentiment on the anticipated output isn't considered.

2.4 Literature Summary

Eventhough sentiment analysis has been in application in a variety of domains, videogaming is still a generally modern subject for Natural Language Processing, particularly in the setting of active online gameplay. The literature Thompson et al. (2017) was found to be the closest literature to the research question for the project with regards to scope and problem statement. The study takes another game chat for sentiment classification. The research also uses a lexicon based approach rather than a ML model due to the isolation of game chats and their different nuances as compared to normal coversations and review.

3 Methodology

For this project rule based sentimental analysis was chosen for determining the sentiment of the chats. The project employs numerous dataset during various implementation stage, hence a focus on data pre-processing is necessary for accurate results. In lexicon-based approach, the specific words and nuances are added to set of negative and positive words, which in turn are then used as rule to analyse the given dataset.

Taking note of various literature regarding sentiment analysis topic CRISP-DM methodology is chosen for this project. The following diagram 1 which is taken from the research paper (Wirth and Hipp; 2000) is a flow representation of CRISP-DM methodology.

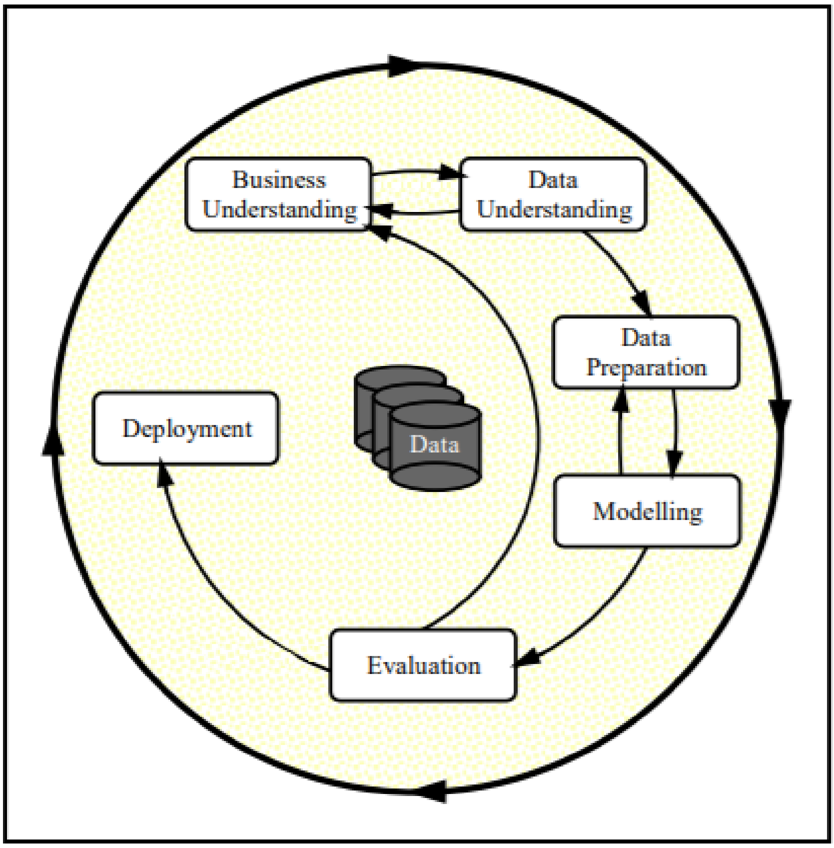

Figure 1: CRISP-DM Methodology

3.1 Business Understanding

In recent years, a number of occasions have exponentially accelerated the development of the digital gaming commerce. Due to onset of the covid pandemic, resident side interests such as video entertainement have risen to the cutting edge of amusement. The esport scene saw the same development growth, which ventured in to supply live substance whereas conventional sports and occasions were ended globally. The increment was supported by unused stage participation of common folks. As a result, industry income is anticipated to reach $175 billion in 2020, up 20% from 2019. Growth may be inspected from two viewpoints: gadget and geology. Mobile video game player base proceeded to outperform investment as compared to gaming consoles and PCs in 2020, up 26% from 2019 to $86 billion [2].

Hence looking at the current trends, there is a lot of business opportunity that is still untapped and video game research holds huge business potential. The project focuses on the gamer experience domain of the games and hence the aim coincides with the growth in user experience of the gaming software. A gamer who has a good time is more likely to invest more in the source of amusement, therefore the research is in line with interest of videogame creators in terms of paying attention to players' emotions and common harmful features.

3.2 Data Understanding

The first dataset is a video game in game chat of DOTA 2 online video game downloaded from kaggle [3]. Dataset spans 1 million rows and 4 columns. The dataset contains chat messages in various languages and many characters. The corresponding columns have time and player slot of the message.

The next dataset is a list of positive and negative opinion words or sentiment words for English (around 6800 words). This list was compiled over many years starting from the author's first paper(Hu and Liu; 2004). The dataset has various useful properties such as misspellings, morphological variants, slang, and social-media mark-up. Misspellings are common in game chats due to the urgent nature of the following. The list has 2006 positive words and 4783 negative words.

These datasets contains altogether more information than earlier benchmark datasets for double opinion categorization in movie reviews for the same category. The data was downloaded from Github as a public availabe dataset [4] [5]. The dataset contains a set of 1,000 profoundly polar motion picture audits for both negative and positive opinion. The main purpose of this dataset is to provide benchmarks after including game specific nuances and words in the lexicon dictionary.

3.2.1 Exploratory Data Analysis

On preliminary exploratory analysis of data, we can see the following trends and information.

[2]https://newzoo.com/insights/articles/game-engagement-during-covid-pandemic-adds-15-billion-to-global-games-market-revenue-forecast/

[3]https://www.kaggle.com/romovpa/gosuai-dota-2-game-chats?select=dota2_chat_messages.csv

[4]https://github.com/MiyainNYC/Text-Sentiment-Analysis-/tree/master/neg

[5]https://github.com/MiyainNYC/Text-Sentiment-Analysis-/tree/master/pos

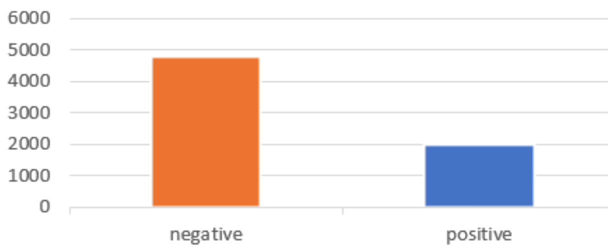

Figure 2: Bing Dictionary composition

The dataset contains a collection of positive and negative conclusion words, also known as assumption words, for the English language (around 6800 words). There are 6800 positive and negative terms within the Bing dictionary collection. Incorrect spellings, morphological fluctuations, slang, and social-media mark-up are among the dataset's numerous vital highlights. Due of the criticalness of the taking after, incorrect spellings are ordinary in amusement discourses. Most used terms will be added to the dictionary to based on their positive or negative implications. The above figure 2 shows the composition

Figure 3: Most Frequent term

The most frequently utilized terms within the dota discussion are counted. This will be helpful to take out the most significant terms that are updated in the Bing lexicon dictionary. Figure 3 and 4 are analysis study for the data.

3.3 Data Preparation

The data preparation for this project is done differently for different datasets. The DOTA 2 chat data is first cleaned for all null values and any non-ASCII characters. The rows with chats in different languages are dropped. For this project the sole focus is on English chat. Some sentences in the datasets have website referrals and hence must be dropped. Several entries with URLs are also dropped as they are of no use.

A count of most frequent words is taken out from the dota chat. This will be used to add to the lexicon dataset. The Bing lexicon dataset contains 6800 words positive and negative words. The dataset is divided into 2 separate datasets each for positive and negative words. The labelled opinion dataset is a zip file of separate text files of 1000 each of negative and positive opinions. The pre-processing is done to append all the different text file in a common data frame. The new dataframe is made of columns each for negative and positive opinions.

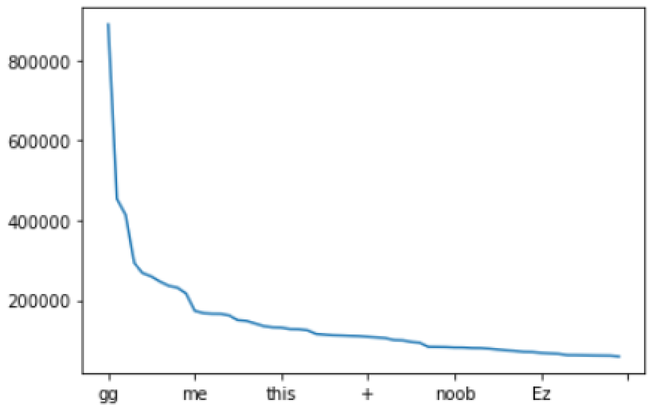

Figure 4: Term Count

3.4 Model

3.4.1 Reason for Choosing VADER (Valence Aware Dictionary for Sentiment Reasoning)

A preliminary VADER model is implemented to predict the sentiment of the text with specific nuances to DOTA 2. VADER is a popular an opinion examination tool that employs a lexicon and rules-based technique to analyse assumptions posted on informal texts. It is utilized to analyse the feeling of fabric that has both positive and negative extremity. VADER is very instrumental and trusted for calculating the sum of positive and negative feeling in a content, as well as the intensity of that feeling. There are several benefits of utilizing VADER, which makes a part of assignments simpler. There's no requirement for any preparing of information in most cases. It can decode the meaning of a content that incorporates emoticons, slang, conjunctions, capital letters, accentuation, and more. It's incredible for social media composing and works over a few and selected spaces (Hutto and Gilbert; 2015).

For this particular instance, the use of accentuation predominantly in gaming chats was a major reason for choosing of VADER. Other tools are more suited to formal discourse and hence maybe ineffective for the present research. This analyser uses the VADER lexicon to analyse the sentiment on DOTA 2 words to convey the inability of the normal sentiment analysis tools to accurately determine even the most basics of game chats nuances.

3.4.2 Reason for Choosing Rule-based lexicon methods over Machine Learning models

Rule-based strategies make sense when we have to start with no previous labelled data in Machine Learning. It's coherent to form rules so that the framework can start giving. This guarantees that data is at long last accumulated. In the long run, it will be possible to gather named information and utilize it to make directed machine learning models.(Hutto and Gilbert; 2015) Rule-based methods provide a number of points of interest. There's no requirement for preparing information, and precisely exact. It's a superb method to assemble information since the framework will be set up with rules and after that the information can be streamed. Rule-based methods have a number of disadvantages such as the running time is higher. It's troublesome and time-consuming to list all of the directions.

In this instance, there is no labeled data for game chats and hence the data has been labeled and added to the Bing lexicon dictionary. The rule-based approach with vanilla Bing Liu dictionary is implemented to test the sentiment of game to test efficiency of the lexicon-based approach on the game terms. Finally, an updated dictionary with DOTA 2 specific lexicons will be added and the rule based approach will be implemented again and tested. Adding the ingame common words with negative and positive sentiment to an existing dictionary is predicted to give better results as compared to normal words dictionary.

3.5 Evaluation

The foremost suitable degree ought to be utilized depending on the balance of classes within the dataset. For multi-class circumstances, normal measurements such as large scale, smaller scale, and weighted F1-scores are too pertinent. Sentiment Analysis utilizes the appraisal criteria of Precision, Recall, F-score, and Accuracy as a classification issue.

3.6 Deployment

The sentiment analysis model can be deployed using Flask API. Flask API is most appropriate as sentiment analysis is not high load enterprise and since Flask is a single source and handle every request in turns. This is done by pickling the model onto a PKL file. Pickle by Python is the foremost common source of PKL files. Pickle is a Python module that serializes objects so they can be saved to a record and reloaded when the program calls it.

4 Implementation

4.1 Data Processing

The first dataset is a video game in game chat of DOTA 2 online video game downloaded from kaggle 2 . Dataset spans 1 million rows and 4 columns. The dataset contains chat messages in various languages and many characters. The corresponding columns have time and player slot of the message.

The information planning for this process changes depending on the dataset. All invalid values and non-ASCII characters are expelled from the DOTA 2 chat information to begin with. In the dataset rows with URLs are dropped from chats since they give no opinion data and deter assumption examination. In case the word "rage" shows up in "https://www.twitch.tv/rage channel," for case, it'll certainly modify the estimation rating result on the off chance that it is taken into consideration, in spite of the reality that it regularly does not reflect the reviewer's perspective. Since particular images (such as () @ # $ percent, etc.) are commonly utilized in audits and have no impact on the word taken method, they are removed as well. The rows including talks in different languages have been dropped as well. Since certain sentences within the datasets contain site referrals are also removed. The most frequently utilized terms within the dota discussion are numbered. From the below table 1 it can be seen that the most of the frequent terms hold different or no meaning in normal discussions.

Table 1: Most Frequent terms in game chat dataset

Term	**Frequency**
gg	891498
?	453902
ez	413832
lol	292857
u	267627
i	259207
report	246282
you	235755
GG	231193

The dataset contains a collection of positive and negative conclusion words, also known as assumption words, for the English language (around 6800 words). There are 6800 positive and negative terms within the Bing dictionary collection. Incorrect spellings, morphological fluctuations, slang, and social-media mark-up are among the dataset's numerous vital highlights. Due of the criticalness of the taking after, incorrect spellings are ordinary in amusement discourses. From the table 1 above, most used terms will be added to the dictionary to based on their positive or negative implications.

Table 2: Sentiment Count for Negative and Positive terms

Sentiment Label	**Count**
Negative	4781
Positive	2005

One of the reasons for high disparity between number of negative and positive words is because of the focus of the research is on the cyberbullying. Negative words have more weightage and hence they are numerous. The more the number of words of a particular label, the more the correct sentiment of the following emotional type will be shown. The table 2 above shows the exact number of sentiment count.

The dataset is divided into two parts, one for positive terms and the other for negative words. The labeled supposition dataset is a zip record containing 1000 negative and positive supposition content records seperately. Pre-processing is carried out in arrange to add all of the person content records into a single dataframe. The dataframe has columns for both negative and positive input. This dataframe is sent used to check the efficiency of the rule based implementation of the model.

4.2 Technique Implementation

At first the data is tokenized. Tokenization is the method of breaking down huge pieces of text data into littler ones. Tokenization isolates the crude content into words and expressions, which are alluded to as tokens. These tokens help within the comprehension of the setting or the improvement of the NLP techniques. By assessing the grouping of words, tokenization helps in translating the meaning of the content.

The first model implmeneted is the VADER sentiment analyzer. This is done to evaluate the performance of normal analyzer when fed with specific gaming terms.

The second method implmented uses vanilla Bing Lexicon database. This does not have any gaming terms and hence it is done to get basic scorimg parameters for comparison.

The third implementation uses the updated Bing lexcion dictionary.

5 Evaluation

In DOTA 2, "gg" stands for "Good Game" and is used primarily at the end of a battle session in conjunction with "wp" which is well played. Contrary to the original usage, the gg is often used as an offensive taunt towards enemy player or a spam message while performing an action. "gg" is a negative sentiment term.

Table 3: Gaming Term Polarity "gg"

Model	**Term**	**Sentiment**	**Correct Sentiment**
VADER	gg	Positive	Negative
Vanilla Bing Lexicon	gg	Neutral	Negative
Updated Bing Lexicon	gg	Negative	Negative

As can be seen from the above table 3, the result show wrong predictions. Only the updated Bing Lexicon shows somewhat results.

The next lexicon for showcasing the model predictions is "?". While a simple question mark holds no meaning in itself in normal discourse, the same character is often used to mark the questionable plays of other players. It is also used as a constant spam in text messages, often disrupting the screen information and decreasing game experience for other players. It is a negative sentiment.

Table 4: Gaming Term Polarity "?"

Model	**Term**	**Sentiment**	**Correct Sentiment**
VADER	?	Neutral	Negative
Vanilla Bing Lexicon	?	Neutral	Negative
Updated Bing Lexicon	?	Negative	Negative

As can be seen from the above table 4, the result show wrong predictions. Only the updated Bing Lexicon shows somewhat results.

The final lexicon for prediction evaluation is "GGWP" which an abbreviation for "Good Game Well Played". It is phrase often used for fair play at the end of the match and as a common greeting before the players leave the session. It is a positive sentiment.

Table 5: Gaming Term Polarity "GGWP"

Model	**Term**	**Sentiment**	**Correct Sentiment**
VADER	GGWP	Neutral	Positive
Vanilla Bing Lexicon	GGWP	Neutral	Positive
Updated Bing Lexicon	GGWP	Positive	Positive

From the above table 5, the result show wrong predictions. Only the updated Bing Lexicon shows somewhat results.

5.1 Vanilla Bing Lexicon / Case Study 1

Getting result for the vanilla Bing Dictionary showed predicted results where there many false positives. Also as predicted there is majority of neutral sentiment as the lexicon dictionary just did not had the appropriate lexicon for most of the sentiment in the dataset.

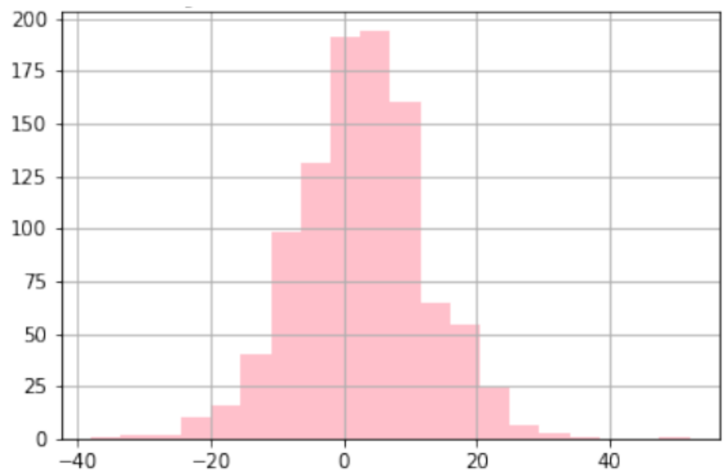

Figure 5: Sentiment Analysis for Positive Sentiment Distribution

The graph 5 shows the positive sentiment distribution in the dataset. As can be seen most of the sentiment lie towards neutrality with the graph skewing towards the negative sentiment.

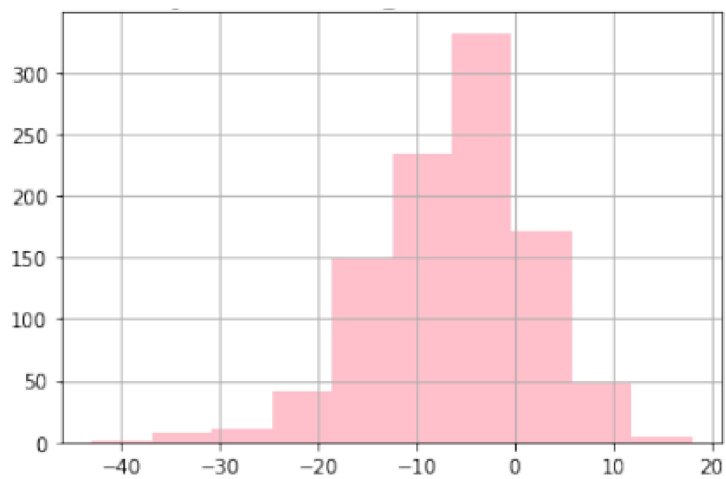

Figure 6: Sentiment Analysis for Negative Sentiment Distribution

The graph 6 shows the negative sentiment distribution in the dataset. As can be seen most of the sentiment lie towards neutrality with the graph skewing towards the negative sentiment.

The table 6 above shows the Evaluation Paremeters for Vanilla Bing Lexicon

Table 6: Evaluation Paremeters for Vanilla Bing Lexicon

Evaluation Parameter	**Score**
Precision	0.72
Recall	0.71
F1-score	0.71
Accuracy	0.77

5.2 Updated Bing Lexicon / Case Study 2

Confusion Matrix is an execution metric for machine learning classification issues with two or more classes as yield. There are four diverse combinations of anticipated and real values in this matrix. Below figure 7 is confusion matrix for the updated Bind Lexicon Dictionary.

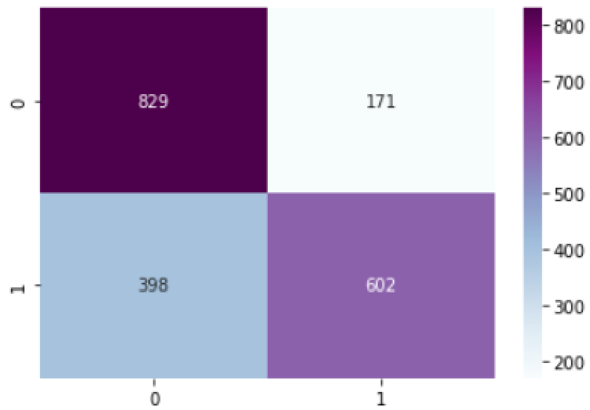

Figure 7: Confusion Matrix

The table 7 below shows the Evaluation Paremeters for Updated Bing Lexicon. When comparing the assessment scores, it is clear that there has been an in general advancement over the board. In spite of the truth that the increment shows up to be minor. Being more exact uncovers less false positives. Although there's no factually noteworthy increment in parameters, there's a diminishment in untrue negatives.

Table 7: Evaluation Paremeters for Updated Bing Lexicon

Evaluation Parameter	**Score**
Precision	0.73
Recall	0.72
F1-score	0.71
Accuracy	0.82

5.3 Discussion

On comparing the the evaluation score, it can be clearly seen that there is an overall increase across the spectrum. Although the rise seems to be insignificant. Accuracy is a metric for how precise a classifier is. Be a more prominent precision shows less false positives, while a lower precision demonstrates the high number of false positives. The completeness, or affectability, of a classifier is measured by recall. The higher the recall, the less the false negatives, while the lower the recall, the more false negatives. Although there is no such significant increase in parameters there is a decrease in false negatives.

6 Limitation

Using CRISP-DM methodology may not be an appropriate approach to the research question and KDD methodology could have been a proper fit. In a scenario without time constraint, the alternate can be used a proper route to obtain results. Another limitation was complex process of word embeddings for specific context. Larger corpus of dictionaries such as google NLP and Wikipedia database is no help due to very specific nature of the sentiment analysis of in game chat. The scope of the project is small due to low number of terms that were updated in the dictionary. Another limitation was absence of a labelled dataset in context of gaming chats. This especially proved to be great limitation as it proved hard to train a Neural Network Model. Hopefully using the methodology in this research, a new labelled data can be generated.

Sentiment Analyses has an inherent weakness to not identify difficult nuances and irony which may exist in the text. Hence it is important to identify the analysis as a tool to perform as an assistant rather than the primary source of implementation of any hard system such as banning players based on sentiment result of the chat. It should be used to identify which chats should be looked upon by the discipline committee. The research also only focuses on the English which is highly limits the application scaling of the project. Gaming is very diverse and players from all over the world enjoy. A analysis which encompasses different languages and also provide translation for chats with different language groups is useful.

7 Conclusion and Future Work

The research focused on a strategy for classifying habitually utilized terms in Multiplayer Online Entertainment literary chat discussion. While the result were assessed on the information from DOTA in this paper, it can be implemented on other MOBAs and possibly other game genre as well. To recognize between fundamental swearing and intentional insuperable, the developed toxicity lexicon is based on relevant data. It can be utilized as a component of a checking system, alongside player reports, to recognize toxic players. There's still much to be done in the the videogame industry in terms of human-machine interaction, and the research will ideally contribute to that exertion. Sentiment analysis of in-game chat to combat cyber-bullying could be a step toward dispensing with the harmfulness that's so predominant in competitive recreations and also leak into society overall. The rule-based approach of the sentiment analysis in this research is a steppingstone for videogame chat analyses. Obtaining labelled data will result in more complex machine learning models. In case of lexicon-based approaches and less time constraint, the list of updated terms can be increased to decrease the number of false negatives and increase accuracy.

The natural competition (i.e., killing each other) of MOBA games genre fills gaming platforms with much aggressiveness, however it is not tied to victory. In the event that gamers can succeed in spite of their noxious behaviour, they'll require a distinctive inspiration to halt insulting one other and begin carrying on way better for the sake of sportsmanship. Rewarding players with in-game incentives and medals for positive behavioural score also needs to be made intrinsic part of the community. This will also require sentiment analysis for identifying such positive interaction hence the research has one more application as well. On the other side, the matchmaking system that organize the players together for a match session can be changed to account for toxic quality in players to maintain a distance between good and bad players. In spite of the fact that no amount of preventive measure will be able to completely eliminate toxicity and aggression, the research maybe able to supply a distantly more pleasant gaming encounter for both newbies and veterans if the topic comes into normal discourse.

The research about too centres exclusively on English, seriously constraining the project's potential scale. Gaming is very diverse community, with people from all around the world taking part. The future scope of the project can be increased potentially if multiple language can also be accounted for by the same model. This will also provide as a benchmark for cross platform and cross region server integration and map the human behaviour in such case.

Sentiment Analysis is as often as possible utilized on literary information to assist organizations track brand and item assumption in buyer input. With the final output being increase in business value. A gamer who experiences a great time is more likely to invest more within the entertainment source, hence the arranged activity will be a watershed moment for videogame developers in terms of following players' feelings and common toxic traits. Hence a combined effort from all the parties to generate resources for AI to combat cyber-bullying is important.

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