Proceedings of the Eighteenth International AAAI Conference on Web and Social Media (ICWSM 2024)

Unraveling User Coordination on Telegram: A Comprehensive Analysis of Political Mobilization during the 2022 Brazilian Presidential Election

Otávio R. Venâncio[1], Carlos H. G. Ferreira[2], Jussara M. Almeida[1], Ana Paula C. da Silva[1]

[1] Department of Computer Science - Universidade Federal de Minas Gerais
[2] Department of Computing and Systems - Universidade Federal de Ouro Preto
otavio.venancio@dcc.ufmg.br, chgferreira@ufop.edu.br, jussara@dcc.ufmg.br, ana.coutosilva@dcc.ufmg.br

Abstract

Social media has gained importance as a channel to influence people's behavior and decisions, affecting not only the online world but also real-life (offline) events. This is especially evident in Brazil, where platforms like Telegram have been instrumental in disseminating political content rapidly and widely. However, the potential coordinated use of Telegram for promoting specific political narratives at critical times, such as the 2022 Brazilian elections, remains an area that requires further investigation. This study aims to investigate this phenomenon, focusing on the first and second rounds of voting and the January 8th riots. To this end, we conducted a comprehensive analysis of 620,000 messages from 256 Telegram groups, focusing on the dynamics of message dissemination and user interactions. Using network backbone extraction and text analysis methods, we identified key users who may be orchestrating the distribution of content. Our findings suggest that these individuals play a central role in the network's topology, relaying messages to a broader audience on dominant topics of discussion that reflect Brazil's political landscape during this turbulent period. This study not only highlights the growing influence of messaging apps on political mobilization but also contributes to our understanding of digital communication strategies in modern electoral contexts, emphasizing the need for further research in this field.

Introduction

Social media (SM) has been a main stage for the organization and development of many important social movements around the world, from the political debates that shaped the Arab Spring in 2011 (Wolfsfeld, Segev, and Sheafer 2013) to the 2020 US presidential election (Ferrara et al. 2020). Indeed, platforms such as Facebook (Ribeiro, Benevenuto, and Zagheni 2020), (former) Twitter[1] (Ruz, Henríquez, and Mascareño 2020) and WhatsApp (Nobre, Ferreira, and Almeida 2020, 2022), have been the focus of many studies that aimed at analyzing how information is disseminated in such platforms and its implications to societies.

More recently, Telegram has emerged as an alternative SM platform with increasing popularity is many countries. In Brazil, in particular, Telegram's popularity has been growing fast since 2019, as many users flocked from WhatsApp to the platform attracted by its greater focus on user privacy and the lack of limitations on the forwarding of messages from members in groups or channels and content moderation (Cavalini et al. 2023; Bär, Pröllochs, and Feuerriegel 2023).[2] However, there have been multiple reports on the use of Telegram for spreading extremist and radicalization content (Guhl and Davey 2020; Walther and McCoy 2021; Schulze et al. 2022) as well as for coordinating transgressive actions such as market manipulations (Sternisko, Cichocka, and Van Bavel 2020; Dhawan, Putnins, and Rasel 2023). In Brazil, specifically, Telegram has been considered a hub of the country's far right.[3] To make matters worse, the platform has been repeatedly criticized for not responding to legal demands during critical periods.[4]

Focusing specifically on user coordination in SM platforms, there have been several studies that addressed this topic, often related to campaigns for promoting particular pieces of content (Himelein-Wachowiak et al. 2021; Pacheco et al. 2021; Nizzoli et al. 2021; Clarke and Kocak 2018). For example, Linhares *et al.* identified groups of coordinated users spreading claims of election fraud on Twitter during the 2020 US election. Similarly, Nobre *et al.* showed evidence of user coordination to promote fake news on WhatsApp during the 2018 Brazilian elections, allegedly contributing to shape the final results[5]. The authors of (Nizzoli et al. 2021) introduced a network-based framework to identify varying degrees of coordination on Twitter during the 2019 UK general election. Yet, to our knowledge, prior efforts to identify and analyze user coordination on Telegram are still scarse and limited (Urman and Katz 2020; Dargahi, Reshadatmand, and Neshati 2017; Slobozhan, Brik, and Sharma 2023; Cavalini et al. 2023; Rossini, Mont'Alverne, and Kalogeropoulos 2023).

[1] Twitter has been recently rebranded as X. Yet, we maintain the reference to the old platform´s name as our study relies on features commonly associated with it.

[2] https://www.nytimes.com/2021/01/13/technology/telegram-signal-apps-big-tech.html

[3] https://www.wired.com/story/brazils-far-right-plots-its-own-january-6-insurrection/

[4] https://www.nbcnews.com/tech/tech-news/brazil-judge-suspends-messaging-app-telegram-ignoring-ruling-rcna20691

[5] https://www.theguardian.com/world/2019/oct/30/whatsapp-fake-news-brazil-election-favoured-jair-bolsonaro-analysis-suggests.

We here take a step in this direction by offering a broad study of user coordination to promote political content on Telegram. Our study takes as case study the most recent (2022) presidential election in Brazil, when Telegram reportedly became a major tool for political mobilization (Cavalini et al. 2023), including the riots that followed the election result and culminated with the mob attack to Brazil's federal government buildings in early January 2023.[6] We crawled Telegram to collect roughly 620K textual messages shared in over 250 politically oriented Telegram groups, covering three 15-day time periods around the days of the two election rounds and the mob attack. Following prior work (Nizzoli et al. 2021; Pacheco et al. 2021; Nobre, Ferreira, and Almeida 2020; Linhares et al. 2022; da Rosa et al. 2022; Chagas 2022), we searched for evidence of user coordination to promote content in each such period by following three steps. First, we model the information spread during each analyzed period using a media-centric network that connects users who shared the same content. Second, we employ alternative backbone extraction methods (Serrano, Boguna, and Vespignani 2009; Nobre, Ferreira, and Almeida 2020; Linhares et al. 2022) to identify network edges with stronger supporting evidence of being related to coordination (as opposed to two users independently sharing the same content). Third, we then thoroughly characterize such set of users with respect to their topological characteristics, engagement in the information dissemination process, properties of the content shared as well as their persistence on participating in the information diffusion over time.

Our main findings are as follows: (i) We observe a temporal trend of increasing complexity in the interaction network and potential coordination within the Telegram networks over the analyzed periods. This trend culminates during the period of riots when we observe the emergence of the most densely networked and well-defined community structures; (ii) There are central users who play a crucial role in promoting content within the Telegram network; (iii) The topics covered by our data align with the primary offline discussions that took place in Brazil during the analyzed period, such as the call for military intervention and protests in Brasília; (iv) We found a non-negligible proportion of potentially coordinated persistent users who stayed active across the most important events of the 2022 Brazilian elections. This behavior is slightly different from that found on other platforms, such as Twitter (Nobre, Ferreira, and Almeida 2020), possibly suggesting the use of the Telegram as a channel for political mobilization.

Related Work

The exploration of coordinated efforts in social media is a significant area of research explored in diverse contexts and methodologies. Focusing on Twitter, in (Nizzoli et al. 2021), a network-based framework was introduced to identify varying degrees of coordination during the 2019 UK general election. Pacheco *et al.* employed a similar network model to link users to analogous tweets and uncover groups that repeatedly share content (Pacheco et al. 2021). Weber *et al.* used a time-window approach to uncover latent collaboration networks between Twitter users, focusing exclusively on account interactions for coordination (Weber and Neumann 2021). Linhares *et al.* (2022) and da Rosa *et al.* (2022) investigated Twitter communities that may have been involved in the coordinated spread of fraudulent content claims during the 2020 US election.

In the context of WhatsApp, the work of Kiran *et al.* opened the way for research into the patterns of messaging within politically oriented groups, laying the foundation for understanding the dissemination of political content in private messages (Garimella and Tyson 2018). Bursztyn *et al.* expanded the scope of this study and analyzed how a group's political affiliation influences the dynamics of large message dissemination (Bursztyn and Birnbaum 2019). Nobre *et al.* took this research further by demonstrating the existence of WhatsApp communities that were actively involved in the coordinated dissemination of information during the 2018 Brazilian elections (Nobre, Ferreira, and Almeida 2020, 2022). Chagas *et al.* investigated digital propaganda and its effects in the same context (Chagas 2022).

Similar to WhatsApp, Telegram's one-on-one and group communication features have garnered academic interest, especially in Brazil[7]. Research on this platform includes network-based analyses of coordinated behaviors. Urman *et al.* studied far-right networks (Urman and Katz 2020), Nobati *et al.* focused on identifying spam through network edges (Dargahi, Reshadatmand, and Neshati 2017), and Slobozhan *et al.* examined Telegram's roles during the 2020 Belarus protests (Slobozhan, Brik, and Sharma 2023), suggesting differentiated treatments in future studies. The authors of (Cavalini et al. 2023) analyzed Jair Bolsonaro's supporters' networks between the 2021 and 2022 September 7th demonstrations, noting changes in network structure and agenda. Lastly, Rossini *et al.* addressed how private messaging apps influence political participation and the spread of electoral misinformation, highlighting a greater belief in misinformation within political groups (Rossini, Mont'Alverne, and Kalogeropoulos 2023).

In contrast to previous studies, our work focuses on the role of users with evidence of possible coordination in the dissemination of information on Telegram, especially during the politically charged period of the 2022 Brazilian presidential elections until the riots two months after the election results. Our study pioneers the in-depth analysis of Telegram, a platform increasingly used for political discourse in Brazil. In doing so, we fill the gap in understanding the dynamics of information dissemination in a large-scale study on this platform and also contribute to a broader discourse on how different network structures and user behavior influence the dissemination of political content. To summarize, our study extends the current understanding of information dissemination on digital platforms and provides an important reference point for future research in the field of political communication and social media analysis.

[6]https://www.nytimes.com/live/2023/01/09/world/brazil-congress-riots-bolsonaro

[7]https://www.bbc.com/news/technology-55634139

Methodology

This section describes our methodology, including data collection, modeling and analysis.

Dataset Collection

We collect messages from public politically-oriented Telegram groups and channels in Brazil published between September 1st, 2022 and January 31st, 2023, which includes a period of great social and political movements in Brazil, including the presidential election and the riots in early January 2023.

The collection was done using a custom crawler that is based on the Telethon API[8], which in turn uses the official Telegram API[9] to give access to messages and users in which the crawler is inserted or in contact. Once configured, our probe entered public Telegram groups, those in which the URL was shared on Twitter, and saved any and all messages shared there. It is important to highlight that Telethon only collects data already permitted for collection by the official Telegram API.

To comprehensively map the political landscape, and try to avoid biases towards particular populations, our study incorporated a detailed amalgamation of keywords that merged the key geopolitical regions of the country such as *North*, *Northeast*, *South*, *Southeast*, and *Central-West* with the political spectrum categories *Right*, *Left*, and *Center*. Additionally, these regional and political terms were combined with the names of the most important presidential candidates[10], namely *Bolsonaro*, *Lula*, *Ciro Gomes*, *Simone Tebet*, and *Soraya*, which represent the whole political spectrum (from left to far right). Each keyword was crafted to reflect the diverse political orientations prevalent in different parts of the country, tied to both regional identities and individual political figures, for instance, *Right North*, *Left Southeast*, *Center Central-West*, *Right Bolsonaro Northeast*, *Left Lula South*, and so on. The integration of regional keywords was crucial to our approach, as it allowed us to capture the diverse political nuances across varied geographical areas.

Each keyword from this set was then fused with the string "t.me/", mirroring the typical format of Telegram group invitations. Utilizing the Twitter API[11], for systematic weekly searches, we scoured for tweets containing these invitation links. Upon discovering these links, our crawler was programmed to join the respective Telegram groups and channels. Once integrated, it could gather all messages posted since the creation of these groups. Furthermore, we scrutinized these messages recursively to unearth more invitation links, thereby broadening our data collection scope. The primary message fields we collected are listed in Table 1. It is important to emphasize that, as stated by Telegram[12], messages forwarded via the application's native sharing feature accumulate the total number of views. However, the number of views may be accurate as the same user's views may be counted multiple times if they view the message at different times. Moreover, if a user copies and pastes the content, the number of views of the newly forwarded message is reset.

Field	Description
message_id	message ID, unique per group/channel
channel_id	channel/group ID
retrieved_utc	Datetime message retrieve
updated_utc	datetime were message was last updated
message	message text
views	telegram view count
forwards	telegram forward count
from_id	author ID
post_author	username of the author
message_utc	datetime message was sent

Table 1: Data collected from Telegram's API.

Event	Period	# Messages	# Users
1º round	09/25/2022 - 10/09/2022	123,715	10,973
2º round	10/23/2022 - 11/06/2022	236,936	20,512
Riots	01/01/2023 - 01/15/2023	258,362	20,008

Table 2: Overview of our Telegram dataset.

Our search heuristic returned 278 groups and 770,148 exchanged *textual messages*, including those with external links (urls). We then filtered out messages shorter than 30 characters,leaving a total of 619,013 messages and 256 groups in our dataset. We focus our analyses on the national general elections on October 2nd (first round)[13] and October 30th (second round)[14], 2022, as well as during the riots at Brazil capital that led to the attempted group d´etat on January 8th, 2023.[15] In order to analyze the build-up and comedown of activities surrounding these events, we leverage our analyses on the messages from a 15-day window centered around each event date. These periods were chosen due to their high political significance and their impact on public discourse. Furthermore, strong evidence suggests that Telegram played a key role in orchestrating these events, leading to several sanctions imposed by the Brazilian judiciary, including channel suspensions and moderation measures.[16]

Table 2 summarizes our dataset. Note the increased use of Telegram over time, both in terms of number of users and number of messages shared, indicating how Telegram was increasingly used to disseminate content in the period.

Network Modeling

To investigate user coordination to spread content on Telegram groups, we employed a network model that has been previously used to study coordination for information dissemination on various platforms (e.g., WhatsApp and Twit-

[8]https://docs.telethon.dev/en/stable/

[9]https://core.telegram.org/

[10]These candidates accounted for over 99% of all votes.

[11]https://developer.twitter.com/en/docs/twitter-api/

[12]https://telegram.org/faq_channels

[13]https://english.elpais.com/international/2022-10-03/lula-narrowly-wins-first-round-of-brazils-presidential-elections-will-face-bolsonaro-in-runoff.html

[14]https://www.nytimes.com/live/2022/10/30/world/brazil-presidential-election

[15]https://www.nytimes.com/live/2023/01/09/world/brazil-congress-riots-bolsonaro

[16]https://www.tse.jus.br/comunicacao/noticias/2022/Outubro/tse-determina-retirada-de-propagandas-ofensivas-a-bolsonaro-e-a-lula

ter), namely a *media-centric* network which connects users who shared similar content (Nobre, Ferreira, and Almeida 2020, 2022; da Rosa et al. 2022; Linhares et al. 2022). By analyzing the properties of such *media-centric* networks, we are able to search for *evidence of possible coordination* among users to promote particular pieces of content, as will be discussed in the next section.

Specifically, we built three graphs, where each graph represents a media-centric network capturing the user sharing patterns during the 15-day window associated with each monitored event. In each graph $G(V, E)$, a node $v \in V$ corresponds to a user who posted a message in one of the Telegram groups during the specified window, and an undirected edge e=(v_i, v_j) is included in E if the users corresponding to v_i and v_j shared the same message (exactly the same textual content) at least once within the same 15-day window. The weight of e is the number of textual messages both users shared in common during the period.

Identifying Evidence of User Coordination

Using our media-centric network model, we aim to identify coordination efforts by detecting tightly connected user groups who frequently share the same content. While we can't definitively confirm coordination, we search for users whose sharing patterns suggest orchestrated efforts rather than independent behavior. However, distinguishing genuine coordination from noise, such as sporadic and weak connections, is challenging. Weak connections may reflect random user activities rather than intentional coordination but can obscure the true underlying structure related to coordination when present in large volumes. Our focus is on identifying consistent and strong co-sharing behaviors indicative of coordination, rather than independent sharing of popular content.

To that end, we used two network backbone extraction methods from the literature to filter out weaker edges, thus retaining only stronger edges that most probably reflect coordination. The first method, Disparity Filter (DF), identifies and retains edges that are substantially stronger than other links connected to the same nodes (Serrano, Boguna, and Vespignani 2009; Nobre, Ferreira, and Almeida 2020). Specifically, DF considers as reference model for a user sharing content independently of the others a uniform distribution of the edge weights incident to the corresponding node. Thus, an edge (v_i, v_j) is retained in the backbone if its weight greatly deviates (from a statistical point of view) from this reference model for both v_i and v_j. This method effectively highlights edges that demonstrate consistent and repeated behavior between pairs of users. Moreover, by characterizing edges according to local node patterns, DF is able to identify evidence of coordination across users with different levels of activity. As such, it is not biased towards only the most active users and is able to identify groups of individually less active users who, in coordination, may still contribute to a large scale of spread. Indeed, DF has been widely used to study coordination across various platforms, including Twitter and WhatsApp (Abbar et al. 2016; Nobre, Ferreira, and Almeida 2020, 2022).

We also experimented with an alternative backbone extraction method, referred to as DF+NB (Linhares et al. 2022), which combines the Disparity Filter with the concept of Neighborhood Overlap. This approach goes further by removing peripheral and bridge connections, focusing on edges between users with common neighbors who also share similar patterns of content dissemination.

Both DF and DF+NB only keep nodes with at least one edge in the resulting backbone, and those nodes represent users for which evidence of coordination was found, according to the method employed. The strength of such evidence can be gauged by the α parameter, employed by both methods, which is the p-value used to test against the assumption of uniform distribution for independent behavior. We here use $\alpha = 0.05$, as done in similar prior efforts (Gomes Ferreira et al. 2022). Also, compared to DF, DF+NB is a more conservative approach, typically retaining smaller fractions of the original nodes and edges and revealing a more core structure of the network. For the filter based on the neighborhood overlap metric, we assume the threshold given by the 95^{th} percentile of the neighborhood overlap distribution Such properties make it particularly effective in scenarios with high levels of noise (Linhares et al. 2022). For fixed α, DF+NB tends to keep in the backbone those nodes for which there is stronger evidence of coordination. Thus, by analyzing the backbones extracted by both methods, we are able to grasp different perspectives of potential coordination efforts (one with stronger supporting evidence than the other).

After extracting the backbones of each graph (using one of the two aforementioned methods), we applied the widely used Louvain community detection algorithm (Blondel et al. 2008) to identify and analyze patterns of user groupings and their organization in each backbone. The goal of the Louvain algorithm is to maximize community modularity, which is a key metric representing the density of connections within communities compared to a hypothetical random network. Modularity values range from -0.5 to +1, with higher scores (above 0.4) indicating well-defined community structures (Newman and Girvan 2004). In other words, higher values of modularity indicate denser networks

Finally, we characterize backbone users not only from the network topology perspective but also in terms of their level of engagement in sharing activities (e.g., message forwards, views, introduction of new messages) and properties of content shared. Such analyses will offer deeper insights into the roles these communities and structures play in the large-scale dissemination and amplification of content across the Telegram network.

Content Analysis

We characterized the user communities identified in the network backbones with respect to the topics of discussion reflected in the textual messages shared by them. To identify these topics, we employed BERTopic, an advanced *framework* that integrates embedding models with clustering techniques for topic extraction (Grootendorst 2022). This method uses vector representations (embeddings) to preserve the semantic essence of sentences, grouping them based on similarity. At the core of BERTopic is Sentence BERT (SBERT), a component crucial for sentence embed-

Network	Period	Nodes	Edges	Avg. Degree	Density	Avg. Clustering	C.C.	Comm.	Mod.
Complete	1st Round	2,048	83,224	81.27	0.0397	0.8167	93	122	0.1664
DF	1st Round	236	814	6.90	0.0294	0.6255	18	25	0.3603
DF+NB	1st Round	54	82	3.04	0.0573	0.7446	12	14	0.6147
Complete	2nd Round	4,209	175,137	83.22	0.0198	0.8058	191	232	0.2325
DF	2nd Round	306	1,162	7.59	0.0249	0.5494	17	24	0.3221
DF+NB	2nd Round	84	117	2.79	0.0336	0.5264	17	19	0.7853
Complete	Riots	5,434	86,252	31.75	0.0058	0.6818	147	166	0.3580
DF	Riots	411	1,048	5.10	0.0124	0.5729	28	34	0.4350
DF+NB	Riots	101	107	2.12	0.0212	0.5362	22	24	0.8627

Table 3: Characterization of the topology of the networks and backbones.

ding, renowned for its effectiveness in semantic text similarity tasks using a pre-trained model available online[17] (Reimers and Gurevych 2019). This approach has been effectively applied in various studies, including analyses of discussions on social media platforms (da Rosa et al. 2022).

The process of BERTopic begins with converting a collection of Telegram's messages into vector representations using SBERT. Subsequently, the dimensionality of these vectors is reduced using the *Uniform Manifold Approximation and Projection for Dimension Reduction* (UMAP) technique, enhancing the efficiency of subsequent clustering processes. Next, the HDBSCAN algorithm groups these low-dimensional vector representations into clusters based on semantic similarities. These clusters, or 'documents', are then analyzed using the *Class Term Frequency-Inverse Document Frequency* (c-TF-IDF) technique to identify distinctive words for each cluster, thereby defining the topics associated with each group of messages (Grootendorst 2022).

In fine-tuning the framework for our particular dataset, we followed the guidelines recommended in the BERTopic documentation to find an optimal balance between the number of topics and the size of the dataset's size[18]. The resulting parameterization led to certain key configurations: The number of neighbors and components for UMAP was set to 10 and 5, respectively. These parameters are crucial for dimensionality reduction and accurate topic modeling. We also set the minimum topic size to 5. This threshold determines the smallest set of unique messages that a given topic can represent and ensures that only significant and well-defined topics are considered for analysis. All the experiments used an infrastructure with a 2.10 GHz Intel Xeon Gold 6130 CPUs (16 cores/socket), an NVIDIA Tesla V100 PCIe GPU (16 GB), and 384 GB DDR-4 RAM.

Results

This section presents our results and their findings.

Topological Analysis

Table 3 shows the analysis of the network topologies over the time periods. It unveils different complexities and structures between the complete networks and their respective backbones. Both the DF and DF+NB methods reveal potential coordination patterns, but differ in terms of selectivity and strength of coordination evidence. Particularly noteworthy is the significant reduction of weak links in these methods, which is characterized by a reduction in the number of nodes and edges. For example, in the first round, the complete network consists of 2,048 nodes and 83,224 edges with an average degree of 81.27. In contrast, the DF method reduces this network to 236 nodes and 814 edges with an average degree of 6.90. The DF+NB method further reduces this network to only 54 nodes and 82 edges and highlights the nodes that are most likely to exhibit coordinated behavior.

When analyzing topological metrics such as density and modularity (Mod.), as shown in Table 3, we find that these metrics, especially modularity, increase significantly in the riots event. The structure of the backbones becomes increasingly important as it indicates an increase in potential coordinated behavioral. The modularity values suggest a high level of community organization and potential coordination during the riots, especially in the DF+NB backbones, where modularity peaks at 0.8627, indicating highly connected and structured community networks.

We observe a temporal trend of increasing complexity in the interaction network and potential coordination within the Telegram networks over the analyzed periods. This trend culminates during the period of riots when we observe the emergence of the most densely networked and well-defined community structures. Our results provide evidence of the increasingly central role of Telegram communities in disseminate protests during the analyzed events.[19]

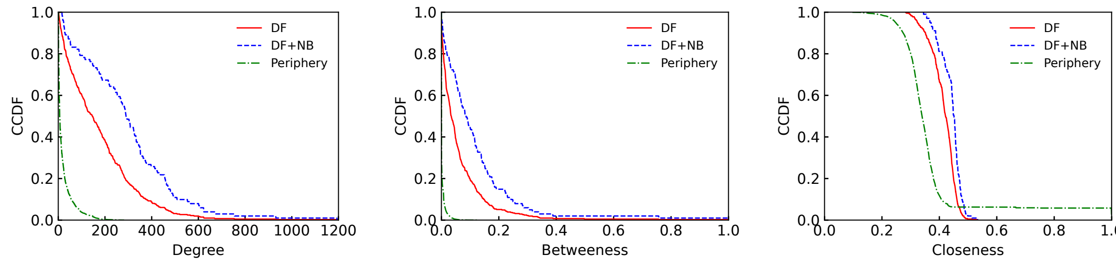
Centrality Analysis

Next, we rely on a set of network centrality measures to understand the potential of backbone users in promoting content. We compute the degree, betweenness, and closeness centrality metrics. These metrics complement each other as they capture different facets of users' role in disseminating information in the network. We categorized all users for each time period into three categories: those who are in the DF+NB backbone, those who are in the DF backbone (possibly also in the DF+NB backbone), and those who are

[17]https://huggingface.co/sentence-transformers/paraphrase-multilingual-MiniLM-L12-v2

[18]https://maartengr.github.io/BERTopic/getting_started/parameter\%20tuning/parametertuning.html

[19]https://www.nytimes.com/2023/01/09/technology/brazil-riots-jan-6-misinformation-social-media.html



(a) Degree Centrality. (b) Betweenness Centrality. (c) Closeness Centrality.

Figure 1: CCDFs of users' centrality measures during the period of riots.

not in any backbone, i.e., at the *periphery* of the network. These measures were then calculated taking into account the complete network topology to measure the actual impact of these users on Telegram's entire content distribution networks. Since we have observed similar behavior in all the periods analyzed, we discuss the results of the riots period for the sake of brevity.

Figure 1a shows the complementary cumulative distribution (CCDF) function of degree centrality for users in the three categories for the period of riots. First of all, it is noticeable that users in the DF+NB category have the highest degree centrality. Users covered by DF have a slightly lower degree centrality. In contrast, peripheral users that do not belong to a backbone have a much lower degree centrality. For example, 80% of these users have a degree centrality of about 30 or less, which means that they are much less connected within the Telegram content dissemination network.

Betweenness centrality[20] is important for determining the degree of influence of a particular node on the dissemination of information within the network. The value ranges from 0 to 1, with 1 representing a node that is critical to the flow of information in the network, while a value close to 0 indicates the opposite. A user with high entanglement centrality acts as a critical channel through which information flows and potentially controls or influences the distribution of content. Moreover, nodes exhibiting high betweenness values act as bridges within the network topology, playing a crucial role in network connectivity. Figure 1b shows the betweenness distributions. DF+NB users are in the center, followed by users in the DF backbone. 50% of the users have betweenness greater than 0.034 and 0.085 in DF+NB and DF networks, respectively. Users in the periphery, on the other hand, differ significantly from those in each backbone (50% of users have betweenness equal zero).

We now analyze the closeness[21] in Figure 1c. Values close to 0 indicate that a node is completely peripheral in terms of distance to other nodes. Conversely, values close to 1 indicate that a node can easily reach all other nodes due to short distances. A user with a high closeness centrality can quickly spread information throughout the network and thus efficiently reach a wide audience. DF+NB users followed by DF users are much more centralized than peripherals.

The DF method shows a steeper curve that begins to rise quickly as we move from left to right along the closeness axis. This indicates that the DF backbone has a relatively high proportion of nodes with high closeness centrality. The nodes identified by the DF method are therefore generally well positioned to disseminate information quickly and widely in the network. The curve for the DF+NB method is shifted even more to the right compared to the DF method. This shows that the nodes in the DF+NB backbone tend to have an even higher closeness centrality than the nodes in the DF backbone. This means that although the DF+NB method identifies fewer nodes due to its more conservative approach, these nodes are potentially even more central to the structure of the network. They are likely to be crucial for the dissemination of information, reflecting the effectiveness of the method in identifying nodes that are not only likely to be coordinated but also strategically located within the network. In contrast, nodes in the periphery exhibit a much flatter curve, suggesting that a significant proportion of these nodes have lower closeness centrality. This confirms that the nodes in the periphery are less centralized and less efficient in disseminating information in the network. The curve also suggests that there are large differences in the closeness centrality of nodes in the Periphery, with a small portion exhibiting a higher closeness centrality and possibly acting as local bridges or influencers within their subnetworks.

In light of the centrality results, it becomes evident that certain users play a crucial role in promoting content within the Telegram network. Despite being in the minority, users in the DF and DF+NB backbones consistently exhibit significantly higher centrality than users in the periphery across all metrics. These users are highly networked and strategically positioned to influence and control the distribution of content as well. They may act as proxies to disseminate messages to a broader audience in a few steps inside the network. This underscores the significant influence that a small but groups with strong evidence of coordination may have on the overall information landscape of a Telegram network.

Content Dissemination Analysis

We explore the potential for information dissemination within backbones that represent users who are potentially

[20] Proportion of shortest paths between pairs of nodes that pass through a particular node.

[21] Shortest path length from a particular node to all other nodes in the network.

Network	Period	# Users (%)	# Messages (%)	# Forwards (%)	# Views (%)	# Groups (%)	# Mess. Sent First (%)
Complete	1st R.	2,590	9,080	1,257,921	393,265,802	146	9,080
DF	1st R.	236 (9.11%)	5,277 (61.57%)	774,519 (61.57%)	306,746,762 (78.00%)	87 (59.59%)	5,032 (55.42%)
DF+NB	1st R.	54 (2.08%)	1,902 (20.94%)	403,745 (32.10%)	218,976,570 (55.68%)	52 (35.62%)	1,706 (18.79%)
Complete	2nd R.	5,132	13,557	1,571,626	518,461,351	176	13,557
DF	2nd R.	306 (5.96%)	6,581 (48.55%)	1,025,466 (65.25%)	417,260,278 (80.48%)	111 (63.07%)	6,162 (45.45%)
DF+NB	2nd R.	84 (1.64%)	3,590 (26.53%)	590,148 (37.55%)	275,670,924 (53.17%)	66 (37.50%)	3,115 (22.98%)
Complete	Riots	6,259	17,374	2,766,123	455,443,651	228	17,374
DF	Riots	411 (6.57%)	7,184 (41.34%)	1,676,729 (60.62%)	288,163,429 (63.27%)	150 (65.79%)	6,197 (35.67%)
DF+NB	Riots	101 (1.61%)	2,884 (16.57%)	852,094 (30.80%)	181,224,365 (39.79%)	85 (37.28%)	2,044 (11.76%)

Table 4: Analysis of the distribution patterns of the coordinated groups found.

coordinated, as opposed to the complete network. Our approach involves examining message metadata across various metrics: number and percentage of users (# users), number of unique messages (# messages), number of forwards (# forwards), number of views (# views), group coverage (# groups), and frequency of message initiation (# messages sent first). These metrics are detailed in Table 4.

We find that the users covered by the DF and DF+NB backbones have a significant impact on information dissemination. Both DF and DF+NB are able to identify groups of users that are very active in information dissemination. To illustrate this, we present key findings from the first round election event: 61.57% of the messages within the DF backbone are generated by just 9.11% of users. Similarly, in the DF+NB backbone, 20.94% of the messages are produced by a mere 2.08% of users. This pattern remains consistent across the other analyzed periods.

For all periods, despite the smaller percentage range of users in DF+NB, fluctuating between 1.6% and 2%, these smaller user groups are proportionally responsible for a significant amount of the sent messages on the platform. The DF+NB method reveals more cohesive community structures in terms of network topology (refer to Table 3). This cohesion benefits these communities, as they hold a proportionally larger share of messages, even with fewer users. This suggests that the denser community structures, indicated by the higher modularity values in DF+NB, facilitate more effective information dissemination. This pattern underscores the crucial role of small but highly active user groups in shaping the flow of information.

The users that belong to the backbones also stand out in the remaining message statistics. Looking again at the DF network for the first round, 55.42% of the messages published for the first time in the groups (# Mess. Sent First) we analyzed came from this small group. For DF+NB, this value is 18.79%, highlighting the central role of these users in possibly guiding the topics to be discussed within the Telegram groups.

In terms of views and forwards, the results are equally revealing: 78% of views and 61.57% of forwards are concentrated among users who belong to the backbone extracted by DF. These high percentages show that these users not only create content, but also play a crucial role in its distribution. Finally, regarding the group coverage metric (# Groups), these few users cover a significant portion of the Telegram groups we analyzed. In DF, they cover 59.59% of the groups, while the coverage in DF+NB is 35.62%. This broad presence in numerous groups indicates a high level of influence and potential coordination. These patterns persist across the other events we analyzed. Based on the discussed results, we argue that the DF and DF+NB backbones exhibit potentially strong patterns of coordination, with a smaller number of users playing a central role in creating, reproducing, disseminating, and initiating discussions in many Telegram groups on the network.

Taking a step further, we now analyze the discussion topics among users within the backbones that form potential coordinated groups. This analysis was performed using the BERTopic framework for the messages posted by all users over the three periods. Our focus here is on analyzing the extent to which the backbones retain and disseminate the topics. Initially, 18 topics were identified through the application of BERTopic. However, in order to focus our analysis on the most influential discussions, we focused on topics with at least 150 messages. By doing that, we prioritize the 13 most popular discussed topics within the possible coordinated groups, being able to shed light on the predominant themes and narratives of the Telegram users.

Table 5 offers a comprehensive overview of the main identified topics, including the number of messages, most discriminating words, topic descriptions and a rounded value of a total views and forwards. The overwhelming number of views, particularly for topics 1 and 8—recording over 420 million and 5 million views respectively—reflects the intense public engagement with issues related to military interventions, blockades, and protest mobilizations. These topics are emblematic of the heated political atmosphere during the election periods and riots in Brazil.[22,23,24] Moreover, we observe a broad spectrum of topics that resonated with the Brazilian population. For instance, topic 2, which combines religious contexts with political figures, such as the presidential candidate Jair Bolsonaro, was viewed over 100 million times. This blending of religion and politics is indicative of the deep-rooted connection between personal beliefs and

[22]https://www.nytimes.com/2022/11/02/world/americas/bolsonaro-election-protests.html

[23]https://apnews.com/article/jair-bolsonaro-caribbean-rio-de-janeiro-e4328ee88323100cdaa1e4e461006cce

[24]https://www.bbc.com/news/world-latin-america-64212627

ID	# Mess.	# Views	# Forwards	Most Discriminative Words	Description
1	38,817	420M	1M	intervention, president, military, blockades	Military intervention and blockades
2	17,350	102M	517K	share, God, Bolsonaro, Israel, brother	God, Israel, and Bolsonaro in a religious context
3	11,990	117M	556K	video, share, free, bot, WhatsApp	Urge the spread of information and videos across various channels
4	1,821	20M	217K	vaccinate, pandemic, mortality, covid	Vaccination, the pandemic, and mandatory vaccines
5	2,982	2M	21K	priest, support, Lula, Marcelo, Rossi	Priest's supposed support for Lula
6	1,353	381K	533	premium, account, few, online, hours, money,	Finance, campaign funding, and betting
7	1,270	48M	71K	Rio, drink, Recife, rain, canoes, bridge	Events in various places, e.g., Rio de Janeiro and Recife
8	993	5M	27K	bus, free, truck, camped, motorbike, rally	Organization of rallies in Brasilia
9	758	48M	60K	inflation, bank, reduction, unemployed, food	Reduction in inflation and food, gas, and gasoline prices
10	2,086	9M	24K	left-wing, Signal, reserve, add, groups,	Alternative channels to avoid moderation policies
11	322	1M	10K	slaughterhouse, Sleeping Giants, boycott	Boycott companies that support certain candidates
12	211	465K	6K	food, synthetic, meat, crisis, laboratory	Associate the creation of lab-grown food with the Brazilian crisis
13	183	1M	8K	China, IPEC, credit, DataFolha, research	Link IPEC and DataFolha survey results as manipulated by China

Table 5: Top discussion topics found in Telegram groups.

political affiliations in Brazil (Linsey Moddelmog 2019).

One of the most controversial topics is the topic 4, which summarizes the debate surrounding the Covid-19 pandemic and mandatory vaccination. These themes have polarized the nation and sparked widespread discussion, as evidenced by the over 20 million message views. The topic not only addresses health concerns but also delves into the broader social and political implications of the pandemic. Topics 9 and 12, which focus on financial crises, inflation and innovative solutions such as lab-grown meat production, address the pressing economic challenges facing Brazil. These topics underscore the public's acute concern for financial stability and food security. Topic 11, which advocates boycotting certain companies due to their political stance, reflects the increasing politicization of trade and consumer choices in Brazil and points to a trend where political ideology feeds into economic behavior. All in all, these topics offer a multifaceted view of the Brazilian socio-political landscape, which is characterized by a complex interplay between political movements, health crises, economic challenges and the evolving nature of public discourse.

We next delve deeper into the temporal evolution of the number of messages, views and forwards of each discussed topic. Figure 2 shows the distributions. Each heatmap cell in a row shows the relative deviation of that topic for a given time period from the other analyzed time periods. In other words, each row (topic) is $z - score$ normalized, i.e. $z = (x - mean)/std$. Thus, each value gets subtracted from the average of the row, then divided by the standard deviation of the row. Cells are color-coded red (resp. blue) when the topic is more (resp. less) present than the average.

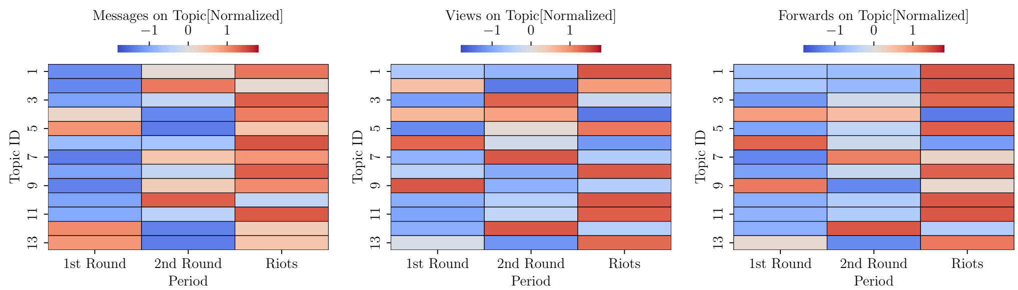
Let's start by looking into the number of messages in Figure 2a. Messages sent about topics 12 (financial crisis) and 13 (Chinese influence in election polls) are more prominent in the first round. In the second round, topics 2 (exploring religion) and 10 (spreading new and alternative communication channels) garnered significant attention. As expected, topics 1, 8 and 11, which are more in line with the riots, are concentrated in the third period we analyzed.

We also assess the distribution of the number of views and forwards, as depicted in Figures 2b and 2c. Overall, the results indicate that messages pertaining to the discussed topics were viewed and forwarded to a greater extent during specific time periods. In other cases, some topics' messages seem to have increased in volume in terms of views and forwards in later periods, suggesting evidence that these topics tend to recur, attracting varying levels of attention at different stages of the 2022 Brazilian elections process. Among all topics, it is noteworthy that topic 1, which centers on not accepting the election results and advocating for a potential military intervention, consistently maintains a significant presence across all the analyzed periods. This finding provides evidence of Telegram being utilized as a means to encourage Brazilian people not to accept the legitimacy of election results. In other words, social media platforms have been employed as a tool to openly and consistently erode confidence in the electoral process and its outcomes, thereby instigating skepticism towards the institutions that safeguard democratic processes as also stated by (Rossini, Mont'Alverne, and Kalogeropoulos 2023).

Finally, we examine the role of potentially coordinated users unveiled by both backbone strategies in the introduction of certain topics. For brevity, Figure 3 shows the percentage of unique messages created according to the backbones for the period of the riots. Although these users generally account for only a small percentage, namely 6% and 1% for DF and DF+NB respectively (see Table 4), they play a significant role in shaping the discourse on the platforms. This is reflected in their significant contribution, as they are the first to post on the topics we found for DF (DF+NB). For example, they reached almost %80 (40%) of the messages on topic 13, which relates to fraud in electoral systems and voter pools and Chinese influence in Brazilian elections. We find that topics closely related to the election period are very frequently shared and discussed, and are widely contributed and shared by users, possibly in a coordinated manner.

Backbone Users' Persistence Analysis

In the prior sections, our results evidence that a small fraction of users, who belong to the cohesive of the backbones, played a crucial role in promoting content within the Telegram network during the 2022 Brazilian elections. We next focus on understanding if these users persist over time. Specifically, we consider the users in the DF and DF+NB and analyze the dynamics of these users over successive events. We define the persistence of elements in a set A from



(a) Total of messages. (b) Total of views. (c) Total of forwards.

Figure 2: Normalized metrics of topic distribution over the analyzed time periods.

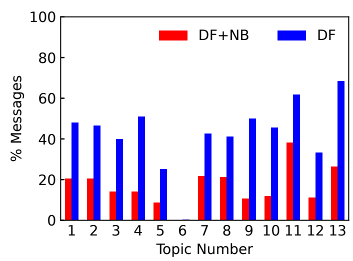


Figure 3: Topic messages disseminated during the riots.

period i to period $i+1$ as the fraction of elements in A at period i that remain in the set period $i+1$.

Table 6 presents the persistence of different sets of users and their engagement in information sharing. Notably, the persistence of users engaged in promoting information across election rounds is high, exceeding 50%. These users demonstrated significant activity, producing and replicating messages at remarkably high volumes, with values reaching at least 62% and 56%, respectively. While the percentage values of users persisting in the second round and riots periods are lower (at most around 24%), their role in contributing new messages to the Telegram network is not negligible.

Our results suggest the presence of key users guiding the narratives during the electoral process and after its conclusion. The main topics they boost the most within Telegram networks are 1, 2, 3 and 9. Topics 1 and 2 are strongly correlated with the main ideas supported and shared by supporters of the candidate Jair Bolsonaro. On the other hand, topic 3, call for the need to spread information and videos across communications channels, notably WhatsApp, which is a widely used platform in Brazil.Topic 9 is closely related to the economic situation in Brazil. It is worth noting the appearance of the term *gasoline*, revealing that the policy of reducing the prices of this type of fuel by the former president Jair Bolsonaro was a topic widely explored during the election period, mainly in the first round.[25] As a final remark, despite not being on the set of topics with the largest number of persistent users engaged into, topic 8, which mainly call for protests in Brasilia, is explored by at least 12% of the persistent users.

Summarizing, our results show that a non-negligible proportion of potentially coordinated users stayed active across the most important events of the 2022 Brazilian elections. This behavior differs slightly from that seen on other platforms such as WhatsApp in previous efforts (Nobre, Ferreira, and Almeida 2020).

Discussion

Social media has grown in importance as a channel for influencing people's behavior and decisions, extending its impact beyond the online world to shape real-life (offline) situations. More specifically, we have witnessed how user mobilization on these platforms can even influence the outcomes of major elections in countries with different levels of social development. This new reality poses significant challenges for those who manage social media platforms, as well as for the institutions responsible for upholding democratic processes across these countries.

Narrowing down to the Brazilian context, the recent years (from 2018 to the early months of 2023) were particularly tense with respect to the relationship among the Judiciary, Executive, and social media platforms. On several occasions, the Judiciary forced social media platforms to ban their users, even going so far as to suspend the operation of Telegram and WhatsApp due to the spread of misinformation related to vaccination, the legitimacy of electronic voting machines, and threats to Brazilian democracy.[26,27] The peak of tension among these various actors occurred during the 2022 Brazilian elections.

To the best of our knowledge, our work offers the first in-depth analysis of the dynamics of information spread on Telegram, unveiling how key users possibly guided political narratives during this period in the recent history of democracy in Brazil. For the sake of illustration, we highlight two milestones occurred in this period and captured in our data.

The first milestone refers to the riots that occurred on Jan-

[25]https://www.cnnbrasil.com.br/politica/bolsonaro-destaca-baixa-do-preco-dos-combustiveis-e-cobra-governadores/

[26]https://www.conjur.com.br/2022-fev-14/direito-eleitoral-tse-possibilidade-bloqueio-telegram-brasil/

[27]https://www.idea.int/sites/default/files/2023-11/case-study-brazil-gsod-2023-report.pdf

Network	From	To	Mess. (%)	Views (%)	Forwards (%)	Persisted Users (%)
DF	1st Round	2nd Round	4,857 (73.80%)	319,588,590 (77%)	728,792 (71%)	127 (53.81%)
DF+NB	1st Round	2nd Round	2,251 (62.70%)	135,905,508 (61%)	558,021 (56%)	27 (50.00%)
DF	2nd Round	Riots	3,297 (45.89%)	169,187,799 (47%)	333,072 (33%)	73 (23.86%)
DF+NB	2nd Round	Riots	1,301 (45.11%)	94,426,352 (52%)	324,337 (38%)	17 (20.24%)

Table 6: Persistence of backbones' users over consecutive events.

uary 8th. Some news Brazilian channels [28,29] reported the use of Telegram as a tool for mobilization before and during the attacks. These channels monitored a set of Telegram groups, which were used to send commands to people in Brasília [30] as well as to encourage the block of roads to make unavailable other country's critical infrastructure, such as airports. As previously shown, topic 8, which is closely related with this theme (Table 5), reached numerous views and forwards and were explored by a subset of persistent users in the backbones we extracted, suggesting evidences of coordination. Moreover, some news media reported the use of codes to coordinate invasions of government buildings in Brasília. One of the terms was the word "Selma", in reference to the military greeting "Selva" adopted by Brazilian military forces.[31] We looked into our messages and filtered those with *Selma* and *jungle* words. We found a total of 1,065 exchanged messages with these keywords, totaling around 157M views and 1M forwards. This indicates the usage of this term as a call for riots.

The second event is closely related with how to curb the spread of harmful narratives on specific widely used digital platforms. While on one hand, institutions apply some policies such as banning accounts and restricting the type of information disseminated to accomplish that, on the other hand, the strong mobilization on these platforms by various political groups encourage users to migrate to a new platform outside the institutions' radar. One of the shifts between platforms occurred in 2021, when, in response to Brazilian justice efforts to ban more accounts contributing to the disturbance of democratic order and the public exposure of companies aiding the propaganda machine on WhatsApp, Jair Bolsonaro's supporters shifted their tactics to Telegram (Cavalini et al. 2023). Interestingly, our data shows evidence of a new migration between platforms, with messages seeking communication alternatives. These messages were grouped into topic 10, and we observe the emergence of the Signal platform as an alternative to establish communication (Table 5).[32] We speculate that the increase in replication and viewing of messages classified in this topic occurred after participants in Bolsonaro-supporting groups on the Telegram messaging app were caught off guard on January 10 when they were shut down by the decision of Supreme Federal Court (STF) Justice (riots period in our data). The blocking of chats sparked a desperate rush among participants to find alternative ways to stay in touch.[33]

In a broader sense, our work presented a comprehensive study of user coordination to promote political content on Telegram. We achieved this by monitoring and collecting messages from 256 Telegram groups over 5 months, obtaining a total of 620K messages. To filter out weaker user interactions, we applied two network backbone extraction methods from the literature. This allowed us to retain only stronger interactions, which most probably reflect coordination. By analyzing the topological characteristics of the extracted backbones, we observed a temporal trend of increasing complexity in the interaction network and potential coordination within the Telegram networks over the analyzed periods. This trend culminates during the period of riots. Moreover, we found that users who are in backbones are highly networked and strategically positioned to influence and control the distribution of content. They act as fast proxies, facilitating the dissemination of messages to a broader audience. Finally, our content topic analysis aligns with discussions on traditional Brazilian news media channels regarding the narratives present in the major Telegram groups during the 2022 Brazilian elections.

Limitations of our data. While this study provides valuable insights into the use of Telegram for the potential coordinated dissemination of political content during the 2022 Brazilian elections based on more than 250 groups and several hundred messages, representing one of the most complete datasets in the literature, our analysis is limited to the data collected from a select number of Telegram groups and may not capture the entire political discourse on the platform. Moreover, the methods used, although robust, cannot definitively prove coordination, but rather suggest possible patterns that merit further investigation.

[28]https://oglobo.globo.com/blogs/sonar-a-escuta-das-redes/post/2023/01/a-mobilizacao-bolsonarista-no-telegram-nos-dias-que-antecederam-as-invasoes-em-brasilia.ghtml

[29]https://noticias.uol.com.br/politica/ultimas-noticias/2023/01/10/grupos-telegram-bolsonaristas.htm

[30]E.g.: *Are they going to invade, or are they going to stay singing, waving flags, smiling, and singing as if they were at a party? It's a war against the system!*

[31]https://www.metropoles.com/distrito-federal/na-mira/festa-da-selma-entenda-codigo-usado-por-extremistas-para-planejar-8-1-em-brasilia

[32]E.g.: *Does anyone have links to groups on the Signal app? If so, please post them here; I would like to participate.*

[33]https://oglobo.globo.com/blogs/malu-gaspar/post/2023/01/comecou-o-expurgo-redes-bolsonaristas-no-telegram-vivem-barata-voa-apos-bloqueio-do-stf.ghtml

Acknowledgements

The research leading to these results has been funded by CNPQ, CAPES and FAPEMIG.

Ethical Statement

The data in this paper is derived from Telethon API, which in turn uses the official Telegram API. It contains data from public politically-oriented groups and channels.

References

Abbar, S.; Zanouda, T.; Berti-Equille, L.; and Borge-Holthoefer, J. 2016. Using Twitter to Understand Public Interest in Climate Change: The Case of Qatar. In *Proc.of ICWSM*.

Blondel, V. D.; Guillaume, J.-L.; Lambiotte, R.; and Lefebvre, E. 2008. Fast unfolding of comm. in large networks. *Journal of Statistical Mechanics: Theory and Experiment*, 2008(10): P10008.

Bursztyn, V. S.; and Birnbaum, L. 2019. Thousands of Small, Constant Rallies: A Large-Scale Analysis of Partisan WhatsApp Groups. In *Proc. of ASONAM*, 484–488.

Bär, D.; Pröllochs, N.; and Feuerriegel, S. 2023. New threats to society from free-speech social media platforms. arXiv:2302.01229.

Cavalini, A.; Malini, F.; Gouveia, F.; and Comarela, G. 2023. Politics and disinf.: Analyzing the use of Telegram's inf. disorder network in Brazil for political mobilization. *First Monday*.

Chagas, V. 2022. WhatsApp and digital astroturfing: a social network analysis of Brazilian political discussion groups of Bolsonaro's supporters. *International journal of communication*, 16.

Clarke, K.; and Kocak, K. 2018. Launching revolution: Social media and the Egyptian Uprising's first movers. *British Journal of Political Science*, 50(3): 1025–1045.

da Rosa, J. M.; Linhares, R. S.; Ferreira, C. H. G.; Nobre, G. P.; Murai, F.; and Almeida, J. M. 2022. Uncovering Discussion Groups on Claims of Election Fraud from Twitter. In *Proc. of Social Informatics: 13th International Conference*.

Dargahi, A.; Reshadatmand, N.; and Neshati, M. 2017. Analysis of Telegram, An Instant Messaging Service. In *Proc. of CIKM*.

Dhawan, A.; Putnins, T. J.; and Rasel, A. R. 2023. Contagious crime: How cryptocurrency manipulation spills into stocks. *SSRN Electronic Journal*.

Ferrara, E.; Chang, H.; Chen, E.; Muric, G.; and Patel, J. 2020. Characterizing social media manipulation in the 2020 U.S. presidential election. *First Monday*.

Garimella, K.; and Tyson, G. 2018. WhatApp Doc? A First Look at WhatsApp Public Group Data. *Proc.of ICWSM*.

Gomes Ferreira, C. H.; Murai, F.; Silva, A. P. C.; Trevisan, M.; Vassio, L.; Drago, I.; Mellia, M.; and Almeida, J. M. 2022. On network backbone extraction for modeling online collective behavior. *PLOS ONE*, 17(9): 1–36.

Grootendorst, M. 2022. BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794*.

Guhl, J.; and Davey, J. 2020. A safe space to hate: White supremacist mobilisation on Telegram. *Strategic Dialogue*.

Himelein-Wachowiak, M.; Giorgi, S.; Devoto, A.; Rahman, M.; Ungar, L.; Schwartz, H. A.; Epstein, D. H.; Leggio, L.; and Curtis, B. 2021. Bots and misinformation spread on social media: Implications for COVID-19. *Journal of medical Internet research*, 23(5).

Linhares, R. S.; Rosa, J. M.; Ferreira, C. H. G.; Murai, F.; Nobre, G.; and Almeida, J. 2022. Uncovering Coordinated Communities on Twitter During the 2020 U.S. Election. In *Proc. of ASONAM*.

Linsey Moddelmog, P. A. d. S. 2019. *Religion and political parties in Brazil*, chapter 16. Routledge.

Newman, M. E. J.; and Girvan, M. 2004. Finding and evaluating community structure in networks. *Phys. Rev. E*, 69: 026113.

Nizzoli, L.; Tardelli, S.; Avvenuti, M.; Cresci, S.; and Tesconi, M. 2021. Coordinated Behavior on Social Media in 2019 UK General Election. *Proc.of ICWSM*, 15(1): 443–454.

Nobre, G.; Ferreira, C.; and Almeida, J. 2020. Beyond Groups: Uncovering Dynamic Communities on the WhatsApp Network of Information Dissemination. In *SocInfo' 2020*.

Nobre, G. P.; Ferreira, C. H.; and Almeida, J. M. 2022. A Hierarchical Network-Oriented Analysis of User Participation in Misinformation Spread on WhatsApp. *Information Processing and Management*, 59(1).

Pacheco, D.; Hui, P.-M.; Torres-Lugo, C.; Truong, B. T.; Flammini, A.; and Menczer, F. 2021. Uncovering Coordinated Networks on Social Media: Methods and Case Studies. *Proc.of ICWSM*.

Reimers, N.; and Gurevych, I. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In Inui, K.; Jiang, J.; Ng, V.; and Wan, X., eds., *Proc.of EMNLP*, 3982–3992.

Ribeiro, F. N.; Benevenuto, F.; and Zagheni, E. 2020. How biased is the population of facebook users? comparing the demographics of Facebook users with census data to generate correction factors. *12th ACM Conference on Web Science*.

Rossini, P.; Mont'Alverne; and Kalogeropoulos, A. 2023. Explaining beliefs in electoral misinformation in the 2022 Brazilian election: The role of ideology, political trust, social media, and messaging apps. *Harvard Kennedy School Misinformation Review.*

Ruz, G. A.; Henríquez, P. A.; and Mascareño, A. 2020. Sentiment analysis of Twitter data during critical events through Bayesian Net. class. *Future Gen. Computer Systems*, 106: 92–104.

Schulze, H.; Hohner, J.; Greipl, S.; Girgnhuber, M.; Desta, I.; and Rieger, D. 2022. Far-right conspiracy groups on fringe platforms: a longitudinal analysis of radicalization dynamics on Telegram. *Convergence: The International Journal of Research into New Media Technologies*, 28(4): 1103–1126.

Serrano, M. A.; Boguna, M.; and Vespignani, A. 2009. Extracting the multiscale backbone of complex weighted networks. *National Academy of Sciences*.

Slobozhan, I.; Brik, T.; and Sharma, R. 2023. Differentiable characteristics of Telegram mediums during protests in Belarus 2020. *Social Network Analysis and Mining*, 13(1): 19.

Sternisko, A.; Cichocka, A.; and Van Bavel, J. J. 2020. The Dark Side of social movements: social identity, non-conformity, and the lure of conspiracy theories. *Current opinion in psychology*.

Urman, A.; and Katz, S. 2020. What they do in the shadows: examining the far-right networks on Telegram. *Information, Communication & Society*, 1–20.

Walther, S.; and McCoy, A. 2021. US extremism on Telegram. *Perspectives on Terrorism*, 15(2): 100–124.

Weber, D.; and Neumann, F. 2021. Amplifying Influence of Coordinated Behaviour in Social Networks. *Social Network Analysis and Mining*.

Wolfsfeld, G.; Segev, E.; and Sheafer, T. 2013. Social Media and the arab spring. *The International Journal of Press/Politics*.

Paper Checklist

1. For most authors...
   (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socio-economic divide, or implying disrespect to societies or cultures? Yes
   (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? Yes
   (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? Yes, see the Methodology section.
   (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? NA
   (e) Did you describe the limitations of your work? Yes, see Discussion section.
   (f) Did you discuss any potential negative societal impacts of your work? NA
   (g) Did you discuss any potential misuse of your work? NA
   (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? Yes
   (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? Yes
2. Additionally, if your study involves hypotheses testing...
   (a) Did you clearly state the assumptions underlying all theoretical results? Yes
   (b) Have you provided justifications for all theoretical results? Yes
   (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? Yes
   (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? Yes
   (e) Did you address potential biases or limitations in your theoretical framework? Yes
   (f) Have you related your theoretical results to the existing literature in social science? Yes
   (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? Yes
3. Additionally, if you are including theoretical proofs...
   (a) Did you state the full set of assumptions of all theoretical results? NA
   (b) Did you include complete proofs of all theoretical results? NA
4. Additionally, if you ran machine learning experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? No, because we are unsure about releasing metadata from the unavailable Theleton API, as it could contain data that harms the moral integrity of various groups and society in general. Also, the API terms of use are not clear in this regard, so we have concerns about whether we can make the dataset available at all.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? Yes
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? NA
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? Yes, see the Methodology section
   (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? Yes
   (f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance? NA
5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...
   (a) If your work uses existing assets, did you cite the creators? Yes, all the methods we used in our analysis were correctly referenced in the paper.
   (b) Did you mention the license of the assets? NA
   (c) Did you include any new assets in the supplemental material or as a URL? NA
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? NA
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? Yes, see Ethical Statement.
   (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets FAIR? NA
   (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset? NA
6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...
   (a) Did you include the full text of instructions given to participants and screenshots? NA
   (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? NA
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? NA
   (d) Did you discuss how data is stored, shared, and disidentified? NA