Analyzing Sentiment of Violent Political Extremism Content

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ABSTRACT

In the century of vast technological developments and intellectual achievements, the emergence of numerous supporters of extreme doctrines is remarkable. In this thesis we show that sentiment analysis can be used for gaining insight into the structure and evolution of an online extremism forum. Additionally, we analyze gender differences and seasonal trends related to sentiment of user-generated posts.

Keywords

sentiment analysis, extremism, forum, trend developments

1. INTRODUCTION

Over the years, technology has significantly changed the way that people interact and communicate. Internet inaugurated the era of instantaneous access to any source and unobstructed communication worldwide, but most importantly the freedom of expression and exchange of ideas.

An enormous number of formal and informal messages are posted every day in social network sites, blogs and discussion forums, giving the opportunity to numerous people to express their ideas, beliefs, ideology, preferences and emotions. Sentiment analysis is the field of study that analyses people's opinions, sentiments and emotions from written language [34] and specifically aims to extract positive or negative opinions from unstructured text [36].

This thesis evolves around extracting and evaluating sentiment scores derived from the extremist forum Stormfront, where members from all over the world communicate and exchange ideas. Our collection contains 2 million extremist posts, associated with various meta data.

Considering that extremism is any political theory that favors immoderate uncompromising policies, an extremist group is a group of individuals whose values, ideals and beliefs differ significantly of what society deems as normal [4]. They operate on the edge of conventional political groups in society and they usually do not view themselves as being extremists, which results in sharing racist or violent ideas without hesitation through social networks.

In this thesis we show that sentiment analysis can be used for gaining insight into the structure and evolution of an online extremism forum. More specifically we investigate whether it is possible to make estimations about the extremeness of ideologies, demographics and trend developments, as well as gender differences and seasonal trends.

A zestful topic to explore is whether Stormfront evolves over time with an increase in number of posts. Furthermore, we assay whether it is possible to estimate the extremeness of ideologies, by analyzing the content of these posts.

Additionally, we investigate the proportion of the users that participate systematically in the forum, as well as the sentiment scores of the most active users. Months with the most positive or negative content can disclose information connected with important events or seasonal trends.

Combining monthly sentiment scores from user-generated data allows for new research opportunities. Gender differences will also be revealed in an in depth review of specific categories. The main research question of this thesis is defined as:

Can sentiment analysis provide insight in the demographics and trend developments of an extremist forum?

Since environmental temperature and seasonality usually affect human behaviour, it is interesting to investigate whether these factors affect the expression of ideologies, resulting to the first research sub question:

Does seasonality affect the expression of extremeness?

Furthermore, we will investigate the way that female members express themselves compared to the general population. This leads to the formulation of the second research sub question as:

Do women extremists express themselves more negatively compared to the general population?

The results of this study may be useful in capturing the evolution and structure of Stormfront. These results can also trigger further investigation on the impact that this evolution has in the wider society.

2. RELATED WORK

In this chapter relevant related work as well as different approaches will be discussed, including information concerning the research questions apposed.

Extremist groups, were among the very early users of the electronic communication network that eventually evolved into the Internet. In 1985, long before most people had heard about the Internet, Tom Metzger, the leader of the White Aryan Resistance, created a computer bulletin board [26]. Since then, these groups' presence online has been very active [33].

Burris, Smith, and Strahm [17] used social network analysis to examine the links between white supremacist[1] sites. They found evidence that the Internet does assist in the creation of an international virtual extremist community, as over two thirds of the links were to international sites. Overall, the most comprehensive content analysis of extremist web sites was an exploratory analysis conducted by Schafer [43]. He concluded that these web sites provide a wide range of information, the opportunity to sell products, and that they are often used as tools to facilitate communication among members.

According to Perry [40], while hate groups[2] used to recruit members or spread their message of intolerance by word of mouth or by pamphleteering, several current factors have contributed to change this. Hate group leaders have become much more sophisticated to the extent of being in position to take advantage of developing technologies. Furthermore, computers became increasingly affordable, easily and cheaply maintained, provided wider and quicker disseminating hate propaganda and could be easily accessed through work, local schools, universities and colleges. Consequently, extremists, such as hate groups espousing racial supremacy or separation, have established an online presence [23].

This thesis examines Stormfront, a social media platform which asserts to be a community of racial realists and idealists that are self-identified as White Nationalists and claim to support true diversity and a homeland for all people. They contend that they are "the voice of the new, embattled White minority" [10]. However, Stormfront is considered by many as the first extremist hate site on the World Wide Web and it represents the pinnacle application of the internet as a means to preach hate and extremist ideologies to the general public [44].

[1]The belief that white people are superior to those of all other races, especially the black race, and should therefore dominate society [8]

[2]Organizations which: spread lies intended to incite hatred toward certain groups of people; advocate violence against certain groups on the basis of sexual orientation, race, colour, religion etc.; claim that their identity (racial, religious etc.) is 'superior' to that of other people; do not value the human rights of other people [7].

Sentiment analysis on political ideology content has been implemented formerly, by Bakliwall et all in 2013, who aimed to analyze political tweets with an accurate classifier [13]. For that purpose two different subjectivity lexicons were used, one part-of-speech tagger (designed specifically for tweets), and one parser (Stanford parser). The identification of sentiment polarity of a word was approached through Subjectivity Lexicon [51], and SentiWordNet 3.0 [45]. This research concluded that through supervised learning techniques, tweets classification as being positive, negative or neutral can be fulfilled with an accuracy of almost 59% based on lexicon look up.

Related research was conducted by Jungherr regarding the role of Twitter in social activism and looked into case studies whereby Twitter was an instrumental tool in disseminating information on terrorist attacks, political dissent, and acts of oppression [3]. Likewise a structured framework to harvest civilian sentiment and response on Twitter during terrorism scenarios, has utilized sentiment analysis to gauge public sentiment. Coupled with intelligent data mining, visualization, and filtering methods data could be collated into a knowledge base and reveal potential response to terrorist threats [18].

2.1 Textual Sentiment Analysis

The history of the phrase *sentiment analysis* resides in the use of the term "sentiment" in reference to the automatic analysis of evaluative text and tracking of the predictive judgments. It appears in 2001 papers by Das and Chen [21] and Tong [50], due to these authors' interest in analyzing market sentiment.

Broadly, there exist two main approaches to the problem of extracting sentiment automatically. The lexicon-based approach, which involves calculating orientation for a document from the semantic orientation of words or phrases within the document, and the machine learning approach, which involves building classifiers from labeled instances of texts or sentences. In this thesis we follow the first approach, in which we use dictionaries of words annotated with the word's semantic orientation [35].

More specifically, machine learning methods often rely on supervised classification approaches, where sentiment detection is framed as binary (i.e., positive or negative). This approach requires labeled data to train classifiers [39]. While one advantage of learning-based methods is their ability to adapt and create trained models for specific purposes and contexts, their drawback is the availability of labeled data and hence the low applicability of the method on new data. This is because labeling data might be costly or even prohibitive for some tasks. A popular machine-learning-based method is SentiStrength, which uses a list of words and other features like punctuation to predict sentiment [48].

On the other hand, the lexical methods vary according to the context in which they were created. For instance, LIWC [47] was originally proposed to analyze sentiment patterns in formally written English texts, whereas PANAS-t [41] and POMS-ex [30] were proposed as psychometric scales adapted to the Web context.

Lexical based approach will be discussed further in section 3.3.

2.2 Sentiment Calculation

Goncalves et al. provide an overview of eight methods for extracting sentiment from text [24]. There are machine-learning-based approaches, such as SVM, Maximum Entropy and Naïve Bayes and lexicon-based approaches, such as LIWC and POMS-ex [25].

Lexicon-based approaches require a lexicon with predefined set of terms that determine sentiments [24], afterwards words are scored according to the amount of sentiment they evoke.

Currently, the primary method used to extract sentiment from the Stormfront forum is a lexicon-rule-based model, called VADER. VADER (Valence Aware Dictionary for Sentiment Reasoning) is a Python package and it is a simple rule-based model for general sentiment analysis. The VADER lexicon performs exceptionally well in the social media domain, it is simple, intuitive and the results are easy to interpret [28]. What makes it distinct from other tools is that it is quickly applied and has no need for extensive learning or training.

More specifically, qualitative and quantitative methods resulted to the empirical validation of a gold-standard sentiment lexicon that is especially attuned to microblog-like contexts [28].

Words are rated not only as positive or negative but to what extend, with the intensity of the sentiment taken into account. When VADER analyses a piece of text it checks to see if any of the words in the text are present in the lexicon, and produces four sentiment metrics from these word ratings: Positive, Negative, Neutral and Compound score.

Positive, neutral and negative sentiment metrics, represent the proportion of the text that falls into those categories, while the compound score is the sum of all of the previous lexicon ratings which have been standardized to range between -1 and 1 [12]. It is remarkable that VADER recognizes emoticons and adapts the scoring according to this sentiment-related information.

The calculation of sentiment analysis scores were derived through VADER and corroborated with Textblob [11], a Python library for processing textual data which provides natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, translation, and more.

According to Hutto [28], VADER was compared concerning its effectiveness to eleven typical state-of-practice benchmarks including LIWC, ANEW, the General Inquirer, SentiWordNet, and machine learning oriented techniques relying on Naive Bayes, Maximum Entropy, and Support Vector Machine (SVM) algorithms, and turned out to generalize more favorably across contexts than any of the benchmarks, as well as outperform individual human raters.

2.3 Seasonality

According to Kallek's definition of seasonality, seasonality refers to regular periodic fluctuations that recur every year with about the same timing and with the same intensity and which, most importantly, can be measured and removed from the time series under review [6]. In studying the causes of violent behaviour and crime, most criminologists have concentrated on traditional socio-demographic variables such as age, sex, race, and socio-economic status. However, some researchers have investigated the influence of the physical environment [19].

There is a recent theoretical basis for research into the influence of weather on violent behaviour and crime: the rational choice theory[3] [9], and routine activities theory[4] [32] suggest that weather could significantly influence violent behaviour and crime rates.

2.4 Gender language differences

The last several decades have seen an explosion of research on the nature and existence of differences between men and women. One particularly popular question has been the extent to which men and women use language differently.

This popularity stems, in part, from the fact that language is an inherently social phenomenon and can provide insight into how men and women approach their social worlds. Within the social sciences, an increasing consensus of findings suggests that men, relative to women, tend to use language more for the instrumental purpose of conveying information and that women are more likely to use verbal interaction for social purposes with verbal communication serving as an end in itself [16] [20] [5].

Textual differences as well as differences in terms of emotional and linguistic expression can be observed in different genders. Newman et al. [37] found that women express more positive emotion when interacting with others, but not in written context. Generally, societal expectations usually discourage women from showing anger compared to men that have an advantage in the use of anger words [29].

At the same time, a number of theorists have argued against the existence of any meaningful differences in men's and women's language [15]. While there is a disbelief whether male extremists forum members present higher levels of extremeness compared to female, it is not clear whether there is a gender advantage in the expression of negative emotion.

Some authors argue that women express more negative emotions than men [49], while others (e.g. [37]) report the opposite. One contributor to this doubt may be the lack of

[3]Rational choice theory: violent behaviour (crime) is the result of a choice made by the individual offender [2]

[4]Most criminal acts require convergence in space and time of likely offenders, suitable targets and the absence of capable guardians against crime [32]

a commonly accepted metric of analysis among empirical studies of language. Multiple studies, for example, have analyzed a small number of text samples and then made broad generalizations about the differences between women and men.

In this research, language expression differences were approached through a very large data set of written text samples (2 million posts) using an automated sentiment analysis tool. The aim of this exploration, is to detect whether there are differences in the way that female members express extremeness compared to the general population.

3. RESEARCH METHODOLOGY

The research methodology of this thesis, is based on a combination of qualitative and quantitative analysis. The basic components of this methodology are apposed and explained below.

3.1 Data Collection

The data collection includes user posts from the extremist forum, Stormfront.

The available dataset of 5.3 GB, contains 2 million extremist posts broadly divided in 40 categories. It is associated with various metadata, such as the publication date of posts, the document id, the name of the user that wrote the post, whether it was a reply or an initial post, the topic and category of the post, the content of the post and the entities [38] [22] automatically extracted from the post.

People from all over the world take part in the discussions and these available metadata can be used to reveal hidden aspects of extremists' relationships and how like minded people communicate.

3.2 Data Processing

Computations were done with a DAS-4 supercomputer (fourth generation DAS). The Distributed ASCI Supercomputer (DAS) is a Computer Science infrastructure designed by the Advanced School for Computing and Imaging (ASCI) for controlled experiments with parallel and distributed systems. It was designed as a testbed for cloud computing, accelerators, and green IT.

Access is allowed to the entire distributed system and multiple clusters can be allocated at the same time. Its core (CPUs, LAN, OS) is still homogeneous but various types of accelerators were added to the different sites, allowing performance comparisons between different GPU types within otherwise identical compute nodes [27].

3.3 Statistical Analysis and Research hypothesis

This section will discuss the statistical analysis of the acquired sentiment scores and how the data will be analyzed for possible correlations. It is noteworthy that after calculating the sentiment scores of some data, aggregations were implemented by finding the mean compound sentiment scores of the respective data.

In order to examine whether there are correlations between our data, Pearson r correlation tests were conducted. By applying Pearson r correlation coefficient, we can understand the strength of the linear relationship between two variables. The values can fluctuate between +1 and -1, where 1 is total positive correlation, 0 is no correlation, and -1 is negative correlation.

4. EXPERIMENTAL RESULTS

Several experiments were conducted in order to evaluate and support the aforementioned research questions.

4.1 Demographics and trend developments

Firstly, in order to support whether sentiment analysis can provide insight in the demographics and trend developments of an extremist forum, sentiment analysis was conducted to extract the average sentiment score of posts that had been posted, for each month of each year in the data set.

The Pearson r correlation test between the average compound sentiment score of each month of each year and the timeline of the data, indicates the evolution of Stormfront users' sentiment over time and has revealed a strong downhill (negative) linear relationship of p = -0.79578923, which shows that users' sentiment score has become more negative over time (Figure 1).

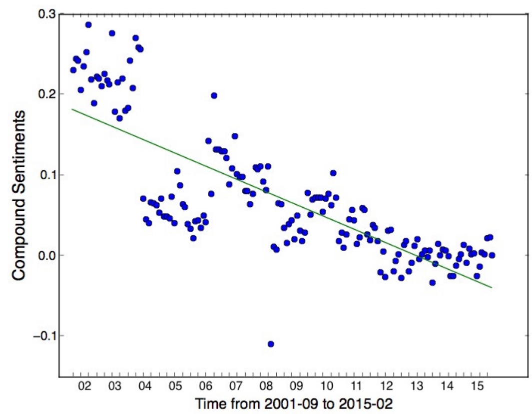

Figure 1: Correlation between monthly average compound sentiment scores and time line over months/years

Furthermore, the correlation between the average compound sentiment score of each month of each year with the number of posts of each month has also revealed a strong downhill (negative) linear relationship of p = -0.73970208 (Figure 2), showing that as the number of posts increase, the more negative they become. Therefore we can arrive to the conclusion that Stormfront has evolved over time, with an increasing number of posts and the content of these posts has become more negative.

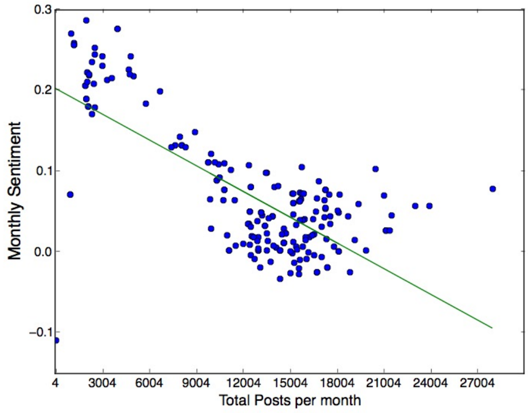

Figure 2: Correlation between monthly average compound sentiment scores and total number of posts per month

Subsequently, we aimed to explore the nature of the data set and discover how many users are systematically active and their respective sentiments. For that purpose, Stormfront users have been divided into 5 groups: lowest, low, medium, high and highest frequency level users, according to the total number of posts that they have contributed in Stormfront.

Overall, out of the 55.872 Stormfront users and 2 million posts, lowest frequency level users is the category of users that have participated in Stormfront only with 1 post, low frequency are the users with 1-10 posts, medium are the users with 10-200 posts, high frequency level are the users with 200-800posts and highest frequency level users are the most active users with 800+ posts (Figure 3).

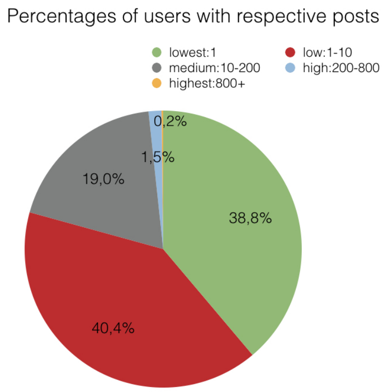

Figure 3: Percentages of users with respective number of posts and usage frequency levels

The above pie chart illustrates that the largest proportion of users who have contributed with 1 - 10 posts in Stormfront forum, was 40.4% (22580 users) with average compound sentiment score of those posts = 0.151, compared to the most active users that are significantly less, reaching the 0.2% of the total percentage (132 users) and have posted more than 800 posts per person, with average compound sentiment score of the posts = -0.030, which indicates more negative content.

Lowest frequency level users, those with only 1 post, hold the second biggest part of the pie 38.8% (21683 users) with average compound sentiment score = 0.16979. Followingly, moderate users with 10-200 posts, occupy 19% of the pie (10621 users), with average compound sentiment score = 0.07822, while high frequency level users with 200-800 posts, hold 1.5% of the percentage (856 users) with average compound sentiment score = 0.03521. (All user groups, posts range, number of users, percentages of users and average sentiment score of posts are provided in Appendix A).

Further analysis shows that no significant correlation can be found between the number of posts of every user and the average of the sentiment score of these posts per user (p = -0.01819576).

The traffic of Stormfront throughout the years is clearly increasing, starting with 27.145 total posts in 2002 (2001 data did not include all months), and growing to 161.324 total posts in 2014 (2015 data do not include all months) (Figure 4).

The following histogram shows the annual Stormfront traffic evolution, measured in number of yearly posts. The year with the highest traffic is 2009, with 222.111 posts. (Total numbers of monthly posts, as well as total number of yearly posts are provided in Appendix B).

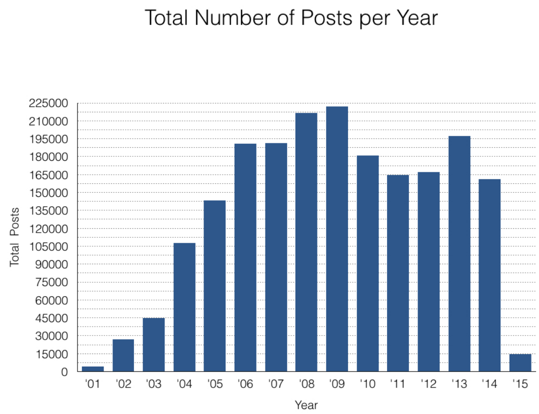

Figure 4: Total number of posts per year

Another interesting observation is that the aggregated monthly sentiment scores fluctuate widely over the years and tend to become more negative over time, forming the following Sentiment time line (Figure 5).

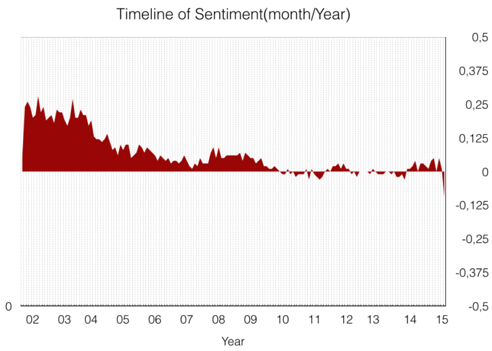

Figure 5: Sentiment over time

As research has shown, the months with the highest positive scores are March 2002 and June 2000 (with sentiment scores 0.2861 and 0.2052 respectively). The analysis of the automatically extracted entities reveals that the most discussed entities in both months, are Jews, Race and ethnicity in the United States Census, Aragorn[5], Peter the Great, Sieg Heil[6] and Sieg Fein, as well as Don.

Remarkable are the highest negative sentiment scores, which correspond to more negative content and the months are February 2015 and November 2013, with sentiment scores -0.1099 and -0.3395 respectively.

The most discussed entities within these two months were Sonderweg[7], Ahmad ibn Rustah[8],Rugii[9], Opel Omega and International court of Justice, for February 2015, as well as Jews, Race and ethnicity in United States Census, Iran, Gender and Adolf Hitler, for November 2013.

It is noteworthy that in January 2015 one of the most deadly and symbolic attacks occurred in France at the offices of the satirical magazine Charlie Hebdo in Paris, by Islamic terrorists [1]. Analyzing the most usual words in the content of the most active categories of February 2015, we can assume that this incident has affected the public opinion, contributing to one of the most negative monthly sentiment scores. Most usual words are: people, killed, murder, police, white, race, war, hate, equal, black, freedom, liberal, religion, free, national, right, kids.

Subsequently, Tf-idf measurement is applied in order to adduce which are the most important words that appear in one of the highest negative months (November 2013), compared to the rest of the months.

[5]fictional character from J. R. R. Tolkien's legendarium
[6]Nazi salute
[7]German Ideology and policy, Nazistic philosophy
[8]Persian explorer in the 10th century, important personality of Islam
[9]East Germanic tribe

Tf-idf works by determining the relative frequency of a word in a specific document (here month) compared to the inverse proportion of that word over the entire document corpus [42] (in this case the document corpus consists of the total content of each month's posts). The first 6 extracted words, descending from the word with the highest weight to the word with the lowest weight (importance), are the following: Canada, joins, move, felt, aggression, group, leading to assumptions about the content of the posts for this month.

What is remarkable is that the most active user of the whole dataset, appears as the most active user, within this month. He contributed 286 posts out of the total 14356 posts of November 2013, and his overall compound Sentiment score (derived from Sentiment Analysis at his overall posts) was -0.0045866 (Top 5 most active users, the number of their total posts, as well as the total compound Sentiment Scores of their posts, are cited in Appendix C).

Furthermore, by gathering all posts that are connected with one entity and computing the average sentiment score of these posts we can gain insight on the extremeness of ideologies, by recognizing the most negative entities. Therefore, we can distinguish the entities that are associated with negative or positive sentiment and have a better insight on the content of this forum. Top-40 negative entities are shown in Appendix D (for example: Rosa Parks, Kermit Gosnell, Minstrel show, Miley Cyrus, Phil Robertson, Jack McMahon, School voucher etc.)

4.2 Seasonality

In order to investigate whether seasonality affects the expression of ideas, firstly the average compound sentiment scores of the posts of every season were computed by the respective scores of the months which comprise each season. The results show that there is no considerable difference between seasons (Autumn = 0,0487107, Spring = 0,0435988, Winter = 0,045224 and Summer = 0,044475).

Secondly, the average sentiment scores of the posts that belong to each season of each year formulate the graph below which shows that the sentiment scores of all seasons fluctuate similarly, following approximately the same line over the years of our dataset (Figure 6).

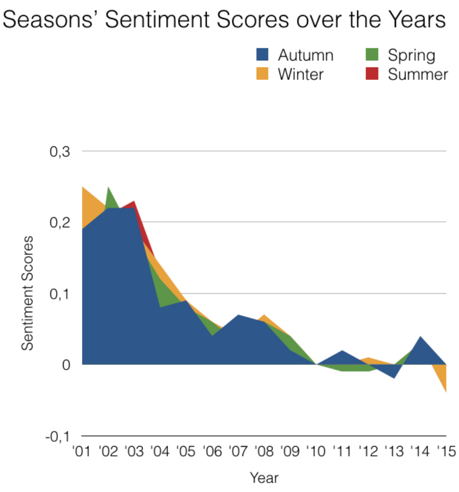

Figure 6: Sentiment and seasonality

4.3 Gender language differences

Analyzing the gender differences in expression of ideas, we compared a category known to attract mostly female forum members, "For Stormfront Ladies Only", with the general population, which consists of all other categories of the Stormfront forum.

By extracting the content of posts of each category (women - general population) and applying sentiment analysis, the outcome of the aggregated compound sentiment score of the respective posts was 0.06120770 for women and 0.03346303 for the general population, revealing that women express themselves more positively than the rest of the population. The following word cloud shows the most frequent words in discussions on the "For Stormfront Ladies Only" category (Figure 7).

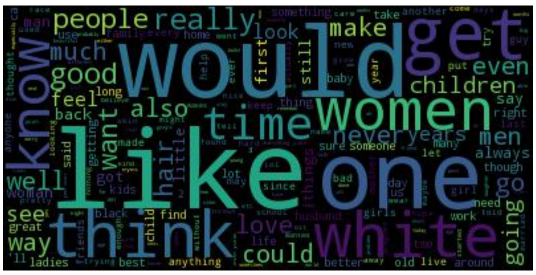

Figure 7: Female users wordCloud

The second word cloud refers to the general population category (Figure 8).

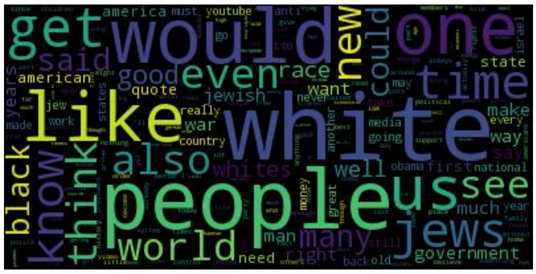

Figure 8: General population wordCloud

In both word clouds, the main (bigger) words are very similar, showing that both groups express themselves in a similar way. Female users' word cloud reveals that the words that appear most in their posts are: women, like, know, would, one, good, think, time and get. Respectively, in the general population word cloud, we see almost the same words. Terms that differ are: white, people, and world.

What is of great importance and discloses significant information, is that the slightly smaller and consequently less frequent words yet still prevalent enough to appear in the world clouds, reveal a lot about the essential differences in the forum discussions of these two groups.

Firstly, in the female users' word cloud, the terms of the specific category as compared to the general population are: hair, love, baby, proud, men, friends, life, better, child, home, racist, and feel. However, in the general population's word cloud these are: Jew, culture, never, hate, European, believe, hope, learn, little, white people, showing that women's posts often cover the topics commonly perceived as more feminine and talk about family, relationships, beauty tips and children. The conclusions are in line with the results presented in [46].

5. DISCUSSION AND CONCLUSION

The purpose of this research was to investigate whether sentiment analysis can be used for gaining insight into the structure and evolution of an online extremism forum, such as Stormfront. An additional aim was to explore the deeper gender differences and seasonal trends related to the sentiment of user-generated posts.

This research showed that a strong negative correlation was found between the monthly average compound sentiment scores of the posts over the specific time frame of our data, revealing that as time passes the posts are becoming increasingly negative. Withal, another strong negative correlation between the average compound sentiment score of each month of each year over the number of monthly posts has shown that as the number of posts increase the more negative their content becomes. Therefore, there is indication that Stormfront has evolved over time, with an increasing number of posts and the content of these posts has become more negative.

According to Knigge there could be three explanations of the rise of contemporary extremism: the impact of economic conditions (unemployment and inflation), social developments (immigration), and political trends (public's dissatisfaction with the political regime) [31], which could explain the results of our analysis.

Another interesting finding of our research is that only 0.2% of the sample population corresponds to the highly active users, which is translated as 132 users. These users are contributing to the forum with negative posts. Furthermore, it is remarkable that 38.8% of all users, have participated in the forum with only 1 post, which raises questions about the way that the platform is used.

Furthermore, seasonality appears not to affect the expression of ideas, as the aggregated sentiment scores of the posts that belong to the seasons of each year fluctuate similarly, following approximately the same line over the years of our dataset. This leads to the conclusion that the expression of extreme ideas, is part of a deeply ingrained ideology rather than a temporary reaction [14].

Similarities and differences have emerged between female members and the general population. While the first impression was that both general population and women express similarly based on the word clouds that showed no significant difference, further investigation showed that women are more frequently involved in discussions about family, relationships, beauty and children. This is in agreement with having more positive scores derived through sentiment analysis compared to the general population scores.

To further improve this research, it would be interesting to investigate how Stormfront users react after various events, and whether such events have an interactive audience which could function as a mechanism for instigating subsequent reactions in physical world.

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Appendices

A. Proportion of users and sentiment

Table 1: Pie chart detailed characteristics

UserGroups	PostsRange	NumberOfusers	PercentageUsers	AverageSentimentOfPosts
lowest	1	21683	38.8%	0.16979
low	1-10	22580	40.4%	0.15133
medium	10-200	10621	19%	0.07822
high	200-800	856	1.5%	0.03521
highest	800+	132	0.2%	-0.03032

B. Stormfront Traffic Over the Years

Table 2: Number of Monthly Posts over the Years

Month	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15
Jan		2115	3237	6681	10456	15589	16620	20472	23861	15110	17007	13494	16507	16226	14573
Feb		1967	2053	7939	9750	15160	17511	15623	19330	15778	13066	14450	13742	17005	
Mar		1955	2272	7389	10754	18151	16499	17216	18692	16388	15030	15251	16147	17537	
Apr		2289	2480	7604	11407	15547	15802	15095	21457	15998	15573	15396	13935	17295	
May		2467	3592	8282	10738	17218	15358	15822	22997	15192	14083	16681	17770	15613	
Jun		1878	3916	8047	12455	15657	15152	15723	21086	17379	12651	14315	18078	12317	
Jul		1976	2422	8915	10180	16430	13625	15168	21367	15351	13482	15000	19861	9916	
Aug		2092	4700	9918	12311	18084	17171	17488	19121	12458	12485	12952	18814	10960	
Sept	895	1960	4771	10292	14184	13141	13864	17228	14706	12964	13362	11048	16705	12402	
Oct	1138	2503	4959	11180	13451	15912	16823	18035	14550	12910	12880	12695	15591	9859	
Nov	963	2978	4650	10786	13464	13173	15727	27955	12946	15539	12542	13534	14356	11500	
Dec	1128	2965	5732	10401	13998	16666	17189	20971	11998	15995	12290	12382	15977	10694	

Table 3: Total number of Yearly posts

Years	TotalPosts
2001	4.124
2002	27.145
2003	44.784
2004	107.434
2005	143.148
2006	190.728
2007	191.341
2008	216.796
2009	222.111
2010	181.062
2011	164.451
2012	167.198
2013	197.483
2014	161.324
2015	14.573

Appendices

C. Most Active Users

Table 4: Most active users, total number of posts and Sentiment Scores

Users	Posts	SentimScores
revision	19992	-0,0045866
SDY6401	12032	0,0049658
ADAMANT	11668	0,0224922
kazan188	8990	-0,0088649
junkers88	8616	-0,0089848

D.Sorted entities

Table 5: Top-40 entities associated with the most negative average compound sentiment scores

Entity	SentimentScore	Entity	SentimentScore
Rosa Parks	-0.9999	Library of Alexandria	-0.9932
Kermit Gosnell	-0.9999	Mel Gibson	-0.9932
Minstrel show	-0.9999	Fiat money	-0.9834
Miley Cyrus	-0.9999	Fifth column	-0.9828
Phil Robertson	-0.9999	Kenya	-0.9823
Jack McMahon	-0.9999	Uganda	-0.9823
School voucher	-0.9999	Killas	-0.9812
Blackface	-0.9999	Norman Lear	-0.9651
Abner Louima	-0.9999	Lena Dunham	-0.9651
Dora the Explorer	-0.9999	Barbara Walters	-0.9651
Don Lemon	-0.9999	Harvey Weinstein	-0.9651
Teach-in	-0.9967	European American	-0.9573
Greater Netherlands	-0.9962	German Empire	-0.9547
Uri Rosenthal	-0.9962	Freemasonry	-0.933
Julius Malema	-0.9962	North West England	-0.9194
Geert Wilders	-0.9962	Neuro-linguistic programming	-0.9083
African National Congress	-0.9962	Reddit	-0.9062
Carjacking	-0.9951	Hurricane Katrina	-0.9052
Apocalypto	-0.9932	Skrewdriver	-0.8762
Royal Navy	-0.9932	James Traficant	-0.8577

E. Seasonality and Extremeness

Table 6: Pearson r Correlation scores, between General population sample (of 39 users) and Aggregated Compound Sentiment scores of Seasons

Season	CorrelationScore
autumn	0,04807868
winter	-0,05384657
spring	-0,04180299
summer	-0,07269894