How the US Presidential Elections and the Capitol Attack Shaped the Online Hate Landscape

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ABSTRACT: In the digital age, online hate networks thrive as platforms for spreading extremist ideologies and hate speech, posing a significant threat to societal cohesion. This study examines the impact of key real-world events, notably the 2020 U.S. presidential election and the January 6 Capitol attack, on the evolution of online hate networks. Using data collected from hate communities between November 1, 2020, and January 10, 2021, this research analyzes shifts in hate speech themes and network topology. Following the presidential election, an increase in hate speech targeting immigration, ethnicity, and antisemitism was observed. The January 6 Capitol attack further intensified these trends. Central to this investigation is the examination of two key aspects of online hate networks: the content they disseminate and the underlying structure of their connections. By studying shifts in hate themes and network topology, including changes in centrality and community structure, this study seeks to uncover the mechanisms driving the evolution of online hate networks. The analysis reveals significant changes in network cohesion post-attack, characterized by increased clustering and assortativity. This research sheds light on the role of online platforms in radicalization and mobilization efforts, emphasizing the need for proactive measures to combat hate speech online. Despite its niche presence, Telegram has become a key hub for propagating extremist ideologies and coordinating malicious activities.

1 INTRODUCTION

In the digital age, the internet has become a breeding ground for the dissemination of hate speech and extremist ideologies, fostering the formation of online hate networks [1, 2]. These networks, characterized by their interconnected web of individuals sharing common ideologies rooted in hatred and discrimination, pose a significant threat to societal harmony and individual safety [3]. Understanding the dynamics of these networks is paramount in combating the proliferation of hate speech and mitigating its harmful consequences [4, 5]. A science-informed approach is crucial as online groups quickly learn to adapt collectively to threats posed by content moderation [6–8].

This research looks into the intricate relationship between polarizing real-world events and the evolution of online hate networks [9, 10]. By analysing the activities of hate communities online, this study aims to show how these networks undergo a transformation in the aftermath of pivotal events. Specifically, this research looks at the 2020 presidential election and the January 6 Capitol attack in the United States.

The highly contentious 2020 US presidential election, exacerbated by the proliferation of misinformation and divisive rhetoric, served as a catalyst for amplifying existing tensions within online communities [11]. Subsequently, the violent insurrection at the Capitol on January 6, 2021, further underscored the potency of online platforms as breeding grounds for radicalization and mobilization.

Central to this investigation is the analysis of two key facets of online hate networks: the content disseminated within these networks and the underlying topology of the network. By examining shifts in hate themes within hate communities, we aim to discern patterns of adaptation in response to external triggers. Furthermore, by examining alterations in network topology, including changes in centrality, community structure, and clustering, we seek to work out the structural dynamics driving the evolution of online hate networks. Our study therefore contributes to a lesser-studied aspect of social media research: the structural effects at scale. When combined with other existing work that seeks to understand why people spread mis/disinformation online [12–14], this growing body of work can be extremely useful in curtailing its rampant spread.

2 DATA

The data for this study was collected by the Dynamic Online Network Lab at George Washington University (GWU). Data collection commenced with the identification of online hate communities, followed by continuous monitoring for cross-posts. Initial identification of online hate communities was carried out in previously-published work [15, 16]. We refer to this for full discussions and definitions of "hate".

This study goes beyond prior work in its examination of cross-posts. For instance, if a user in a hate community posted a link to another community, a directed edge was established from the hate community towards the linked community.

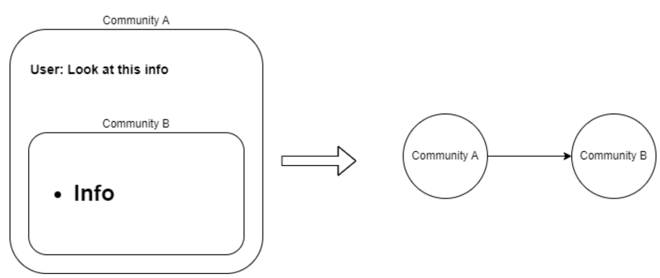

Fig. 1. Representation of how links are assigned in the network

While all the source nodes belong to identified hate communities, the target nodes may or may not belong to identified hate communities.

This study focuses on the period surrounding the 2020 U.S. presidential election and the events of January 6, 2021. Specifically, data was analyzed from November 1, 2020, to January 10, 2021.

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In addition to monitoring cross-posting activities within these hate communities, the posts were also classified to identify various types of hate speech prevalent within the posts. Seven types of hate speech were classified, targeting race, gender, religion, anti-semitism, gender identity/sexual orientation (GISO), immigration, and ethnicity/identitarian/nationalism (EIN). We refer to [15] for full discussion of this automated classifier, but note that the method has been checked against human reviewers and has a high degree of accuracy.

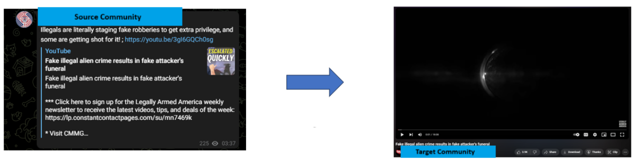

Fig. 2. An example of cross-post of a YouTube video in a Telegram channel identified as a hate community

3 RESULTS

The analysis of the hate network following the 2020 presidential election on Nov 3, 2020, and the United States Capitol attack on Jan 6, 2021, sheds light on the complex interplay of online dynamics and real world events. Through an examination of network cohesion and the change in hate content, we discover compelling insights into the transformative forces at play within this digital hate ecosystem. This section looks into the changes observed within the network.

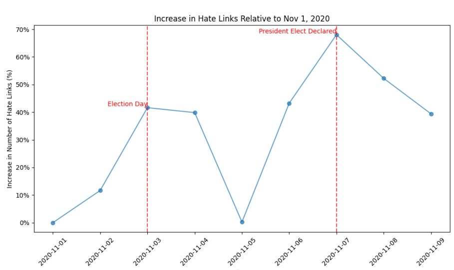

Fig. 3. Percentage increase in number of links relative to Nov. 1, 2020

The initial observation that stood out was the substantial increase in the number of links within the network during both time intervals. On November 3, the day of the presidential elections, there was a notable surge in hate links, showing a 41.6% increase compared to November 1. Subsequently, on November 7, when Joe Biden was declared president-elect, the number of links spiked even further, rising by 68% compared to November 1.

We observed a similar spike in our network surrounding the events of the January 6th, 2021 Capitol attacks. On January 6, there was a significant increase in the number of links, rising by 67.59% compared to January 1.

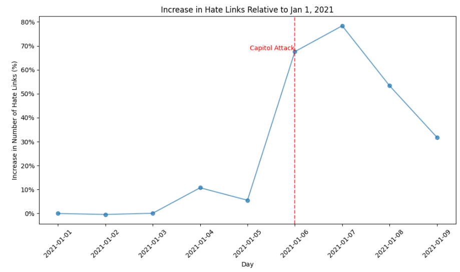

Fig. 4. Percentage increase in number of links relative to Jan. 1, 2021

3.1 Network Cohesion

Our analysis of the network following the Jan. 6, 2021 Capitol attacks reveals a significant increase in network cohesion. This tightening of connections is evident through three key network metrics: clustering coefficient, assortativity, and community dynamics.

Table 1. Comparison of Network Metrics post Jan 6 2021 Capitol Attack

Property	Pre Jan 6 (Jan 1 to 5, 2021)	Post Jan 6 (Jan 6 to 10, 2021)	% Change
Number of Communities	115	86	-25.2%
Size of the Largest Community	5632	7068	25.5%
Clustering Coefficient	0.011	0.028	159.2%
Assortativity	-0.49	-0.35	25.1%

The clustering coefficient, which measures the tendency of nodes (online communities) to form triangles (connected groups of three), jumped by a substantial 159% after the Jan. 6 capitol attack. This dramatic rise suggests a significant shift in the network structure. Nodes previously on the periphery formed connections with their neighbors, leading to a denser network with well-defined clusters. This implies that individual nodes within the hate network became more interconnected and entrenched within their specific groups [17].

Furthermore, assortativity, which reflects the tendency of nodes to connect with similar nodes, also increased by 25.1%. This rise in assortativity strengthens the notion of increased cohesion and homophily; Individuals within the network preferentially connected with others who shared characteristics. This potentially indicates a strengthening of existing ideologies within the network, fostering a more homogenous and an environment resilient to outside intervention [18, 19].

Finally, the observed changes in the number of communities and the size of the largest community paint a convincing picture of network consolidation. The number of communities decreased by a significant 25.2%, hinting at smaller communities merging to form larger communities. Furthermore, the size of the largest community grew by 25.5%, suggesting a convergence of individual communities towards a more dominant, potentially extreme, viewpoint. This

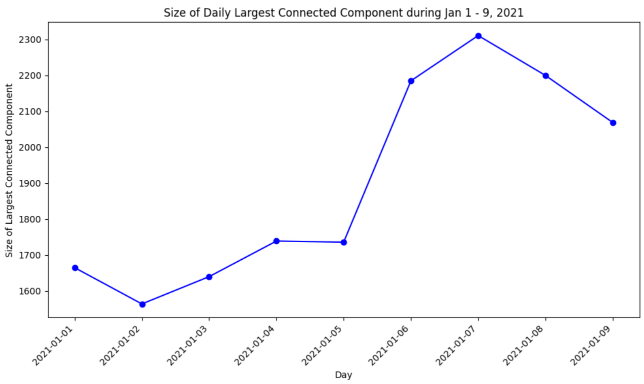

Fig. 5. Size of the largest connected component on each day during Jan. 1 - 10, 2021

dynamic implies a less diverse network with a more unified ideology, potentially amplifying the spread of hate speech or coordinated actions.

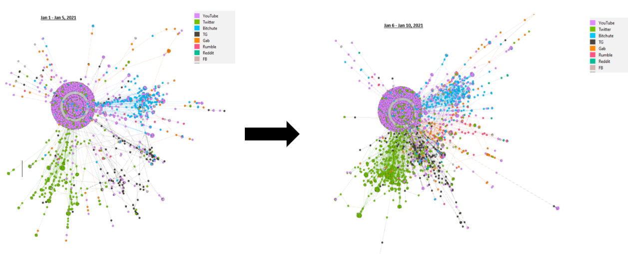

Fig. 6. Visualization of the pre-Capitol attack network and the post-Capitol attack network

These findings on network metrics are further corroborated by visualizations of the network before and after the event. Network visualization tools like Gephi can visualize the structure and connectivity of the network. Examining these visualizations reveals a shift towards a more cohesively connected network structure.

The trends observed following the November 3, 2020 elections exhibit a similar pattern, albeit with smaller variations compared to those that appeared after the January 6 Capitol attack.

The relatively smaller changes observed following the 2020 elections, compared to the upheaval witnessed after the January 6 Capitol attack, could potentially be attributed to the elections being a less unexpected event, thus resulting in more moderate alterations in the network metrics.

3.2 Change in Hate Content

Following the analysis of network cohesion, this subsection explores the changes in hate content within the network during the same period (November 1, 2020 – January 10, 2021). Here, "hate content" refers to speech targeting individuals or groups based on characteristics like immigration status, race, or gender identity.

Table 2. Comparison of Network Metrics post the 2020 US Presidential Election

Property	Pre Nov 3 (Nov 1 to 2, 2020)	Post Nov3 (Nov 3 to 4, 2020)	% Change
Number of Communities	70	68	-2.85%
Size of the Largest Community	4334	4726	9.0%
Clustering Coefficient	0.012	0.014	12.4%
Assortativity	-0.52	-0.49	5.3%

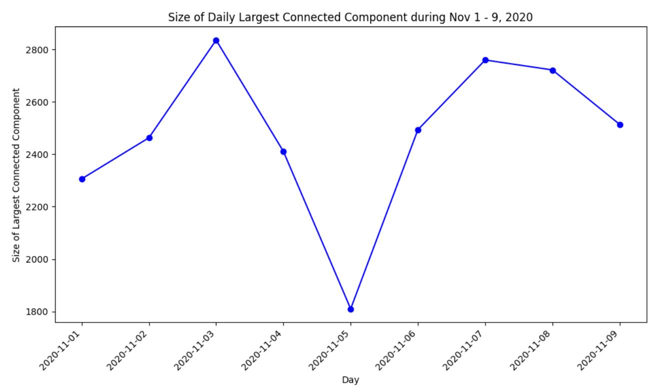

Fig. 7. Size of the largest connected component on each day during Nov. 1 - 10, 2020

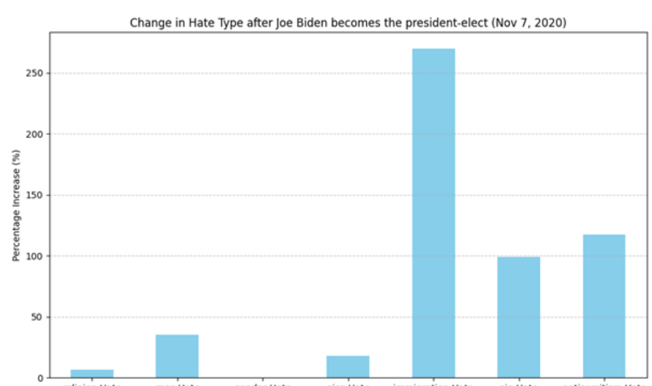

Fig. 8. Percentage change observed in the hate network after Nov. 7, 2020.

Following the declaration of Joe Biden as president-elect on November 7, 2020, a significant uptick in hate speech targeting immigration, ethnicity, and antisemitism was detected within the network. Particularly noteworthy were the observed increases: a 269.5% surge in anti-immigration sentiments, a 98.7% rise in ethnically-based hatred, and a 117.57% escalation in expressions of antisemitism between November 7 and November 11, compared to November 2 to November 6. These trends are indicative of the immigration anxieties harbored by far-right communities, which often align with the Great Replacement conspiracy theory, attributing perceived demographic shifts to Jewish influence [20].

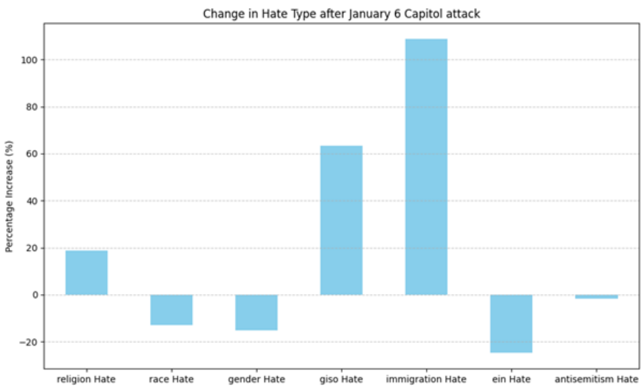

Fig. 9. Percentage change observed in the hate network after Jan 6, 2021.

Following the Capitol attack on January 6th, a comparable surge in anti-immigration sentiments was evident, with a notable 108.69% rise in posts containing anti-immigration messages between January 6th and January 10th, in contrast to the period of January 1st to January 5th, 2020.

The analysis also reveals a strong correlation between the daily link counts originating from specific social networks and the incidence of hate speech detected within the network spanning from November 1, 2020, to January 10, 2021.

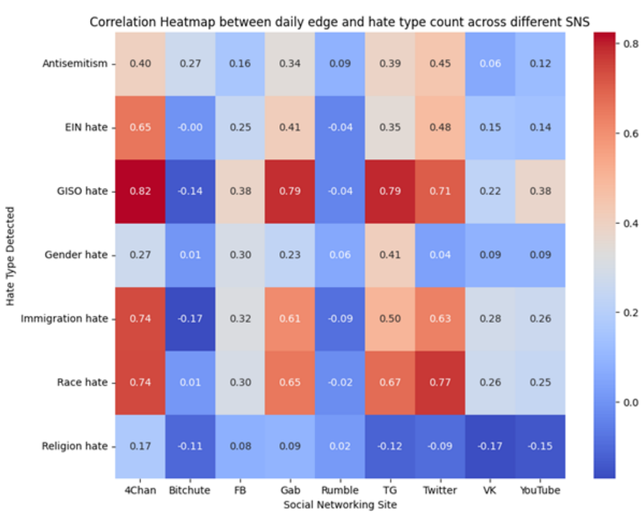

Fig. 10. Correlation between count of links origination from different social networking sites and count of hate type detected in the network

Specifically, an increase in links originating from 4chan, Gab, Twitter, and Telegram exhibits a strong correlation with instances of hate speech targeting immigration, race, and gender/sexual identity (GISO). While the correlation suggests a potential link between these events and the rise in hate content, further investigation is needed to determine causality.

3.3 Role of Telegram

Following the Presidential Elections on Nov. 3, Telegram emerged as a significant player in shaping the dynamics of the hate network. During Nov. 4–7, there was a remarkable surge in connectivity within the network, evidenced by a substantial 299% increase in the number of connections involving Telegram compared to November 1–3, 2020 (from 592 to 2366). Telegram's importance both as a target and source node within the hate network saw a considerable rise from this volume perspective. Specifically, Telegram's representation as a target node increased from 18.22% to 33.47%, while its presence as a source node increased from 21.73% to 37.24% of all links present in the hate core network post-election. This rise in Telegram's connections highlights its growing significance as a central platform for communication and coordination among hate groups within the network [21].

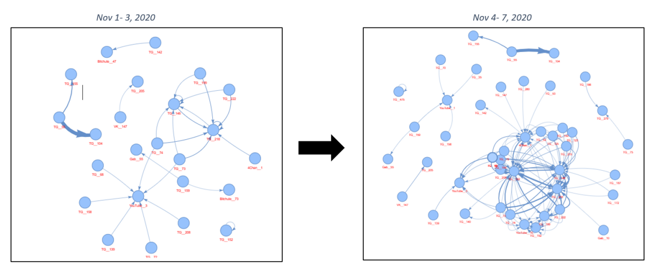

Fig. 11. Network where Telegram is either the source or target node

One Telegram community, identified by the codename "TG__122", warrants particular attention. "TG__122" which is now named "US Voter Fraud & Coup-Ops Intel 2020 – 2022" was initially absent from the network between November 1 and 3, but rapidly ascended to become one of the most crucial and interconnected nodes within the November 4–7 network. Moreover, "TG__122" exhibits strong associations with two other Telegram channels, "TG__218", a right-wing podcast, and "TG__146", a right-wing telegram channel named "Exposing Cultural Marxism", both of which were highly active in the network before November 3. The substantial influx of links directed towards "TG__122" signifies its pivotal role as a central hub for disseminating dis/misinformation concerning the presidential election and alleged instances of voter fraud.

Moreover, the rise of Telegram is particularly fascinating given its relatively limited ubiquity compared to mainstream social networking sites in the United States. However, as reported by CNN, Telegram has emerged as a source of concern for law enforcement agencies due to its association with 'Q-anon' and 'Pro-Trump Conspiracy theories' [22]. Despite its niche presence, Telegram has become a preferred platform for individuals seeking to propagate hate speech and coordinate malicious activities [23, 24]. This association further solidifies Telegram's significant influence on the perpetuation of extremist ideologies and the dissemination of hate speech within the studied network.

4 CONCLUSION

This study illuminates the changes in online hate networks in response to significant real-world events, particularly the 2020 U.S. presidential election and the January 6 Capitol attack.

Firstly, an increase in hate speech targeting immigration, ethnicity, and antisemitism following pivotal events, indicative of underlying societal tensions and extremist ideologies. The observed correlations between specific social networks and the incidence of hate speech highlight the role of online platforms in propagating extremist narratives. Secondly, network cohesion significantly increased post-attack, evidenced by tighter clustering and homophily within hate networks. This suggests a consolidation of extremist ideologies and a more resilient environment for hate speech dissemination.

Furthermore, the rise of Telegram as a central hub within hate networks underscores the evolving landscape of online extremism. Despite its niche presence in the United States, Telegram has emerged as a significant platform for coordinating malicious activities and disseminating hate speech.

Overall, this research emphasizes the urgent need for proactive measures to combat online extremism and promote digital resilience. By understanding the mechanisms driving the evolution of online hate networks, policymakers, researchers, and platform providers can develop targeted interventions to mitigate the harmful consequences of hate speech online and safeguard societal harmony and individual safety.

5 DATA AVAILABILITY

The datasets used in this study contain sensitive information from social media platforms. To comply with data protection standards and avoid potential misuse, the raw data cannot be shared publicly; however, the processed derivative datasets, which can be used to reproduce the results in the study, are available at https://github.com/gwdonlab/data-access.

6 CODE AVAILABILITY

Figure 3, 4, 5, 9, 7, 8, 10 were created using Python (Matplotlib [25]). The code is available at https://github.com/gwdonlab/data-access. The network visualization 6 was created using Gephi and the network visualization 11 was create using Pyviz. Together, this provides readers with access to the minimum dataset that is necessary to interpret, verify, and extend the research in the article.

7 FUNDING

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