Trends in Online Propaganda: A Comparative Study

Anirban Sen,[1] **Soham De,** [1] **Joyojeet Pal** [2]
[1] Microsoft Research, India
[2] University of Michigan
t-anirbansen@microsoft.com, t-sohamde@microsoft.com, joyojeet@umich.edu

Abstract

Social media is increasingly becoming a source of propaganda and misinformation. We collect twitter data on two propaganda events and one non-propaganda event with varying degrees of propagandist messaging, and study the participation of mainstream media, digital influencers, and politicians in the networks around them. We find that the extent of participation of these influential entities varies across events, depending on the nature, target groups, and frequency of the events. Temporal analysis of social media communities around these events also provides evidence of how their communities vary in their leadership over time.

Introduction

Social media is one of the most important sources of news and a range of daily information in today's age. Alongside changing peoples' access to networks, and giving them voice and communities to engage with, social media has also been a central force in the spread of misinformation and propaganda, with speed and engagement that was never before possible. Examples abound where a social media movement leads to popularization of a propagandist idea with ferocity and footprint in a way that not only obscures reality, but actively makes facts in an issue look like minority perspectives.

Much has been studied on the provenance and propagation of information, on networks, on the role of individual actors in it, and on the affective nature of content and its likelihood of reaction. In short, we know by now that bad behavior gets more attention online. However, there are still gaps in understanding what brings these factors together, specifically, how events and emotive content that is driven by vested interests differs from that which does not share the same attributes. For this, we turn to the notion of propaganda, which encompasses content engineered and driven by vested interests.

The Institute for Propaganda Analysis defines propaganda as the *"expression of opinion or action by individuals or groups deliberately designed to influence opinions or actions of other individuals or groups with reference to predetermined ends"*. Propaganda varies in its degree and type depending on the event or topic considered, and can have both positive and negative valence, based on whether its purpose is to degrade or to edify (Jowett and O'donnell 2018). When propaganda is disseminated using computational means, it is termed as *computational propaganda*.

In this paper, we present a comparative analysis of the social media user and network characteristics around two propaganda events and one non-propaganda event, each with a varying degree of propagandist messaging and different target groups involved. The hypothesis that we attempt to verify through this work is that the social media output on Twitter around different types of propaganda events leaves different traces in their user and network characteristics. These characteristics can also be used to distinguish them from a non-propaganda event.

We conducted this study in India, the world's largest democracy as well as the country with the highest installed base of social media users in the world. India has also been in the news over social media use in large part due to news coverage of polarization and political media use. Our analysis was solely on Twitter, for which India is the world's third-largest market, and although Facebook and WhatsApp have a far higher installed base, Twitter continues to play a central role in driving the national discourse, particularly because it is the platform of choice for politicians.

The three events considered in this paper – CAA-NRC, Budget 2022, and Boycott Bollywood – are all events of Indian origin (hereafter referred to as CAA, Budget, and Bollywood). The Citizenship (Amendment) Act (CAA) was passed by the Indian Parliament in December 2019, with the purpose of providing a pathway to Indian citizenship for persecuted religious minorities from other countries, who arrived in India before the end of December 2014. The NRC stands for the National Register of Citizens, an effort to gather proof of residency and claim to citizenship of people living within India's borders. The two were meant to work in tandem. The act drew global criticism since it for the first time codified faith as a factor for access to citizenship, in a nation-state that has secularism enshrined in its constitution. The act also set off alarm bells for citizens who had no connection to neighboring states, since proving citizenship involved significant documentation, and Muslims felt vulnerable unlike the Hindu majority.

The second event considered was the Union Budget Report for the year 2022. The budget is one of the most important policy documents in India, since it lays out annually what are the funds apportioned to various ministries, initiatives etc, as well as the rates of taxation for various goods and services. The budget is typically a politically contentious issue since it inevitably has winners and losers. In the 2022 Budget, the government primarily pushed for capital expenditure and private investment, but drew flak from the opposition and social media for its lack of initiatives to enhance employment opportunities or mitigate inflation, which has been a significant issue in the aftermath of COVID-19.

The third event considered was the Boycott Bollywood social media campaign that frequently encourages people to boycott films made by a certain cohort of the Hindi-language film actors industry, referred to as Bollywood since it is largely run of Mumbai, earlier known as Bombay. The campaign started gaining momentum starting in the early days of COVID-19, with the death of a popular Indian actor named Sushant Singh Rajput (SSR) in June 2020, which his fans claimed was either pre-meditated murder or a suicide triggered by systemic bullying from a nepotistic clique in the Mumbai film industry. Although initial investigations into the matter concluded that the death was by suicide, the campaign to investigate various angles as well as to boycott the output of the industry was kept alive by a set of dedicated social media fans or micro-influencers (Deb August 2022). While the actor's death was a precipitating event, Boycott Bollywood took a communal turn as the discourse turned its attention to Muslim actors in the Hindi film industry, some of who are the highest-paid and most successful stars.

To examine the contours of the three events, we consider a theoretical approach that helps to classify the events based on their characteristics. We turn to the literature on social movements, which helps understand events within the context of their social and political meaning. Anthropologist David Aberle (Aberle, Moore, and Johnston 1966) categorized social movements into four categories, namely revolutionary, reformative, alternative, and redemptive movements. While the notion of a movement may bring to mind broad-based national events that dramatically change the society, the characteristics of movements defined by Aberle can be used in much smaller events that aim to "convert" a subset of people to a certain point of view.

Revolutionary movements are dedicated to carrying out revolutionary and radical reforms and gain control of the state, but the idea can be extended to think about control of an institution or broad-based discourse. Reformative social movements are incremental in nature, advocating for minor changes instead of radical changes for a large section of people. Alternative movements attempt to bring partial change in the life of individuals (e.g., back-to-the-land movement in the US in 1960s that encouraged urban to rural migration with sustainable and alternative use of resources). Unlike alternative movements, redemptive movements are radical in scope and seek complete change in individuals (e.g., the Alcoholics Anonymous movement that tried to bring complete recovery from alcoholism) . Two of the three events we see fit closely within the characteristics set about by Aberle – CAA-NRC which aims to radically change the idea of India and who has access to it, while Boycott Bollywood attempts to incrementally change the film industry by boycotting and sidelining a set of key actors who are seen as a 'problem'. Both of these events consist of significant propagandist messaging. Budget 2022 is a mainstream political event that does not have the characteristics of a movement, although there are some elements of propaganda from the sides that have vested interests. Based on these definitions, the target groups, the percentage of propagandist tweets as identified through qualitative analysis of the top retweeted 200 tweets per event, and the frequency of the events, we present the categorization of the three events in table 1. From the qualitative analysis, we find that Budget is essentially a non-propaganda event, since it contains very few propagandist tweets (12%) among its top retweeted messages. The highest propagandist messaging is seen for Boycott Bollywood (72%) followed by CAA (50%), both of which are propaganda events as also established in previous studies (Dash et al. 2022; Menon 2020). We provide some examples of propagandist and non-propagandist tweets in the Appendix.

To understand the distinguishing characteristics of the three events along the different axes shown in table 1, we perform analysis of their user and retweet network characteristics on Twitter. Our analysis reveals that: (A) The social media discourse of a mainstream political, non-propaganda event like Budget is primarily led by mainstream media houses and accounts of high level politicians, while that of a revolutionary propaganda event (CAA) is led by media houses, digital influencers, and lower-level political accounts, (B) Revolutionary movements (CAA) also see the active involvement of lesser known micro-influencers, (C) Fringe reformative propaganda events (Boycott Bollywood) see minimal participation from media, influencer, and political accounts, but are sustained almost solely by micro-influencers, (D) Political accounts choose to engage on an event's discourse on Twitter based on their levels – non-propaganda events show more engagement by high level politicians and vice versa, and (E) The retweet networks of these events form moderately isolated communities of influence, and this influence is unevenly distributed within these communities, i.e., a few influential leaders guide the narrative of the entire community. We also find that this inequality is significantly higher for propaganda events than the non-propagandist one.

While several studies have been carried out in the area of propaganda detection on Twitter, to the best of our knowledge, ours is the first work that performs a comparative analysis of the distinguishing user and network characteristics of events with varying levels of propaganda. Thus, we show that not only do propaganda events vary from non-propaganda events in terms of these characteristics, but propaganda events even show variation among themselves, depending on their type. Additionally, we also present interesting findings around temporal evolution of event communities. The framework of analysis proposed can act as the first step towards early categorization of a social media event based on its type, its target groups, its frequency, and the amount of propagandist discourse around it.

Event	Movement Type	Primary Target Groups	Frequency	Propaganda (%)
CAA-NRC	Revolutionary	Religious groups, political parties, political affiliations, politicians	One time (since 2019)	50
Budget 2022	Mainstream Political	Political parties, politicians	Yearly	12
Boycott Bollywood	Reformative	Hindi-language Film fraternity (actors, directors, and producers)	Sustained, repetitive movement since 2020	72

Table 1: Categorization of events based on qualitative analysis: Two annotators independently annotated 200 top retweeted tweets for each event as propaganda/non-propaganda, with inter-tagger agreement of annotation $> 95\%$ for each event

Related Work

Several earlier studies have touched upon the topic of propaganda analysis. We describe in this section this body of work along two methodological directions, namely propaganda detection using text classification techniques and that using network analysis methods. Studies on text classification-based methods used supervised techniques to predict propaganda in a multi-class (Rashkin et al. 2017) and binary classification set up (Barrón-Cedeno et al. 2019). These approaches used word n-grams, formal text representations like readability and writing style, and lexicon based methods for propaganda prediction. Martino et al. (Da San Martino et al. 2019) proposed an extractive propaganda detection method using deep neural networks, which unlike the other studies, detected the technique of propaganda spread along with the text fragment responsible. Network analysis techniques for propaganda detection initially focused on the problem of node detection, i.e., these techniques classified a user node as propagandist or not in isolation (Kudugunta and Ferrara 2018), using supervised techniques on various user level features including network features (Yang et al. 2015, 2019), textual content used (Rangel and Rosso 2019), and profile information (Lee and Kim 2014).

There are three limitations of these approaches: (A) They significantly rely on annotated datasets/corpora used for training, thus being dependent on the amount of annotation, its subjectivity, and its quality, (B) They are vulnerable to automated text generation techniques that are often used to game them, and (C) It is often difficult to tag a node/user as propagandist in isolation, since such nodes often deliberately use techniques to evade detection. Researchers in this area thus eventually focused on detecting coordinated behavior among a set of user nodes, rather than considering a node in isolation, using semi-supervised and unsupervised techniques (Cai, Li, and Zeng 2017; Echeverrï£¡ a et al. 2018; Yang et al. 2018). In this direction, studies on detecting suspicious user connectivity patterns (Liu, Hooi, and Faloutsos 2017; Chetan et al. 2019; Pacheco, Flammini, and Menczer 2020) and temporal tweeting/retweeting patterns (Chavoshi, Hamooni, and Mueen 2016; Mazza et al. 2019) have been developed.

Our work is motivated by these previous studies, and attempts to look at propaganda analysis through a different lens. Instead of focusing on user, group, or message level detection/classification of propaganda, we study how different events consisting of some level of propagandist messaging vary from each other with respect to their user, network, and community level characteristics. More specifically, we want to understand the various domains to which the primary users driving the social media discourse on propaganda and non-propaganda events belong, and the way their influence in the discourse evolves over time.

Methodology

Data Sampling

For each event, we collected publicly available tweet data using the Twitter V2 API. These included basic metadata (such as the time of posting, contents, mentions) as well as network level features (such as user IDs referenced in the tweets and retweets). For each event, we qualitatively analyzed the top 200 most retweeted tweets, and curated a set H_1 of initial hashtags or keywords specific to the event (see Appendix). Then we pulled a representative sample of tweets containing any hashtag that belongs to H_1. Using these tweets, we expanded the keyword set to set H_2, containing keywords and hashtags that frequently co-occur with those in H_1 and are unique to the specific event. Using the expanded set H_2, we then pulled all tweets over the full timeline of the event and at least one month before and after it. We finally obtained 104533, 843936, and 643663 tweets for CAA-NRC (Dec-April 2019), Budget 2022 (Jan-June 2022), and Boycott Bollywood (Jan-April 2022) respectively, including retweets. This data was used for further analysis.

Community Detection

We wanted to understand how the various user accounts on Twitter cluster together to form retweet communities where members within a community heavily retweet each other, and engage in minimal cross-community retweeting. For this purpose, we first considered the retweet network for accounts belonging to mainstream media houses, major digital influencers (identified from the *DISMISS* dataset(Arya et al. 2022)), political accounts (identified from the *Niva-Duck* dataest (Panda et al. 2020)), the top 20 percentile user accounts with highest retweets received, and the top 0.3 percentile user accounts with highest number of retweets posted on the event based on the cumulative distributions (CDF) of the corresponding metrics. This sampling was done to

Event	#Nodes	#Edges	Modularity
CAA-NRC (P)	10655	17898	0.58
Budget 2022 (NP)	3631	13033	0.59
Boycott Bollywood (P)	11948	124299	0.27

Table 2: Details of the retweet networks for the events after filtering (P: Propaganda, NP: Non-Propaganda)

ensure that we remove the inconsequential users from the network, who are only sporadically active during the event timeline, and also to reduce the time complexity of the community analysis exercise. The retweet network for an event is a directed, unweighted graph with the user accounts as nodes, and directed edges (u, v) where an edge from node u to node v denotes that u has retweeted v at least once regarding the event, during the event timeline. The details of the retweet networks for each event after this sampling is shown in table 2. For community analysis on each event's retweet network, we used the Greedy Modularity community detection technique (Clauset, Newman, and Moore 2004). This maximization technique begins with each node in its own community, and repeatedly joins the pair of communities that lead to the largest modularity (a measure of isolation between communities), till convergence. We see in figure 1 the retweet network communities for the three events. It is clear from the figures that the event networks form around three to five major communities each. We also cross-checked this finding by calculating the number of intra-community edges for each community per event. For all further experiments on community analysis, we experimentally considered the top five communities in terms of their number of intra-community edges, since the rest consisted of significantly fewer number of retweet edges (< 100), and were inconsequential hence.

Results

User Characteristics

We find significant social media participation of political, media, and influencer accounts for the events considered, alongside sustained activity by lesser known micro-influencers in the two propaganda events (figure 7 in Appendix). In this section, we take a deeper look at these user characteristics empirically.

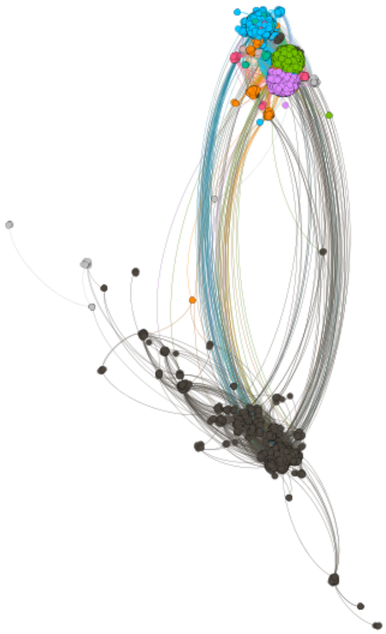
Media and Influencer Accounts To understand the tweeting pattern of mainstream digital influencer and media accounts for the three events, we compare in figure 2 the number of overall tweets by digital influencers and mainstream media accounts during the event timeline, with the number of tweets posted by them on event specific hashtags. From the plots, we see that both influencers and media houses tweet similarly across events. Budget (non-propaganda) shows a sharp peak and a subsequent drop in tweeting during the first week of February 2022 for both. This is the period when the Budget was presented in the Parliament, and most discussions on Twitter happened on this mainstream political event. CAA being a comparatively longer term revolutionary propaganda event shows a sharp peak for both media and influencers at the time of its inception (December 2019), but a gradual drop. Finally, Boycott Bollywood being a fringe reformative movement with the highest propaganda, shows no tweeting by either the media or the influencers (plots in Appendix). This indicates that its social media campaign is primarily maintained by lesser known dedicated users or micro-influencers.

Political Accounts We observed that the three events considered in this study show potential of politicians' interaction on social media. CAA being a revolutionary movement, involved long term protests for and against the decision of the ruling dispensation related to citizenship. Budget is a mainstream political event. Boycott Bollywood, while involving discussions primarily on Indian film fraternity, also brought in tweets by influential politicians (Entertainment Desk August 2022). Hence, we wanted to understand the participation of political accounts around these events. For this purpose, we plotted the number of original tweets posted by political accounts for the three events against the percentile of their number of followers in figure 3a. The number of followers serves as an indicator of a politician's influence on social media. We find that each event shows a different characteristic in terms of the political accounts interacting on them. For CAA and Boycott Bollywood (propaganda events), we see that the low influence political accounts (primarily 0-40 percentile) interact the most on social media. Additionally, between the two events, CAA shows a significantly higher number of tweets by political accounts compared to Bollywood. This is due to the fact that CAA being a core political issue attracted a lot of tweets and propaganda from aggressive politicians with relatively lower number of followers (Varma February 2020). Similarly, Boycott Bollywood being a fringe reformative movement with mostly non-political target groups attracted fewer propagandist tweets mostly from low influence politicians. For both of these events, the high influence politicians stayed away from tweeting, probably owing to the necessity of maintaining their social and political image. For Budget (non-propaganda), we find the activity is highly skewed towards the high influence politicians (80-100 percentile), since most of them tweeted on the justification or criticism of the mainstream political event. We observe a similar trend for the number of retweets received by the political accounts, which we do not show in the paper owing to space constraints.

Network Characteristics

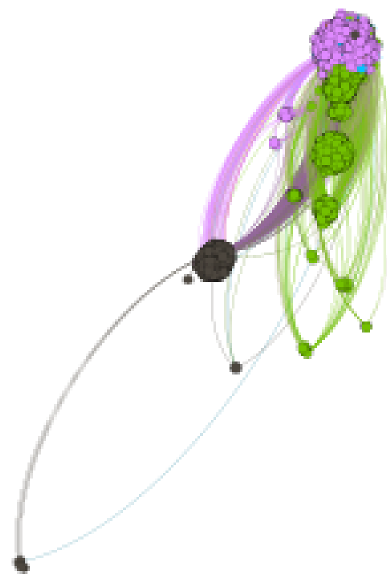
Here, we analyze the characteristics of network influence that the users identified in the previous section exhibit, and its temporal evolution.

Influence Distribution To understand how influence within the retweet networks is distributed among the user accounts, we show the CDFs of PageRank of user accounts or nodes within the event retweet networks in figure 3b. The PageRank of a node within a retweet network indicates its influence in terms of the number of retweets received by it, by other high influence accounts. It is evident from the plot that a very small set of user accounts show a significantly higher PageRank compared to the rest, for all the events.This



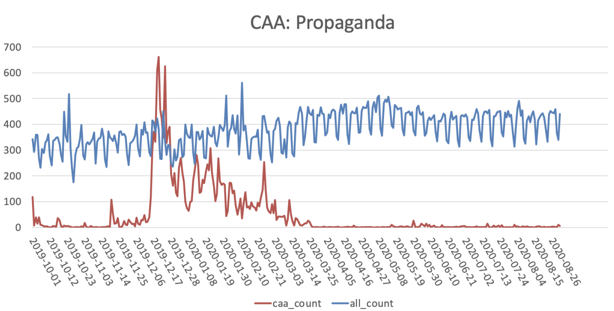
(a) CAA-NRC (Propaganda)

(b) Budget 2022 (Non-Propaganda)

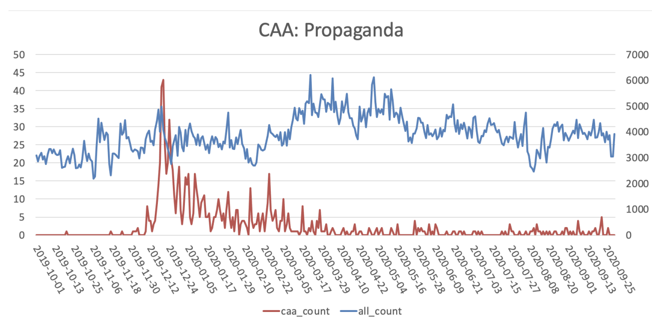


(c) Boycott Bollywood (Propaganda)

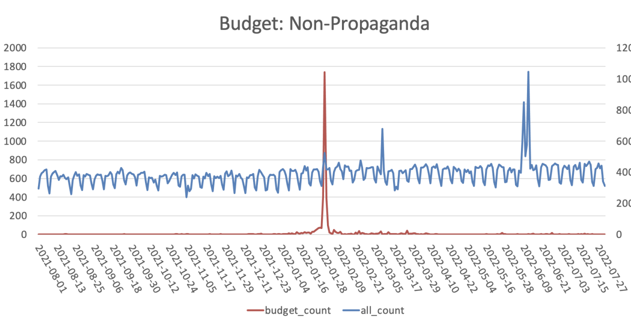
Figure 1: Retweet network communities for the three events after removing outliers: Each color represents a separate community within the retweet network



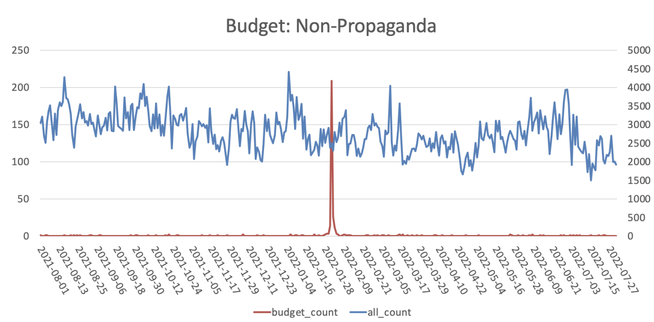
(a) Media



(b) Influencers

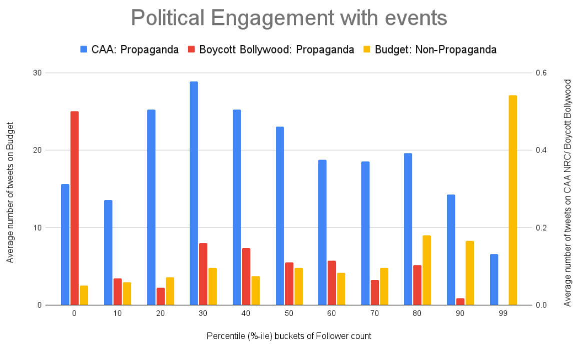


(c) Media

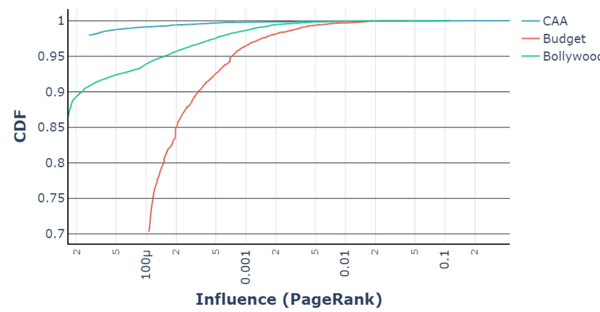


(d) Influencers

Figure 2: Number of original tweets posted by media houses and digital influencers on the events (red) vs. their overall tweets (blue). Plot for Boycott Bollywood is present in the appendix.



(a) Original tweets by political accounts



(b) PageRank distribution

Figure 3: Original tweets by political accounts against their number of followers, and distribution of PageRank for all user accounts in retweet networks for three events

inequality of influence distribution is the highest for CAA, followed by Boycott Bollywood and Budget (the differences between PageRank vectors for each pair of events is significant with $p < 0.05$). This indicates that a mainstream political event like Budget (non-propaganda) often exhibits a relatively equitable influence distribution in its retweet network, compared to the other two propaganda events with more centralized influence.

Spread of Information Generated Since we have established the influence that mainstream media, digital influencers, and political accounts have on each of the events, we analyze here the spread of information or tweets generated by these accounts, within the event retweet networks. We measure the spread achieved by an account as the percentage of nodes in the retweet network who retweet an original tweet by the account. Table 3 shows the spread achieved by the media, influencer, and political accounts.

Spreader	CAA-NRC	BoycottBollywood	Budget
Influencers	0.28	0.05	0.21
Politicians	1.03	0.03	0.52
Media houses	0.34	0.03	0.06
All	1.98	0.92	0.84

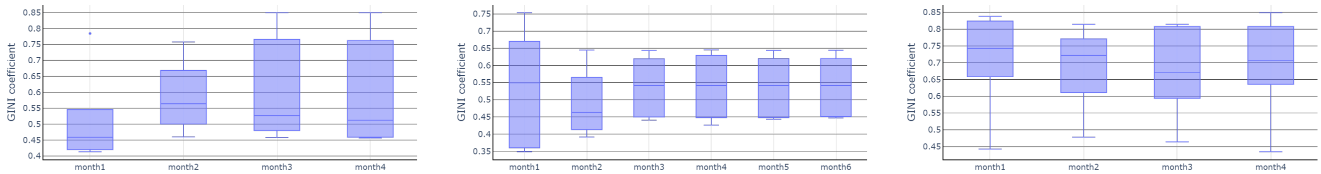
Table 3: Spread achieved by influential accounts (in %)

We find that as expected, the two propaganda events CAA and Boycott Bollywood exhibit a significantly higher overall spread than Budget, a mainstream political, non-propaganda event. Thus, we see that for propaganda events, the influential accounts receive a much higher network reach in terms of retweets than for non-propaganda events. Additionally, Boycott Bollywood being a fringe, reformative movement, shows a much lower spread than CAA for media, political, and influencer accounts, since the former is chiefly sustained by lesser known micro-influencers.

Community Analysis As discussed in the Related Work section, propagandist users often work in coordination. We wanted to see if the user accounts form distinct communities with minimal inter-community communications, for the three events. We find from table 2 that the CAA and Budget networks show a significantly higher modularity, when compared with the modularity of the Bollywood network. This is primarily due to the fact that Boycott Bollywood is a fringe reformative movement where a set of lesser known (non-politician and non-influencer) but dedicated micro-influencers maintain the campaign by significantly retweeting each other from multiple communities. Thus, the communities are less isolated for the event, compared to the mainstream political and revolutionary movements.

Next, we analyze the temporal evolution of communities for each event. For this purpose, we considered the retweet network formed till the end of each month in the event timeline, since the start date of the event. Thus, the i^{th} retweet network (n_i) contains the retweet network of users who participated till the i^{th} month since the start of the event. We considered monthly evolution of the retweet networks for ease of analysis, and also because we observed that it generally takes a month for significant change to happen in the networks in terms of the number of retweet edges. To understand how intra-community influence of accounts evolve over time, we next calculated the intra-community GINI coefficient for the top five communities for each event, considering the intra-community PageRank of member user accounts. A GINI value closer to 0 indicates high equality in the distribution, while that closer to 1 indicates high inequality. Figure 4 shows the intra-community GINI coefficients over time for each event.

We see that for CAA, Budget, and Boycott Bollywood, the GINI values between lower and upper quartile are in the range of [0.4,0.8], [0.3,0.7] [0.4,0.9] respectively, indicating the lowest inequality in distribution of influence for Budget, a non-propaganda event. Based on the median values, we also find that while CAA and Budget show an overall increasing trend, Bollywood maintains a mostly static inequality in terms of intra-community influence distribution (for each pair of events, difference between median GINI values is significant with $p < 0.05$). From these findings,



(a) CAA-NRC (Propaganda)

(b) Budget 2022 (Non-Propaganda)

(c) Boycott Bollywood (Propaganda)

Figure 4: GINI coefficient of communities over time for each event

we can argue that Budget being a non-propaganda political event consists of communities in the retweet network that exhibit a more equitable distribution of influence, when compared to the other two propaganda events, which seem to form much more centralized communities where a set of influential leaders guide the community narrative. Additionally, repetitive and reformative movements like Boycott Bollywood show a steady inequality in influence distribution within its communities for the timeline considered.

To also understand if the community leaders remain constant over time for the top five communities, we calculated the Jaccard Coefficient between the top 15 leaders (top three leaders from each of the top five communities) for each temporally consecutive pair of retweet networks. We find that initially for all three events, the leadership of the top communities show some change. However, over time the top communities stabilize in terms of leadership as seen from the high values of jaccard coefficient as shown in figure 5. The observable trait here is that CAA being a short term and one-time event shows a significant change in leadership of its top communities in the first couple of months, and shows a much higher slope in the plot compared to the other two events, which are repetitive and have been sustained for a significant time. Thus, it seems that for revolutionary social movements like CAA, the initial leadership is usurped eventually by newer leaders as the movement matures in the social media. Long sustained reformative movements like Boycott Bollywood do not show an equally significant change in leadership, owing to the maturity of the movement. Finally, mainstream political events show the highest commonality in leadership by their end, since only a small subset of politicians and experts capture the narrative eventually.

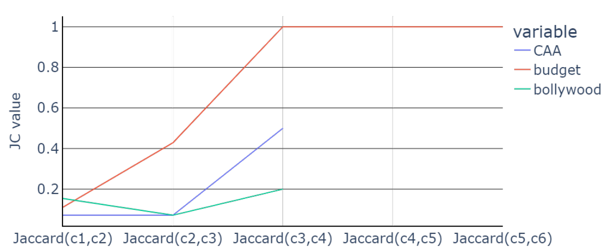


Figure 5: Jaccard coefficient of top communities over time: ci denotes the set of top five communities for n_i, i.e., retweet network till the i_{th} month

	CAA (P)	Budget (NP)	Bollywood (P)
month 1	(20,7,40)	(60,7,33)	(0,0,0)
month 2	(27,13,27)	(33,0,67)	(0,0,0)
month 3	(13,0,33)	(40,0,60)	(0,0,7)
month 4	(20,0,27)	(40,0,60)	(0,0,0)

Table 4: Percentage (rounded off) of media houses, influencers, and politicians in the community leadership over time, for the three events (P: Propaganda, NP: Non-Propaganda)

Finally, we see if the leaders of the top five communities are political accounts, media accounts, or digital influencers. Table 4 shows the percentage of each of these types of accounts among the community leaders over time. Corroborating our earlier findings, we see that Budget (non-propaganda) being a mainstream political event exhibits the maximum activity by media houses and politicians, followed by CAA. Digital influencers constitute the community leadership more for the revolutionary event CAA than Budget. Boycott Bollywood shows negligible presence of any of these types of entities, being a fringe propaganda event. Additionally, we find that the communities and their leadership for Budget becomes fixed third month onwards, since there is negligible discussion after the third month on the event (as also seen from figure 2). On the contrary, CAA communities show significant change in community leadership till the fourth month of the event. CAA being a revolutionary event with public protests also exhibits community leadership by lesser known user accounts (non-media/influencer/political), unlike Budget where the community leadership is captured exhaustively by one of these three types of accounts (and the percentages add up to 100).

Conclusion and Discussion

The rise of social media as an important source of news and daily information has also resulted in it being a primary force in the spread of misinformation and propaganda. While several previous studies have tackled the problem of propaganda detection at the message, user, and group levels, we examine the contours of three Indian events – CAA-

NRC, Budget 2022, and Boycott Bollywood – through a comparative analysis of their social media user and network characteristics, provided that these events are already known to consist of varying degrees of propaganda. CAA-NRC, an act passed by the Indian Parliament, drew global criticism since it codified faith as a factor for access to Indian citizenship. The Union Budget Report for 2022 is a politically contentious issue that exhibited polarised messaging on social media from both the ruling dispensation and its opposition. Boycott Bollywood is a social media campaign that encourages people to boycott films made by a certain group of the Hindi-language film industry, involving repetitive propagandist messaging from a group of dedicated campaigners. Based on the nature and target groups of these events, we categorize two of them based on the theoretical framework for social movement classification proposed by Aberle (Aberle, Moore, and Johnston 1966). CAA-NRC is categorized as a revolutionary propaganda event, since it targets revolutionary and radical reforms at the national level, and contains significant propagandist messaging. Boycott Bollywood is categorized as a reformative propaganda event as it attempts to target mostly the Hindi-film industry with highest levels of propaganda. Budget 2022 is a non-propaganda event, which is categorized as mainstream political.

We find that the events show significant differences in the user and network level characteristics. CAA, the revolutionary event, shows a significantly higher activity by digital influencers compared to the other two events, even after mainstream media attention has subsided for the issue. This is indicative of influencers' need to engage over revolutionary events to appeal to the masses. Neither mainstream media nor influencer accounts show significant activity for Boycott Bollywood, since it is a fringe reformative movement almost solely maintained by lesser known but dedicated users or micro-influencers. For these two events, low level politicians with relatively lesser number of followers on Twitter show the most tweeting activity, probably to stay relevant in their political careers. On the other hand, high level politicians tend to tweet less on these movements to avoid the risk of over-engaging in propaganda events, while showing significant activity for Budget, which is a non-propaganda event.

In terms of the retweet network characteristics, CAA and Budget show a higher modularity, or isolation of intra-network communities, compared to Boycott Bollywood. This is indicative of significant cross-community retweeting for the latter. We also find that these communities consist of "community leaders" – influential accounts who attract the most retweets and direct the event discourse – that become increasingly static as the communities evolve. For all three events, the intra-community influence distribution is skewed, i.e., the community leaders hold a disproportionately higher influence than others in terms of retweets received within the communities. However, this skew is the highest for the revolutionary propaganda event CAA, followed by Boycott Bollywood (propaganda) and Budget (non-propaganda). Thus, propaganda communities seem to exhibit higher centralization of influence than non-propaganda communities. Finally, a deeper look at these community leaders reveals that while both CAA and Budget shows significant community leadership by mainstream media and political accounts, the former also contains communities that are led by lesser known micro-influencers who do not belong to any of these cohorts.

Thus, we find that other than distinguishable traits between propaganda and non-propaganda events, there are traits that vary among propaganda events as well, depending on the type of the movement they target. These observations open different directions for future work. First, our analyses can be used to study other events across geographies, and it will be important to observe if these findings hold for them. Second, while we studied each of the events in isolation in this work, an interesting direction would be to understand if and how these event communities overlap or merge over time as shown in previous works (McQuillan et al. 2020). Third, an attempt to understand the connection between textual content of tweets, with the user and network dynamics for the events can reveal more of the underlying causes for the patterns observed. In this direction, study of multi-lingual and code-mixed content will be indispensable.

Ethics Statement

This paper presents a comparative analysis of the user and network characteristics of three Indian events with varying levels of propaganda. We find that different events show clearly distinguishable patterns in these characteristics over time, which could aid platform policies in regulating propagandist communities of practice. However, this work must be viewed as a prototype, and is not ready for deployment on platforms due to the following scopes for improvement: First, we understand that the measurements provided in this paper might vary across events, and further sophisticated and robust methods need to be devised to make causal claims, if any. Second, the analysis also needs to be replicated across multiple other events with varied nature, frequency, and target groups. Third, while we have tried to perform the qualitative analysis of tweets with minimal bias and using established qualitative analysis techniques, the definition of propaganda itself is subjective, and we have used the extant definition according to previous literature in the field. While we pinpoint some Twitter accounts as part of our analyzes, all of these accounts are publicly available. The influencer, media, and political accounts that are highlighted by name are all major figures on social media in India and we feel it is important to highlight their role in the issues we see unfolding, and the remaining work is aggregate reporting on Twitter activity around the events.

References

Aberle, D. F.; Moore, H. C.; and Johnston, D. F. 1966. The peyote religion among the Navaho .

Arya, A.; De, S.; Mishra, D.; Shekhawat, G.; Sharma, A.; Panda, A.; Lalani, F.; Singh, P.; Mothilal, R. K.; Grover, R.; et al. 2022. DISMISS: Database of Indian Social Media Influencers on Twitter. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 16, 1201–1207.

Barrón-Cedeno, A.; Jaradat, I.; Da San Martino, G.; and Nakov, P. 2019. Proppy: Organizing the news based on their propagandistic content. *Information Processing & Management* 56(5): 1849–1864.

Cai, C.; Li, L.; and Zeng, D. 2017. Detecting social bots by jointly modeling deep behavior and content information. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, 1995–1998.

Chavoshi, N.; Hamooni, H.; and Mueen, A. 2016. Debot: Twitter bot detection via warped correlation. In *Icdm*, 817–822.

Chetan, A.; Joshi, B.; Dutta, H. S.; and Chakraborty, T. 2019. Corerank: Ranking to detect users involved in blackmarket-based collusive retweeting activities. In *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*, 330–338.

Clauset, A.; Newman, M. E.; and Moore, C. 2004. Finding community structure in very large networks. *Physical review E* 70(6): 066111.

Da San Martino, G.; Yu, S.; Barrón-Cedeno, A.; Petrov, R.; and Nakov, P. 2019. Fine-grained analysis of propaganda in news article. In *Proceedings of the 2019 conference on empirical methods in natural language processing and the 9th international joint conference on natural language processing (EMNLP-IJCNLP)*, 5636–5646.

Dash, S.; Arya, A.; Kaur, S.; and Pal, J. 2022. Narrative Building in Propaganda Networks on Indian Twitter. In *14th ACM Web Science Conference 2022*, 239–244.

Deb, S. August 2022. The politics of boycott Bollywood. https://www.moneycontrol.com/news/trends/entertainment/the-politics-of-boycott-bollywood-9058811.html.

Echeverrï£¡ a, J.; De Cristofaro, E.; Kourtellis, N.; Leontiadis, I.; Stringhini, G.; and Zhou, S. 2018. LOBO: Evaluation of generalization deficiencies in Twitter bot classifiers. In *Proceedings of the 34th annual computer security applications conference*, 137–146.

Entertainment Desk, T. August 2022. Akshay Kumar lands in trouble; BJP MP Subramanian Swamy issues legal notice, accuses team of distorting Ram Setu saga. https://www.timesnownews.com/entertainment-news/akshay-kumar-lands-in-trouble-bjp-mp-subramanian-swamy-issues-legal-notice-accuses-team-of-distorting-ram-setu-saga-bollywood-news-entertainment-news-article-93830877.

Jowett, G. S.; and O'donnell, V. 2018. *Propaganda & persuasion*. Sage publications.

Kudugunta, S.; and Ferrara, E. 2018. Deep neural networks for bot detection. *Information Sciences* 467: 312–322.

Lee, S.; and Kim, J. 2014. Early filtering of ephemeral malicious accounts on Twitter. *Computer communications* 54: 48–57.

Liu, S.; Hooi, B.; and Faloutsos, C. 2017. Holoscope: Topology-and-spike aware fraud detection. In *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, 1539–1548.

Mazza, M.; Cresci, S.; Avvenuti, M.; Quattrociocchi, W.; and Tesconi, M. 2019. Rtbust: Exploiting temporal patterns for botnet detection on twitter. In *Proceedings of the 10th ACM conference on web science*, 183–192.

McQuillan, L.; McAweeney, E.; Bargar, A.; and Ruch, A. 2020. Cultural convergence: Insights into the behavior of misinformation networks on twitter. *arXiv preprint arXiv:2007.03443* .

Menon, N. 2020. Hindu Rashtra and Bollywood: A New Front in the Battle for Cultural Hegemony. *South Asia Multidisciplinary Academic Journal* (24/25).

Pacheco, D.; Flammini, A.; and Menczer, F. 2020. Unveiling coordinated groups behind white helmets disinformation. In *Companion proceedings of the web conference 2020*, 611–616.

Panda, A.; Gonawela, A.; Acharyya, S.; Mishra, D.; Mohapatra, M.; Chandrasekaran, R.; and Pal, J. 2020. Nivaduck-a scalable pipeline to build a database of political twitter handles for india and the united states. In *International Conference on Social Media and Society*, 200–209.

Rangel, F.; and Rosso, P. 2019. Overview of the 7th author profiling task at PAN 2019: bots and gender profiling in twitter. In *Proceedings of the CEUR Workshop, Lugano, Switzerland*, 1–36.

Rashkin, H.; Choi, E.; Jang, J. Y.; Volkova, S.; and Choi, Y. 2017. Truth of varying shades: Analyzing language in fake news and political fact-checking. In *Proceedings of the 2017 conference on empirical methods in natural language processing*, 2931–2937.

Sen, A.; and Pal, J. September 2022. The Structure And Style Of A Dogma Community: Conspiracy Theories And Organized Twitter Engagement On Sushant Singh Rajput. https://www.medianama.com/2022/09/223-how-ssr-sushant-singh-rajput-fans-gamed-twitter-algorithm/.

Varma, S. February 2020. "They Are Calling Me Terrorist": Defiant, BJP's Kapil Mishra Tweets Again. https://www.ndtv.com/delhi-news/delhi-violence-bjps-kapil-mishra-tweets-again-says-they-are-calling-me-terrorist-2185804.

Yang, K.-C.; Varol, O.; Davis, C. A.; Ferrara, E.; Flammini, A.; and Menczer, F. 2019. Arming the public with artificial intelligence to counter social bots. *Human Behavior and Emerging Technologies* 1(1): 48–61.

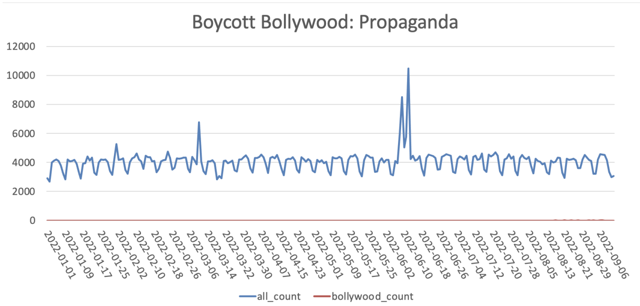
Yang, Z.; Hu, Z.; Dyer, C.; Xing, E. P.; and Berg-Kirkpatrick, T. 2018. Unsupervised text style transfer using language models as discriminators. *Advances in Neural Information Processing Systems* 31.

Yang, Z.; Xue, J.; Yang, X.; Wang, X.; and Dai, Y. 2015. VoteTrust: Leveraging friend invitation graph to defend against social network sybils. *IEEE Transactions on dependable and secure computing* 13(4): 488–501.

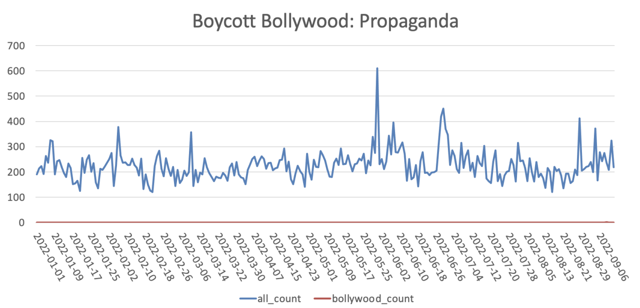
Appendix

Media and Influencer Activity for Boycott Bollywood

Figure 6 shows the media and influencer activity for the event Boycott Bollywood. As discussed in the main paper, the event shows no activity from mainstream media and influencer accounts.



(a) Media



(b) Influencers

Figure 6: Number of original tweets posted by media houses and digital influencers on the events (red) vs. their overall tweets (blue) for Boycott Bollywood

Users with Consistent Activity

To understand the users who are consistently active over time through tweeting about the events, we consider users who have authored at least one original tweet about the event every month. We then generate monthly word-clouds of these user account handles based on their tweet count and color the consistent users in red. This allows us to visualise the cohesiveness and sustenance of discourse, in terms of which types of users are consistent in activity. In Figure 7, we show these clouds for the first three months of each event. We find that for CAA-NRC and especially for #BoycottBollywood, the discourse is sustained by individual accounts, many of whom do not belong to mainstream media, influencer, and political accounts. These users are often micro-influencers and have the social capital to sustain the discourse. We also note that highly propagandist fringe, reformative events, such as #BoycottBollywood are driven by an extremely consistent group of these micro-influencers, and have very limited activity from non-consistent (non-red) users. In essence, this is a distinguishing characteristic of such fringe, reformative events. On the other hand, we observe that discussions on Budget 2022 are primarily sustained by media organizations that typically cover finance or business related news. The activity of these consistent accounts varies in intensity (number of tweets) over time for the events. These findings motivated us to further look into the participation of different types of user accounts in maintaining the discourse on the events.

Initial Hashtags for Data Sampling

We used a keyword/hashtag augmentation based method for tweet collection as described in the Data Sampling section. Table 5 shows the list of initial hashtags for data collection.

Examples of Tweets

Table 6 shows a few examples of propagandist and non-propagandist tweets for the three events, to provide an idea of the qualitative analysis done by the two annotators. The tweets also provide an idea of the kind of propaganda spread for the two propaganda events. While CAA-NRC shows propaganda tweeting primarily targeting a certain religious group, Boycott Bollywood consists of propagandist messaging around Sushant Singh Rajput's death, alongside encouraging people to abandon Hindi films made by a certain cohort of actors/directors. We also see the evidence of coordinated propaganda spread through taglines in Boycott Bollywood. Taglines are text snippets that are copy pasted as is by a massive number of users on instruction from an influential user, at a specific time of the day, thereby avoiding the use of hashtags which may lead to account banning/suspension (Sen and Pal September 2022). These taglines often contain very specific instructions on the timing, content, and frequency of tweeting.

(a) CAA NRC: Month 1

(b) CAA NRC: Month 2

(c) CAA NRC: Month 3

(d) Budget: Month 1

(e) Budget: Month 2

(f) Budget: Month 3

(g) Boycott Bollywood: Month 1

(h) Boycott Bollywood: Month 2

(i) Boycott Bollywood: Month 3

Figure 7: Word-clouds visualising consistently active accounts (in red) across events

Event	Hashtags
CAA-NRC (P)	caanrc, caanrcnpr, anticaa, caanrcprotest
Budget 2022 (NP)	budget2022, unionbudget2022, budget22, unionbudget22, unionbudget
Boycott Bollywood (P)	BoycottBollywood, Boycottbollywoodcompletely, Boycottbollywood-forever, BoycottAlia, BoycottGangubai

Table 5: Initial hashtags used for data collection (P: Propaganda, NP: Non-Propaganda)

Event	Example Tweets
CAA-NRC (P)	"Show me one percent Muslim in India who has condemned Islamic radicalism. One percent Muslim who has condemned the AntiCAA protest. One percent Muslim who have condemned the rants of the Owaisi brothers. https://t.co/lkbAI2W3YJ"
Budget 2022 (NP)	"On 1st February 2022 #Budget2022 was released in the houses of the parliament by respected Union Finance Minister #NirmalaSitharaman. Read the News to know what this year's budget has for the common people. https://t.co/tI2b6iAyQj"
Boycott Bollywood (P)	"Good Morning Awakened Ones! Morning TL: CBI Make SSR Case A Priority Evening TL: Sushant A Self Made Man And of course #Boy-cottBollywood"

Table 6: Examples of propagandist and non-propagandist tweets identified using qualitative analysis (P: Propaganda, NP: Non-Propaganda) – The last tweet on Boycott Bollywood shows how propaganda is spread using taglines (TL)