Leveraging Natural Language Processing to Analyse the Temporal Behavior of Extremists on Social Media

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Original scientific article

Abstract—**Aiming at achieving sustainability and quality of life for citizens, future smart cities adopt a data-centric approach to decision making in which assets, people, and events are constantly monitored to inform decisions. Public opinion monitoring is of particular importance to governments and intelligence agencies, who seek to monitor extreme views and attempts of radicalizing individuals in society. While social media platforms provide increased visibility and a platform to express public views freely, such platforms can also be used to manipulate public opinion, spread hate speech, and radicalize others. Natural language processing and data mining techniques have gained popularity for the analysis of social media content and the detection of extremists and radical views expressed online. However, existing approaches simplify the concept of radicalization to a binary problem in which individuals are classified as extremists or non-extremists. Such binary approaches do not capture the radicalization process's complexity that is influenced by many aspects such as social interactions, the impact of opinion leaders, and peer pressure. Moreover, the longitudinal analysis of users' interactions and profile evolution over time is lacking in the literature. Aiming at addressing those limitations, this work proposes a sophisticated framework for the analysis of the temporal behavior of extremists on social media platforms. Far-right extremism during the Trump presidency was used as a case study, and a large dataset of over 259,000 tweets was collected to train and test our models. The results obtained are very promising and encourage the use of advanced social media analytics in the support of effective and timely decision-making.**

Index Terms—**smart cities, social media analytics, extreme views, temporal behavior, natural language processing.**

I. INTRODUCTION

Future smart cities aim at achieving sustainability and quality of life using a combination of smart technologies [1]. To attain such a goal, smart cities rely on a data-centric approach in which assets, people, and events are constantly monitored, and the data is analyzed to extract insights informing decision-making.

Falling under the umbrella of data analytics, social media analytics have gained significant popularity recently due to the potential it offers in understanding public opinion and sentiments about current events and issues. Public opinion, which represents the predominant views about a certain topic, is significant to governments and businesses [2]. Extreme public opinion consists of the radical views held by extremists aiming at radicalizing others [3].

Radicalization is a multidimensional concept that has several definitions. The VEEM Framework (Violent Extremism Evaluation Measurement) is a methodology that allows for assessing and classifying the extent to which an individual is radicalized [4]. The framework classifies violent extremism into 3 main stages: "Initial states of extremism"; "Initial manifestation of extremism"; and "Extremist manifestations". McCauley and Moskalenko define radicalization as a "change in beliefs, feelings, and behaviors in directions that increasingly justify intergroup violence and demand sacrifice in defense of the ingroup" [5]. Moreover, the idea that radicalization is a process is supported in the literature. For instance, Hogan highlights the progression from legal activism, to violent actions, to terrorism [6]. Being dissatisfied can make an individual vulnerable to the influence of prominent extremists. Silber and Bhatt's findings, based on a study of several jihadist plots in several Western countries, identify the following stages of radicalization for homegrown terrorists: 1) Pre-radicalization; 2) Self-identification whereby the individuals adopt Salafi ideology in the context of cognitive opening or personal crisis; 3) Indoctrination where the adoption of new beliefs accelerates and where the role of the group is important, and 4) Jihadization leading to starting planning operations [6]. Finally, Wiktorowicz suggests a four-stage radicalization model, which starts with being open to new ideas, to a connection with activists, to the acceptance of a figure of authority, then lastly the belief in violent action [6]. Doosje et al. [7] identify macro, meso, and micro factors of radicalization, including determining an individual's sensitivity to influence; the individual becoming a member of a radical group, and taking violent actions.

With the proliferation and widespread usage of social media, social media platforms are now used as channels and tools for the expression of public opinion. The influence of social media platforms on public opinion has been highlighted in several studies [8]-[10]. The authors in [8] addressed the virality of social media content and its impact on youth. The researchers in [9] found that social media is being used to further political

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interests, while the authors in [10] argue that social media is a powerful tool for persuasion and can be used to manipulate public opinion.

Due to the significant use of social media as a tool for radicalization, the monitoring of extremists and extreme views expressed online becomes critical for understanding and predicting the radicalization of individuals in society. Recently, machine learning, data mining, and natural language processing techniques have been used for the detection of radicalization and extremism online. Lara-Cabrera et al. [9] utilized data mining techniques to analyze a set of parameters that can indicate the risk of radicalization on Twitter. Ashcroft et al. [10] proposed a machine learning-based framework for identifying tweets that contain messages in support of Jihadist groups. Ferrara et al. [11] proposed a machine learning-based approach to identify extremist users and predict their interactions with other users and the spread of extremist content. Wadhwa et al. [12] proposed a method for the detection of the behavior of radical groups on social network platforms.

Despite the merits of existing approaches, they suffer from some limitations. Radicalization identification approaches simplify radicalization to a binary problem in which an individual is classified as extremist or non-extremist. Instead, radicalization should be studied as a complex process that is influenced by a multitude of factors such as social interactions, peer pressure, ideology and beliefs, and prominent figures' influence. As for the existing predictive approaches, they reply on techniques that fail to capture the temporal behavior and evolution of the user's profile over time. Indeed, consistency of behavior over time is critical for the accurate classification of extremist profiles. Since radical individuals are driven by a belief system and specific ideologies, they exhibit extremist behavior consistently, rather than occasionally in reaction to certain events.

This work aims to contribute to the social media analytics area, by proposing a sophisticated framework for the analysis of the temporal behavior of extremists on social media platforms. Twitter was chosen as the social media platform due to its popularity for the expression of political discourse, while far-right extremism was chosen as our case study due to its increased popularity and devastating impact in recent years. Far-right terrorism has increasingly become a significant security concern on the agenda of several Western states [13]-[16]. The Counter-Terrorism Committee Executive Directorate of the United Nations Security Council defines far-right terrorism as a "unique form of political violence with often fluid boundaries between hate crime and organized terrorism" and considers that right-wing individuals and groups adopt "different but related ideologies, often linked by hatred and racism toward minorities, xenophobia, islamophobia or anti-Semitism" [15]. Across the world, the Global Terrorism Index thus notes a 250% increase in far-right attacks since 2014 and a 709% in related deaths in the same time frame [16]. This is particularly true for the United States, in which two-thirds of terrorist attacks were perpetrated by right-wing extremists in 2019, and over 90% of attacks between January and May 2020 [13]. Building on the approach we proposed in [17] in which sentiment and links analysis was used, our proposed framework aims at examining the behavioral and social dynamics of extremists on social media, by leveraging advanced natural language processing techniques, including 1) data augmentation and clustering; 2) social circle analysis; 3) content analysis, and 4) temporal behavior analysis. The proposed framework can serve as a decision support tool for government officials and intelligence agencies seeking to monitor and analyze extreme views expressed online.

The contributions of this research are:

1. This work proposes a sophisticated framework for the analysis of the temporal behavior of extremists on social media platforms. The proposed approach combines multiple data mining and natural language processing techniques, such as sentiment and emotion analysis, named entity recognition, data clustering, opinion leader identification, social circle analysis, and temporal behavior analysis.
2. Far-right extremism during the Trump presidency is used as a case study, and a large dataset of over 259,000 tweets was collected to train and test our models.
3. Extensive analytics and results are provided, giving insights into the longitudinal analysis of users' interactions and profiles evolution over time.

The rest of the paper is organized as follows: in section II, we present some relevant background information and related work. Section III details our proposed framework. This is followed by the results analysis and the conclusion in sections IV and V, respectively.

II. Background and Related Work

In this section, we present relevant background information and highlight related work that is relevant to our research. We start by discussing the far-right movements online extremism, to define the context for our study. We then move to the Alt-Right (Alternative Right) and its digital sub-culture. We end with how online radicalization can be classified using behavior analysis.

A. The Far-Right Ideology

Far-right or right-wing extremism can be defined as "the use or threat of violence by sub-national or non-state entities whose goals may include racial or ethnic supremacy; opposition to government authority; anger at women; and outrage against certain policies, such as abortion" [13]. The Alt-Right is not a phenomenon specific to the United States as the "fachosphere" (fascist sphere) in France is another example [18]. However, the United States stands out as the country counting the highest levels of extreme right activism on the Web [19]. The tweet sampling operated at the final clustering stage in this article will thus exclusively focus on tweets connected to the American context.

The far-right can be considered as a galaxy of several movements, most notably the alt-right in the case of the United States. Hodge and Hallgrimsdottir [20] characterize the alt-right as an "ideological movement that has existed online since at least 2012 and was known largely for its virulent racism, misogyny, homophobia, transphobia, and xenophobia". Ganesh [21] defines it as an "umbrella term for a set of radical right social movements active primarily (but not exclusively) in

Anglophone countries. It has come to be understood in the literature as a contingent coalition of activists, usually networked online, that span online troll cultures, misogynists in the manosphere, neofascists, ultranationalists, identitarians, and white supremacists, with significant variance in the influences, practices, and vernaculars of groups associated with the alt-right". Hodge and Hallgrimsdottir characterize it as a social movement based on Tilly's definition [20].

The Alt-Right can seem elusive given its fluidity [20]. Its opposition to progressive activism, extremist nationalism, and concomitant rejection of values perceived as mainstream such as inclusion or multiculturalism stand out as common denominators [20]. Its fluidity also makes it appealing to diverse individuals [20]. De Cook characterizes the alt-right as a "neo-conservative white supremacist movement" with at its core the idea of Western civilization decline [22]. The alt-right particularly stands out due to this image-based culture translating into memes [23].

Trump's victory in the presidential elections in 2016 provided the movement with additional resonance as some of its figures were evolving in the White House [13] [20]. The movement which was largely an online phenomenon started translating into actual offline spaces, the most spectacular manifestation being the protest in Charlottesville resulting in the death of Heather Heyer [20]. Therefore, the time frame for the collection of data in our study starts in 2016 and ends in early 2021, corresponding to Trump's presidential term.

B. Far-Right Movements, the Alt-Right, and Digital Sub-Culture

Online communication via the Internet contributes to strengthening ties between individuals adopting far-right ideologies [13]. Tools used online include and are not limited to "Facebook, Twitter, YouTube, Gab, Reddit, 4Chan, 8kun (formerly 8Chan), Endchan, Telegram, Vkontakte, MeWe, Discord, Wire, Twitch, and other online communication platforms" [13]. Breitbart is also effectively considered the main platform of the Alt-right [20]. These groups may operate differently: white supremacist groups prefer the dark web or underground fora, and the Alt-Right adopted Twitter [22].

Alt-right groups and more generally far-right groups thus use the internet for several purposes: sharing ideas, recruiting, and connecting individuals and organizations [24]. The individuals connecting online are looking to be part of a community, even if a virtual one as they "can find a common identity through extreme-right websites" [24]. This contributes to building a full "radical right digital subculture" [14] even though the alt-right is not limited to the online troll culture blending racism sexism and xenophobia [23]. Gaudette et al [25] conducted interviews with former far-right extremists and their findings showed the interaction between their online and offline activities. Participants explained their continued and increasing immersion into extremist content fulfilling a need for connection to supportive and like-minded people, describing digital spaces as empowering [25]. The Proud Boys, for instance, have a "heavy and strategic use of social media" [22]. Social media can thus eventually lead to violence and physical confrontation [26]. Klein concludes that "Whereas Antifa often frames the Right as White nationalist or sympathetic to racists, the Proud Boys/Oath Keepers regularly cast liberals and leftists as unpatriotic or communist" [26]. Klein equates the messages carried by the alt-Right "to take America back" with–taking action [26]. Eventually, "Twitter, as a space for political debate, becomes an arena for activating violence" [26].

The Alt-right is usually considered one of the most active groups on Twitter gaining more visibility since the election of Donald Trump to the American presidency [27]. It is thus no surprise that Twitter can precisely be described as "host to some of the most contentious factions of the current hyper-partisan climate", especially "between the alt-Right and antifascist Left" [26]. White nationalists' Twitter accounts grew by 600% between 2012 and mid-2016 [18]. Gallaher goes as far as to consider Twitter as "the Alt-Right's social media platform of choice" [24].

Twitter is popular due to its public interaction nature and the subsequent possibility of spreading information across a user's network [27]. It is as a result particularly attractive to the youth [24]. We thus choose to focus on Twitter as the main platform for this study and the source of the data.

C. Classification of Online Radicalization based on Behaviour Analysis

Cabrera et al. focused on defining indicators that can identify individuals with a high risk of being radicalized online [28]. Five indicators related to users' activity on Twitter were suggested. The first indicator is whether the user is frustrated or not. The second one is related to the user's introversion level. The third is the feeling of being discriminated against due to one's religion or faith. The fourth focuses on the user's hatred of western societies. The final indicator is related to the individual's expression of positive feelings about Jihad. The study was conducted on 17,000 tweets collected from Pro-ISIS accounts, since the 2015 Paris attack [28]. The proposed approach starts with pre-processing the data and tokenizing sentences into words to compute measures of the five indicators. A word cloud is computed and features were extracted using TF-IDF (Term Frequency- Inverse Document-Frequency) method. The results obtained show that there is a common behavioral pattern for radicalized users that distinguishes them from users. In addition, higher variability in the values of swearing and negative words is observed for radicalized users. In terms of correlation between the indicators, a strong correlation was observed between expressing positive ideas about Jihadism and the perception of discrimination as well as the use of swear words. Social circle analysis is missing in this study, which focuses on the person as an individual rather than considering the social aspects that can lead to radicalization.

Another study by Wadhwa proposed the use of textual analysis and social network analysis for the identification of the behavior of radical groups posting on Twitter [12]. The following proposal is divided into 3 main sections: the first section is web mining techniques to capture data - to collect the data, a customized web crawler will be used to capture tweets based on a specific hashtag only. Secondly, pre-processing occurs by extracting only English tweets, removing any hyperlinks present, messages will be tokenized, and stemming will be performed. After the identification of the subtopics, the

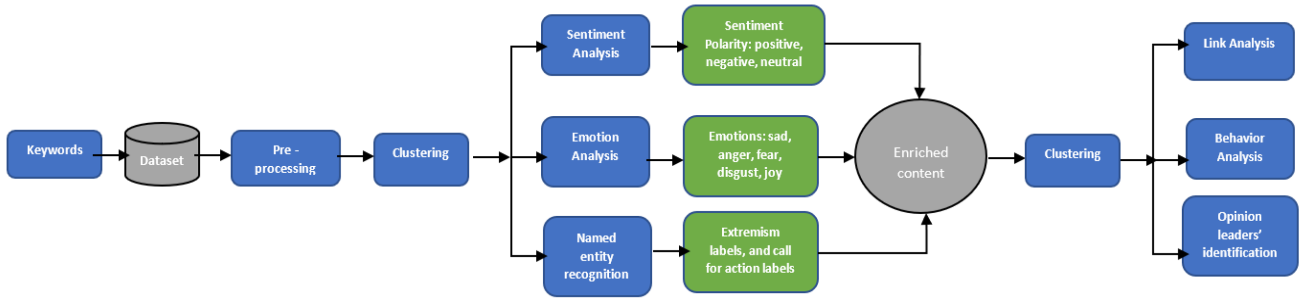


Fig. 1. Overview of temporal behavior analysis framework

tweets obtained will be clustered as per subtopic. The third section is dynamic social network analysis to discover the evolution and tracking of communities by observing the nodes branching from each subtopic at a specific sampled time interval such that the evolution of the community can be observed by applying dynamic community algorithms such as k-means clustering [12]. Results obtained for the following study which has been conducted for an entire day show that the top categories of topics were successfully chosen from the n-gram frequency count. However, drawbacks for the following study are the short duration of testing the model and not knowing how the approach applies with sentences rather than simple hashtags.

III. Proposed Framework

The main aim of this research is to analyze the temporal behavior of extremists on social media platforms. Twitter was chosen as the platform of choice due to its popularity for the expression of political views and opinions. Figure 1 depicts the key elements of our system, which is an extension of the architecture we proposed in [17]. The process begins by extracting the Twitter dataset, then pre-processing it. This is followed by clustering of the data into related tweets, to ease the categorization and analysis. Following the first clustering stage, the dataset is enriched with some meta-data related to sentiments, emotions, and extremism-related labels identified in the text. The enriched dataset is then re-clustered to refine the grouping, then subjected to more advanced analysis including link analysis, text analysis, and temporal behavior analysis. Link analysis allows for the understanding of the social circle and interactions of a user with other users within the community, whereas keyword and context analysis focus more on the individual views expressed by the user. Every user will have a profile associated with them. This profile is subjected to temporal behavioral analysis, to identify if and how the profile evolves along the identified scale of radicalization with time.

Being able to conduct a temporal analysis of extremists' behavior is critical for the accurate classification of extremist profiles. Indeed, since radical individuals are driven by a belief system and specific ideologies, they exhibit extremist behavior in a consistent manner, rather than occasionally in reaction to certain events. Contrary to existing binary approaches for extreme views classification, our approach addresses the complexity of the radicalization process and examines the behavioral and social dynamics of extremists on social media. Such longitudinal analysis of users' interactions and profile evolution over time can help in predicting the radicalization of individuals in society and provide important insights to government and intelligence agencies.

A. Dataset

A large-scale dataset was collected from Twitter to conduct our study. The dataset includes more than 250,000 tweets posted from 2016 to 2021. Ten key opinion leaders were identified in the dataset, with 612 million followers. Appropriate hashtags were used for the collection of this dataset, such as #buildthewall, @whitelivesmatter, and #MAGA. As a case study, we focus on far-right extremism, due to its rise and devastating impact. Table I details the characteristics of our dataset.

TABLE I
Characteristics of Dataset

Number of Opinion Leaders	10
Total Number of tweets	259,904
Total number of followers	612,534,930
Total number of likes	381,369
Total Number of retweets	124,128,861
Total number of replies	39,291
Start date	21/02/2016
End Date	01/05/2021

B. Dataset Pre-processing and Augmentation

Before we proceed with the analysis of the data, we relied on several techniques to pre-process and augment the data with additional information. The techniques used are summarized below:

- *Cleaning and pre-processing:* The cleaning and pre-processing step focuses on filtering the data and keeping only relevant information. For instance, hyperlinks, retweets, emojis, and non-English words were removed from the dataset. Moreover, the text was tokenized to break it down to individual words, stop words were removed, and the words were converted to their base form (lemmatization).
- *Clustering:* In this work, we relied on unsupervised machine learning and clustering for the classification of tweets. Unlike supervised learning which requires manual labeling of tweets, clustering is an approach that reveals

natural clusters in the data without the need for manual labeling. This technique uses similarity to group the data around a defined number of centroids. In our framework, mini-batch K-means clustering [29] was employed. Before the clustering, the TF-IDF value [30] was computed for the tweets' text and the elbow method was used to compute the optimal number of clusters.

- *Data Augmentation:* To enrich our dataset, we employed several NLP techniques to compute additional pieces of information that could add value and reveal insights about the data. More specifically, we employed sentiment and emotion analysis [31] to extract values about the general sentiments and the specific emotions expressed in the tweets. We also relied on named entity recognition (NER) [32] – a popular NLP technique for the identification and labeling of extremism-related work and call for violent action words within the text. All this information was added to the data to form our enriched dataset.

- *Sentiment and Emotion Analysis:* Sentiment and emotion analysis are among the common methods for the classification of radicalization. Sentiment analysis pertains to people's attitude towards a specific topic as either positive, negative, or neutral [33], while emotion analysis focuses on the emotions that underpin those sentiments (such as happiness, sadness, anger…etc). Typically, political extremists tend to use more negative sentiment words compared to non-extremist users [34]. Moreover, the literature shows anger, resentment, insecurity, and powerlessness as pre-dominant emotions associated with the Far-Right [35]. To conduct sentiment analysis, we adopt a similar approach to the one used in [33], in which the feature 'S' in Equation 1 measures the sentiment tendency of an individual based on the overall sentiment of the tweets. After identifying the relevant clusters from the dataset, we assigned each tweet text with a sentiment value ranging between -1 and 1, where -1 corresponds to most negative, 0 for neutral, and 1 for most positive. We conduct an emotion analysis of the collected tweets, with a focus on sadness, joy, fear, disgust, and anger. IBM Watson Natural Language Understanding (NLU) service was employed for the emotions' analysis [36]. The extracted emotion scores were used to enrich our dataset and the subsequent steps of profiling and analytics generation.

$$S = \frac{\sum sentiment\ of\ each\ tweet}{Tweets\ from\ dataset} \qquad (1)$$

- *Named Entity Recognition (NER):* Following clustering, the identified cluster text underwent NER analysis to identify the clusters with the most predominant extremist speech – and thus focus subsequent analysis on those clusters. Named entity recognition is a natural language processing technique that is typically used to identify specific entities in unstructured text (e.g. person name, organization, date, location..etc). In this study, we employed NER to assess the level of extremist speech present in a tweet. While the standard NER algorithm [32] was applied, we enriched the NER dictionary used by the algorithm with extremism-related labels and call for violent action-related labels, as detailed in tables II and III.

TABLE II
NER EXTREMIST LABELS

Named Entity Labels	Named Entities
White Supremacism	"whiteprivilege","whiteterrorism","whitegenocide","whitepower", "whitesupremacy'' "whitediscrimination","gop", "trumpism", "zionists", "anti-semitism"
Anti-Immigration	"refugeesnotwelcome","protectourborders","buildthewall","abolishICE","nobannowall","ban", "radical","refugee","criminals","rapists","immigrants"
Islamophobia	"jihad","stopislam","islamterrorist","isis","radicalIslam","islamophobia","extremist","mujahedeen" "discrimination", "anti-muslimism"
Racism	"nigga", "nigger", "whitelivesmatter", "whiteoutwednesday", "notracist"
Xenophobia	"chinesevirus","chinavirus","asian","chinese"

TABLE III
NER CALL FOR ACTION LABELS

Named Entity Labels	Named Entities
Action	"forcethevote","join us","bombing", "magamillionmarch","blew up", "blow up", "kill all people", "jesusmatters","fellow patriots","patriot","patriotic","patriotic activists", "follow ", "you agree", "trump2020","marchfortrump", "register","expand","wildprotest", "more followers", "fight back", "maga patriots"

The above techniques were implemented using Python in a Jupyter Notebook. Common Python libraries such as pandas and numpy [37] were used for data manipulation of multi-dimentional arrays and matrices, while the sklearn library was used for leveraging machine learning models. Furthermore, the Natural Language Toolkit (NLTK) [38] was utilized to apply different NLP techniques. NLTK is a widely used open source Python library for natural language processing, which implements various algorithms such as stop word removing, text tokenization, stemming, parsing, clustering, and sentiment analysis. Finally, the matplotlib, textblob, wordcloud, and seaborn libraries were used for data visualization purposes.

Table IV shows a snippet of enriched tweets. The first column shows the clean tweet from which links, emojis, and non-English words were removed. The second column depicts the lemmatized tweet, which is broken down to individual words, the stop words removed, and each word is returned to its base form. Columns 3 to 7 show the emotion scores for the five emotions analyzed, namely: sadness, joy, fear, disgust, and anger. The higher the score, the more prominent is the emotion in the analyzed tweet. In column 8, we see the sentiment polarity, with a positive polarity value indicating a positive sentiment, and a negative polarity value indicating a negative sentiment. A neutral sentiment is associated with a zero-polarity value. Column 9 shows the count of extremist labels identified in the text, by the enhanced NER algorithm, while column 10 shows if the number of 'call for action' labels identified by NER.

TABLE IV
EXAMPLES OF ENRICHED TWEET

Clean Tweet	Tweet Lemmatized	Emotion sad	Emotion joy	Emotion fear	Emotion disgust	Emotion anger	Polarity	Extremist Labels	Action Labels
This is the EPITOME of WhitePrivilege. If this guy were Black or Hispanic, he'd be under the jail facing attempted	['epitome', 'whiteprivilege', 'guy', 'black', 'hispanic', 'jail', 'facing', 'attempted', '']	0.320926	0.048544	0.142047	0.618674	0.159057	-0.1333333330	1	0
I found another clown here, folks! foundanotherclown WearA Mask DiaperDonald	['', 'found', 'another', 'clown', 'folk', 'foundanotherclown', 'wearamask', 'diaperdonald', '']	0.186089	0.128018	0.369902	0.059238	0.224152	0.0	0	0
Texas clean living. This is how we role after smoking meat all day! My girls love America, Tex	['', 'texas', 'clean', 'living', 'role', 'smoking', 'meat', 'day', 'girl', 'love', 'america', 'tex']	0.069644	0.535241	0.007416	0.045347	0.009124	0.43333333330	0	0
No amnesty for illegal aliens! BuildTheWall and deport illegals! AmericaFirst Trump2020	['amnesty', 'illegal', 'alien', 'buildthewall', 'deport', 'illegals', 'americafirst', 'trump2020', '']	0.297677	0.113161	0.040477	0.191827	0.295582	-0.375	1	1

IV. ANALYSIS RESULTS

In this section, we present the results of the analysis we conducted on our enriched dataset, including the data clustering results; opinion leaders identified social circle analysis, and temporal behavior analysis of 3 chosen opinion leaders.

A. Clustering Results

In this work, we conducted clustering of data at two stages: 1) the raw data collected after cleaning and pre-processing; and 2) the data after enrichment with sentiment and emotion analysis and NER labeling.

As shown in figures 2a and 2c, the optimal number of clusters for the raw dataset was eight, while this number was reduced to five clusters for the enriched dataset. This can be explained by the fact that the additional information added to enrich the dataset provided more details and nuances about the relationship between the different tweets. Thus, tweets that seemed unrelated were correlated based on the metadata added.

To visualize the clustered data, we relied on PCA (Principle component analysis). Figure 2b shows the clustering obtained for the raw dataset, while figure 2d illustrates the reclustering of the data after enrichment. The clustering of the raw data results in an important overlap between the clusters – notably clusters 0,2,5, and 7 showing important overlap, in addition to the presence of outliers in the dataset. On the other hand, the clustering of the enriched dataset shows a significantly different picture, where the overlap is significantly reduced, leading to more distinct clusters. To better understand the relationship between the new clusters, we used dendrogram based visualization, which revealed that the clustering of the enriched dataset led to better distribution and grouping of the data – where larger clusters were broken into more fine-grained smaller clusters, and some smaller clusters being merged to form a larger more uniform cluster. Thus, we can conclude that the data augmentation led to better clustering and more quality clusters.

Following the clustering step, we drew the word clouds associated with the five resulting data clusters. Figure 3 depicts the obtained word clouds. The analysis of those figures allowed us to identify the key themes addressed in each cluster and infer the stage of extremism expressed, according to the VEEM framework. As shown in figure 3:

- *Cluster 0:* Examining cluster zero's word cloud, the cluster could be classified under the category 'initial manifestation of extremism' as identified from the VEEM framework. This cluster has a range of words such as 'patriots', 'bombing', and 'fighting' that display the acceptance of extremist ideologies such that violence is justifiable.
- *Cluster 1:* The keywords present in cluster 1 focus on frustration and anger and therefore may seem to fall under 2 categories either 'initial state of extremism' or 'angry person' following the social model (VEEM framework).
- *Cluster 2:* By analyzing the keywords identified in the word cloud, it can be identified that the following cluster overall does not have much relation to extremism; therefore, the cluster may classify under the category of 'regular person' as the most commonly used words present are: 'happy birthday', 'Arizona win' etc.…
- *Cluster 3:* Looking at the keywords in cluster 3, it can be identified that the main content of the tweets may fall towards the category of 'political person'. The cluster has some words such as 'George Floyd, 'Breanna Taylor which were large incidents that occurred in the US that have led to some political matters concerning the government.
- *Cluster 4:* The keywords present in cluster 4 display the usage of hate speech which aligns with the category 'initial state of extremism' from the VEEM framework, where such hate speech words identify anger and frustration towards wider society and culture, in addition to the presence of

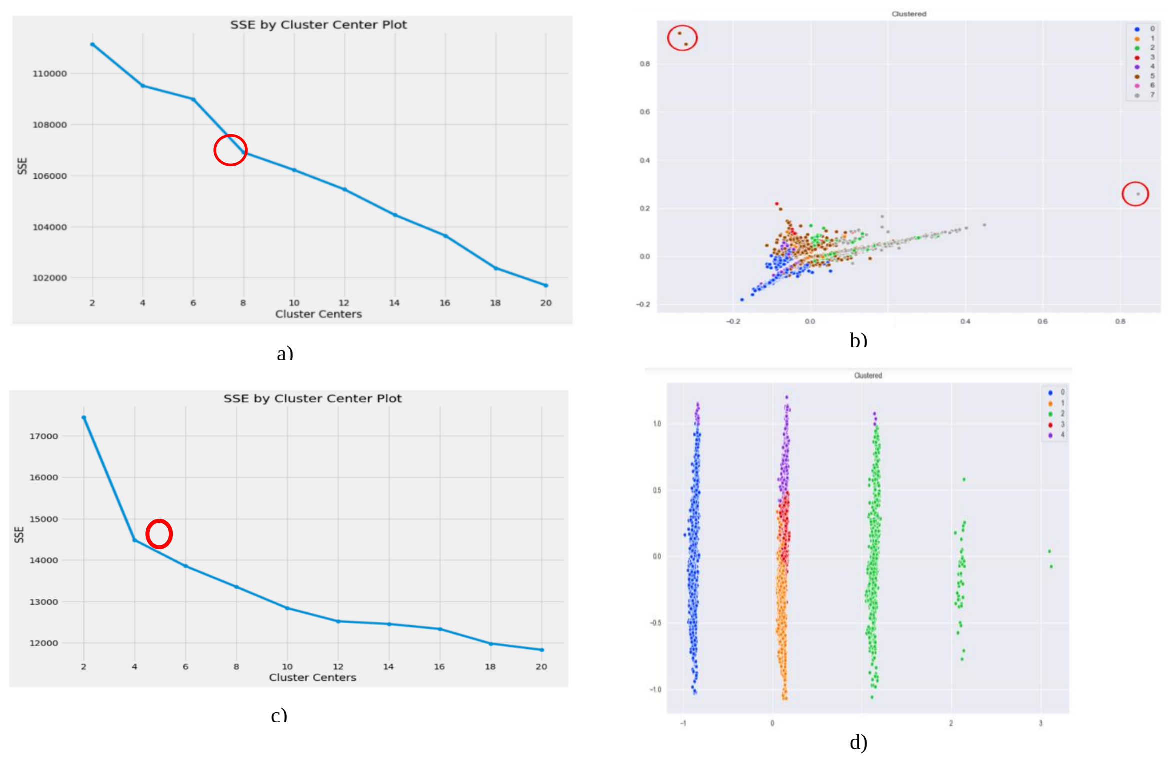


Fig. 2. K-means clustering results: a) SSE plot for the raw dataset, b) PCA clusters' plot for the raw dataset; c) SSE plot for the enriched dataset, d) PCA clusters' plot for enriched dataset

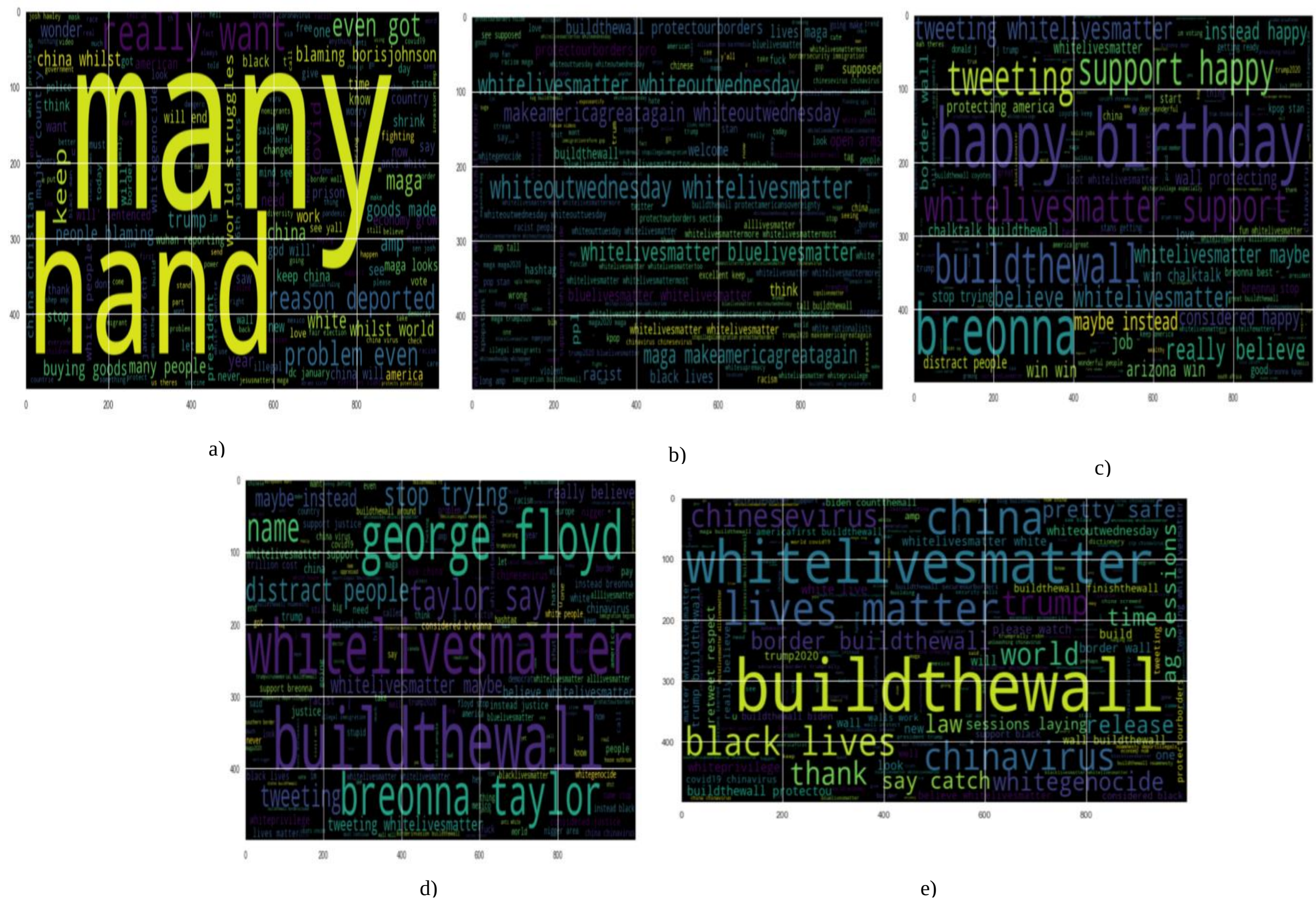


Fig. 3. Word cloud of obtained clusters: a) cluster 0-word cloud; b) cluster 1-word cloud; c) cluster 2-word cloud; d) cluster 3-word cloud; d) cluster 4-word cloud

discrimination present leading to further frustration using words such as ‘buildthewall’, ‘chinesevirus’, ‘whitelivesmatter’.

B. Opinion Leaders and their Sentiments

Following the clustering, we utilized the eigenvector centrality algorithm to identify influential opinion and ring leaders. The identified opinion leaders consisted mainly of activists, politicians, and members of the right-wing movement. Figure 4 shows the top 30 most influential users in our dataset, along with their eigenvalues, while table V presents the characteristics of the tweets of those leaders.

As shown in Table V, the list of leaders is sorted based on the tweets count over time and indicates the percentage of negative tweets associated with each user. The sentiment polarity is a decimal number ranging between -1 and 1 and indicating whether the text sentiment is positive (positive polarity value), negative (negative polarity value), or neutral (zero polarity value). A tweet sentiment polarity is calculated by taking the average of the polarity values of the tweet words. A negative tweet is one for which the tweet polarity value is negative. The percentage of negative tweets is calculated as the number of tweets with negative tweet polarity divided by the total number of tweets posted by a person. A high negative tweets’ percentage may be an indication of hate speech and inflamed discourse.

```
List = ['realDonaldTrump':0.3603,'POTUS'
:0.1162,'ICEgov':0.1186,'CAFFREY1':0.10
76,'IAMONLYCAFFREY':0.0752,'CAFFREY':0.
0732,'StateDept':0.1077,'VP':0.0639,'Ru
dyGiuliani':0.0946,'senatemajldr':0.061
8,'GOPChairwoman':0.0544,'EmmanuelMacro
n':0.0610,'EPhilippePM':0.0909,'hickfie
ld':0.0852,'BrenwoodParrish':0.0512,'Sp
eakerPelosi':0.0708,'Hoosiers1986':0.14
26,'WhiteHouse':0.0434,'NancyPelosi':0.
1288,'JoeBiden':0.0399,'MaziNnamdiKanu'
:0.1169,'BarackObama':0.0548,'CNN':0.03
61,'T':0.0539,'GrizzleMeister':0.1055,'
GOP':0.0234,'LVNancy':0.1033,'foxandfri
ends':0.0510,'cfouca':0.0503,'UKParliam
ent':0.0999]
```

Fig. 4. Top 30 opinion leaders in our dataset

Figure 5 illustrates the fluctuation of negative sentiments of the top 15 opinion leaders identified. We observe that the sentiments fluctuate over time and are highly impacted by current events while maintaining a relatively consistent average. In the coming section, we will present a more detailed temporal behavior analysis of three chosen opinion leaders.

C. Temporal Behavior Analysis

In this section, we will present a more detailed temporal behavior analysis of three chosen opinion leaders, namely: 1) An American politician (SpeakerPelosi); 2) an American right-wing activist (Hoosiers1986), and 3) Alex Marlow who is a senior employee of the well-known radical news agency Breitbart.

Figure 6a depicts SpeakerPelosi's tweets and retweets from 2019 to 2021. As expected, SpeakerPelosi’s tweeting activity is linked to current events including the US presidential elections and the US Capitol attacks, which lead to more online activity. The number of retweets indicates the level of interactions between followers and a prominent figure. As shown in figure 6b, SpeakerPelosi’s retweets declined after January 2021. This indicates a temporary relation to political events, then a decline of those sentiments over time.

TABLE V
CHARACTERISTICS OF OPINION LEADERS’ TWEETS

Screen_name	Tweets’ Count	Percentage of Negative Tweets
EmmanuelMacron	3250	2.985 %
SpeakerPelosi	3246	17.591 %
StateDept	3237	14.118 %
IAMONLYCAFFREY	3237	21.532 %
RudyGiuliani	3125	25.184 %
VP	3079	25.495 %
GOPChairwoman	3067	20.965 %
BrenwoodParrish	3061	15.354 %
Hoosiers1986	2265	20.530 %
MaziNnamdiKanu	1161	33.850 %
ICEgov	1088	31.250 %
JoeBiden	780	14.103 %
POTUS	663	13.424 %
WhiteHouse	580	13.793 %
(Average)	2274	19.298 %

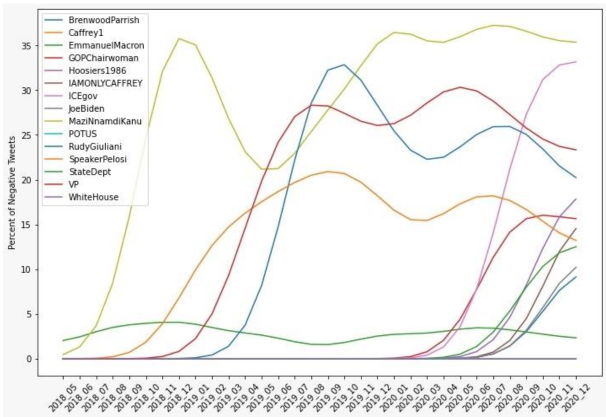
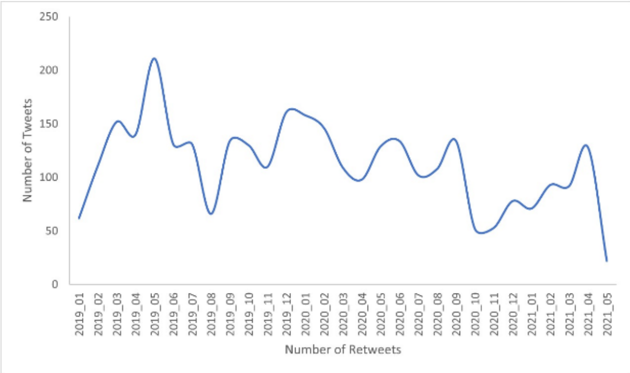
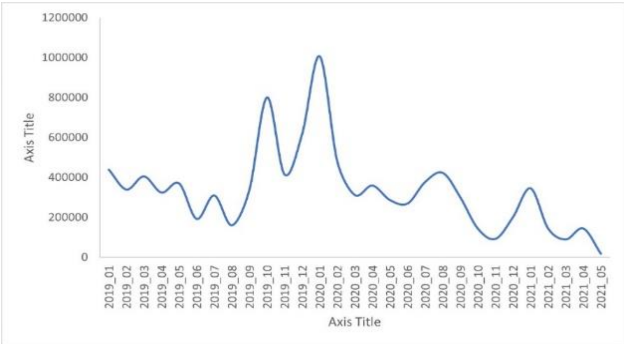


Fig. 5. Fluctuation of the negative sentiments of opinion leaders over time

Subsequently, we applied sentiment analysis to followers’ tweets to correlate those to the opinion leader’s sentiments and drew the social circle graph between the opinion leader and the top 20 followers. As shown in figure 7, which depicts SpeakerPelosi’s social circle graph, two other opinion leaders besides Pelosi are identified in the figure, namely: Whitehouse and VP. Such a dynamic corresponds to a power sphere that is characteristic of US politics. Tables VI and VII show the highest correlated and lower correlated followers respectively. The high correlation values show a significant influence of Pelosi on her followers.



a)



b)

Fig. 6. Speaker Pelosi tweets and retweets over time: (a) tweets from January 2019 to May 2021; (b) retweets from January 2019 to May 2021

TABLE VI
SPEAKER PELOSI'S HIGHEST CORRELATION FOLLOWERS

Screen_name	Correlation
AlMartinWKAR	0.877
RobWhitlock80	0.849
melissa_egg	0.719
Dominkmdomink2	0.659
iwalkalonenroad	0.559

TABLE VII
SPEAKER PELOSI'S LOWEST CORRELATION FOLLOWERS

Screen_name	Correlation
MrTimmons_1	-0.056
cdmducla	-0.061
Reader_Alert	-0.077
chockisses9876	-0.107
gphig62	-0.161

Investigating the correlation between the sentiment of Speaker Pelosi and her top 5 followers, we observe in figure 8 that the sentiments trend of followers follows closely this of the opinion leader. Moreover, we observe a non-increasing average leading us to believe that the expressed negative sentiments are a temporary reaction to political events or attacks on political opponents. This is consistent with non-extremist profiles. Lastly, we examined the percentage of tweets that contain extremism-related labels identified by NER. As shown in figure 9, Pelosi's speech exhibits a low percentage of extremist tweets and a non-increasing trend, which is coincides with a political non-extremist profile in which hate speech is mainly directed towards political opponents and driven by a political agenda rather than radical ideology.

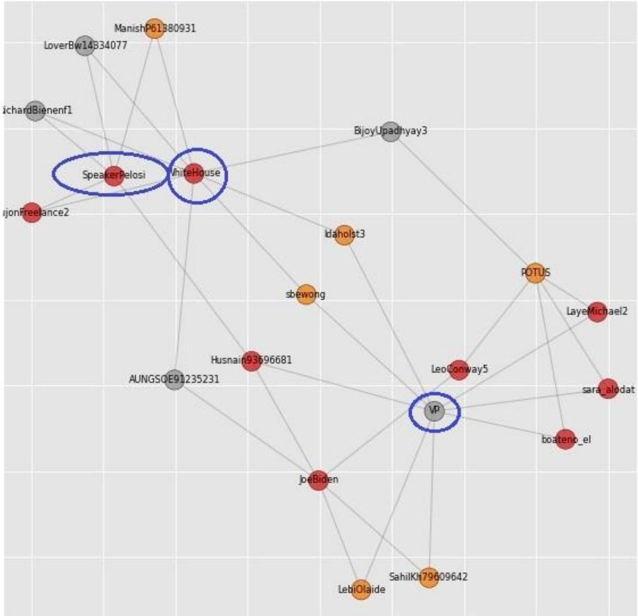


Fig. 7. Speaker Pelosi's Social Circle Grap

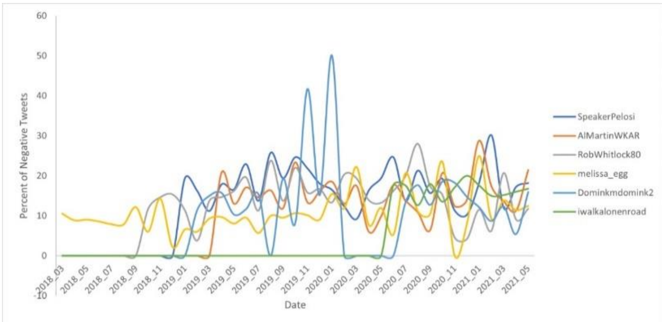


Fig. 8. Speaker Pelosi's highest correlation followers – negative tweets

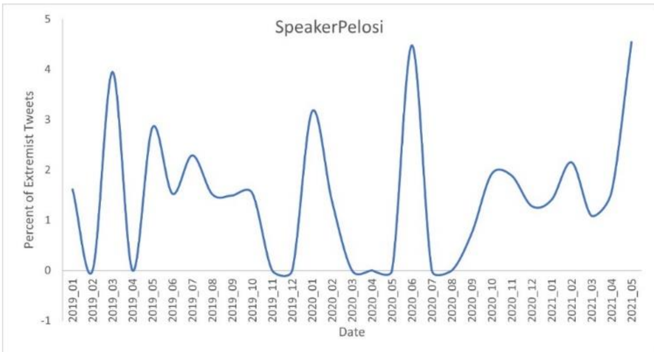
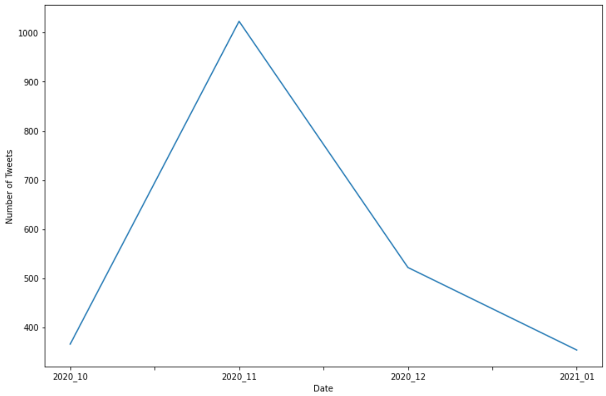


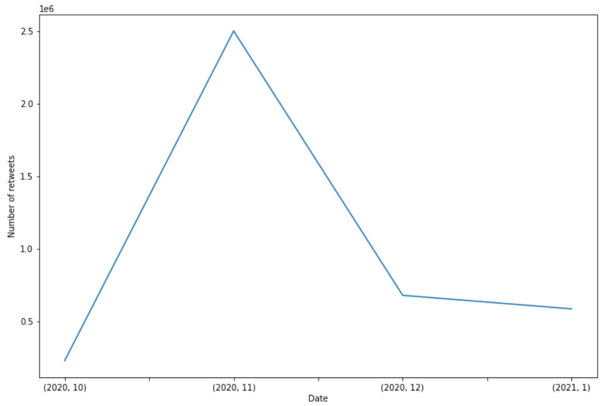
Fig. 9. Speaker Pelosi's percentage of extremist tweets over time

The same analysis was conducted for "Hoosiers1986" – A right-wing activist. Figure 10 depicts Hoosiers1986's tweets and retweets over time – Numbers that show a peak in November 2020, then a decline. This coincides with the US presidential election period, which explains the high level of activity and interactions over social media.

The results of the social circle analysis for Hoosiers1986 show an interesting dynamic, in which another opinion leader (Kathysedai) is identified in the graph (see figure 11). In this case, two opinion leaders of equal influence are collaborating to disseminate and amplify each other messages. Tables VIII and IX highlight the highest and lowest correlation between followers for Hoosiers1986, while figure 12 depicts the correlation between the opinion leader and his followers' negative tweets trends. We notice that the pattern observed in the followers' negative tweets mimics the one exhibited but the opinion leader's tweets – thus demonstrating the influence of this opinion leader on his followers. Finally, figure 13 shows a peak of extremist tweets for Hoosiers1986, in November 2020, then a subsequent decline. This implies a politically driven profile and discourse that is inflamed during certain events (the US presidential election in this case).



(a)



(b)

Fig. 10. Hoosiers1986's tweets and retweets over time: (a) tweets from October 2020 to January 2021; (b) retweets from October 2020 to January 2021

TABLE VIII
HOOSIERS 1986'S HIGHEST CORRELATION FOLLOWERS

Screen_name	Correlation
lindawadman	0.838
Onlinisgoodgma1	0.772
flighthog	0.718
muhammedlaminh2	0.671
Greatestofall	0.668

TABLE IX
HOOSIERS 1986'S LOWEST CORRELATION FOLLOWERS

Screen_name	Correlation
MrTimmons_1	0.151
cdmducla	0.116
Reader_Alert	0.095
chockisses9876	0.032
gphig62	-0.049

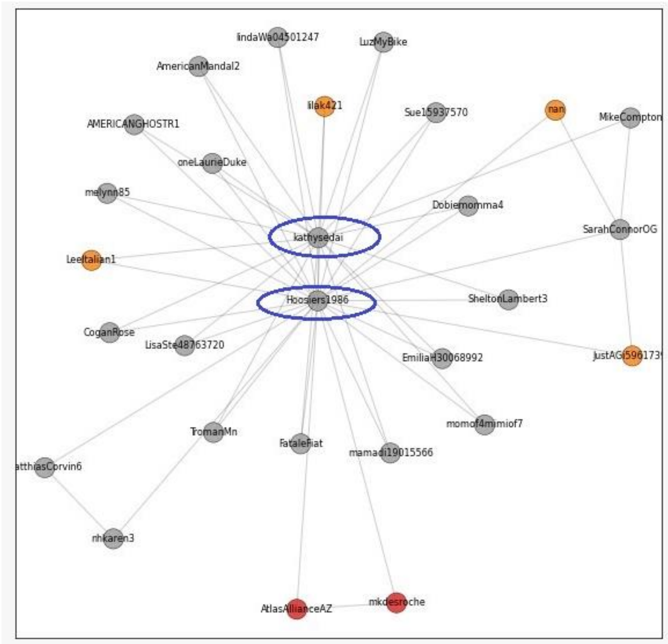


Fig. 11. Hoosiers1986's Social Circle Graph

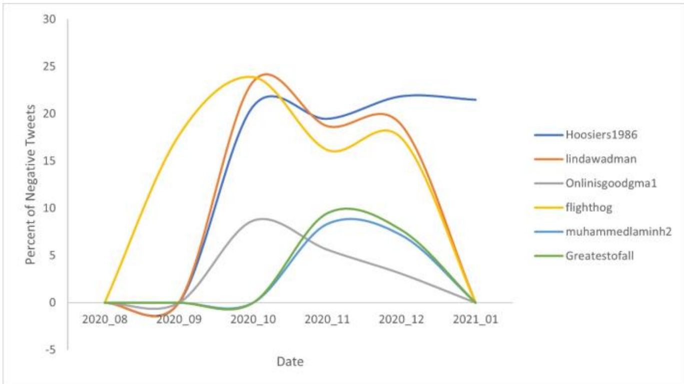


Fig. 12. Hoosiers1986's highest correlation followers – negative tweets

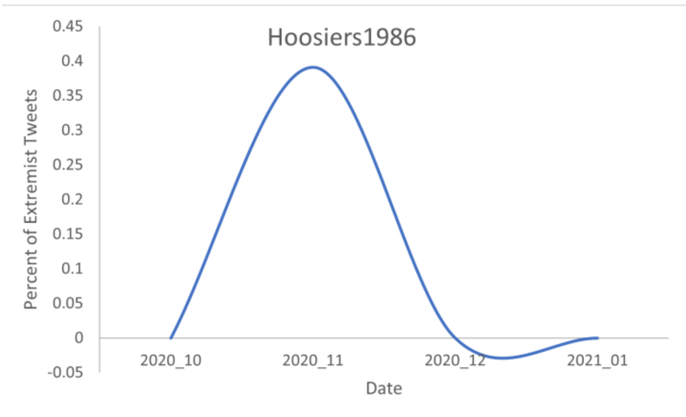
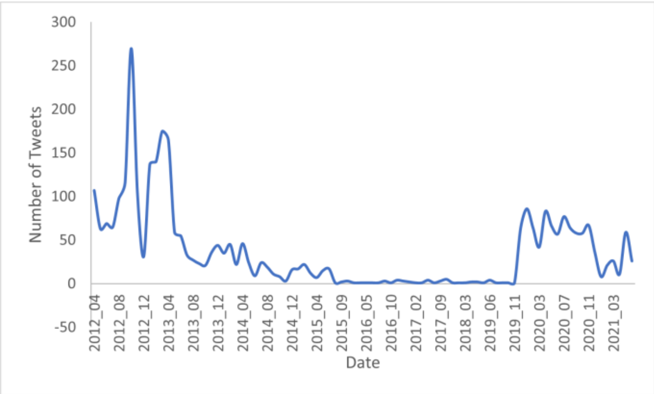
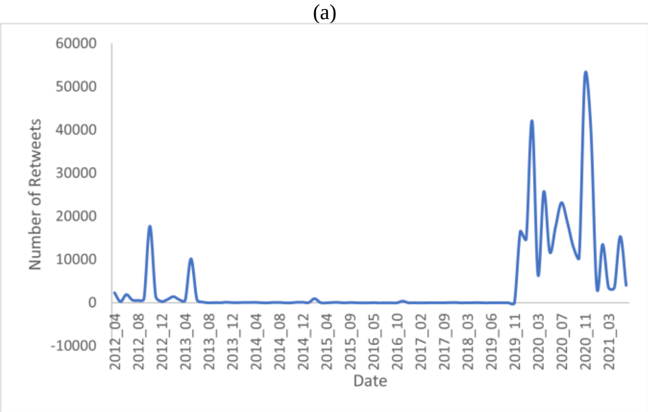


Fig. 13. Hoosiers1986's percentage of extremist tweets over time

Finally, we examined the profile of Alex Marlow – a famous Far-right extremist and editor-in-chief of Breitbart news. As shown in figure 14, Marlow shows periods of high activity on Twitter coinciding with important political events. A similar trend is observed in the reaction to his tweets.



(a)



(b)

Fig. 14. Alex Marlow's tweets and retweets over time:
(a) tweets from April 2012 to March 2021; (b) retweets from April 2012 to March 2021

When examining Marlow's social circle analysis (see figure 15), we observe a unique trend where none of the followers are connected and are only linked to the opinion leader. This implies the popularity of the opinion leader, but the lack of community formed by the followers.

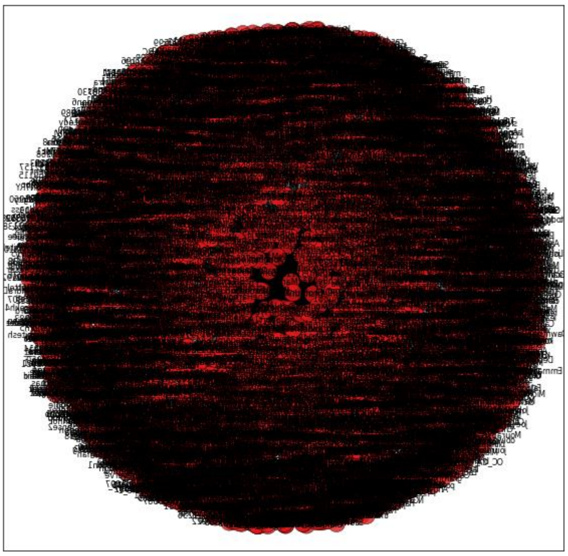


Fig. 15. Alex Marlow's Social Circle Graph

In terms of the correlation between Marlow's negative tweets and those of his top followers, we once again see a clear correlation and mimicking behavior (figure 16). Finally, there is not a clear trend concerning the number of extremist tweets posted by Marlow over time (figure 17). This could be explained by the fact that Twitter's restrictions on hate speech play an important role in shaping and censoring the speech of extremists on this platform. Indeed, knowing that they would be banned from Twitter, extremist users would likely tone down their discourse or express their most radical opinions on other platforms that do not have such restrictions.

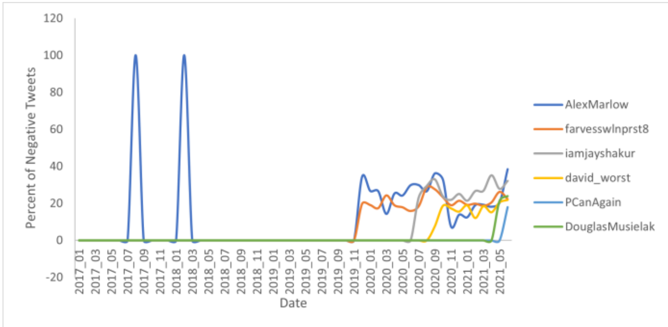


Fig. 16. Alex Marlow's highest correlation followers – negative tweets

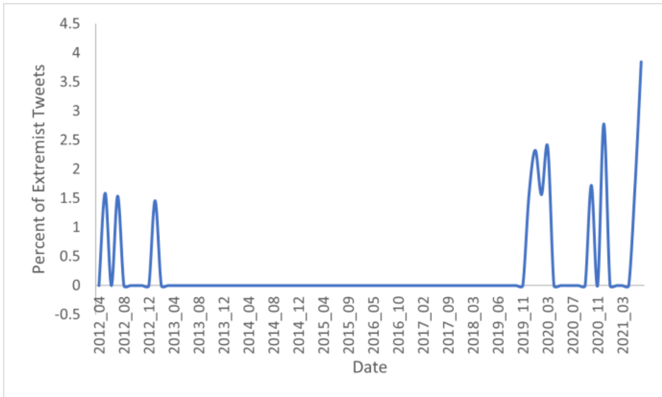


Fig. 17. Alex Marlow's percentage of extremist tweets over time

V. CONCLUSION

With the widespread usage of social media platforms for political discourse, such tools are now employed for the radicalization of individuals in society. Therefore, sophisticated techniques are required for the monitoring and analysis of extreme views expressed online. The temporal behavior analysis of extremists online is of particular importance as it can give insights into the evolution of such individuals within the complex radicalization process. In this work, we combine several natural language processing techniques to capture the nuances and complexities of radicalization and extremism and the impact of social interactions on such a process. We used the Far-right extremism-related discourse expressed during the Trump presidency period as our main case study. More specifically, we collected 259,000 tweets related to far-right extremism during the 2016 to 2020 time period, on which we employed a combination of NLP techniques including data clustering, sentiment and emotion analysis, social circle analysis, and opinion leaders' identification, content, and temporal behavior analysis. Furthermore, we focused on three opinion leaders and presented a detailed analysis of their profiles, as examples. In the future, we plan to propose a predictive model that categorizes the user's profile based on the VEEM framework and would like to provide early warning about the radicalization of individuals online.

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