The Pursuit of Being Heard: An Unsupervised Approach to Narrative Detection in Online Protest

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***Abstract*—Protests and mass mobilization are scarce; however, they may lead to dramatic outcomes when they occur. Social media such as Twitter has become a center point for the organization and development of online protests worldwide. It becomes crucial to decipher various narratives shared during an online protest to understand people's perceptions. In this work, we propose an unsupervised clustering-based framework to understand the narratives present in a given online protest. Through a comparative analysis of tweet clusters in 3 protests around government policy bills, we contribute novel insights about narratives shared during an online protest. Across case studies of government policy-induced online protests in India and the United Kingdom, we found familiar mass mobilization narratives across protests. We found reports of on-ground activities and call-to-action for people's participation narrative clusters in all three protests under study. We also found protest-centric narratives in different protests, such as skepticism around the topic. The results from our analysis can be used to understand and compare people's perceptions of future mass mobilizations.**

***Index Terms*—social media campaign, unsupervised clustering, protests**

I. Introduction

Social media has become integral to various social movements and protests due to easy information dissemination and wider public reach [1]–[5]. Over 230 influential anti-government protests have erupted worldwide in the past six years, covering 110 countries [1]. Irrespective of the different socio-economic circumstances or political agendas, the various online protests share similar morphological features in using social media for self-organization and obtaining a more significant number of participants [6]. Using a hashtag to build a collective narrative makes Twitter one of the prime spots for conducting protest [7]. While Twitter enables a broad reach of the protest, a fine-grained analysis of various narratives present within a protest setting may also help decipher the people's perception and shed light on people's will and social protest's overall focus.

Previous studies on social media movements/protests have focused on different collective narratives in the

[1]https://carnegieendowment.org/publications/interactive/protest-tracker

Fig. 1: Figure showing examples of different narratives expressed by people during online protests. CTA: Call-to-action, OGA: On-ground activities, GRV: personal grievances.

campaign [4], [8]. The narratives range from information dissemination (such as personal grievances) around the topic [3], [9]; to call for participation [10] or reporting of on-ground activities [11], as shown in Figure 1. The grievance narrative might include personal stories of perceived injustice or other forms of hardships related to the cause. On-ground activities are narrative that either comes from people who are witnessing the offline protest or posts about current online activities related to the protest. The call for participation (call-to-action) narrative urges the users to participate in the cause by either being part of the physical protest or using social media to tweet protest-related posts. Although the different narratives during a protest have been studied individually, a unified discussion of various narratives present within a protest is scarce [4].

In this paper, we focus on various narratives in recent instances of the Reform movement [12] in India and the UK, where policies introduced by the government in power were deemed unjust and demanded to be repealed [13]–[15]. According to Social Movement Theory, Reform movements [12] is a subclass of movements that calls for change in a policy/behavior without alteration to the complete social institution. The reform movements studied in this work are as follows -

Citizenship Amendment Act, 2019 (CAA): The

Citizenship amendment Act, 2019 was passed by the Indian Government on December 11, 2019. It allows the illegal immigrants who have faced religious persecution in Afghanistan, Bangladesh, or Pakistan to seek citizenship in India if they have entered India on or before December 31, 2014 [16]. This led to a protest in the country with a debate on the non-secular roots of the Act. The protests were rooted in the exclusion of other religious minority communities like Rohingya Muslims, Jews, Bahais, and Zoroastrians from seeking citizenship.

Farmer's Protest, 2020 (FP): The Indian government proposed the Farmer's bill on September 20, 2020, which stirred the country. The country's farmers feared that the three laws introduced in the bill would result in the abolishment of the minimum support price (MSP), leaving farmers at the mercy of big corporations. Protests broke out in both the online and offline world due to the proposed bill, with people demanding it be repealed. The turn of events in the country led the Indian government to finally repeal the bill on November 09, 2021, ending the year-long protest in the country [13].

Kill the Bill Protest, 2022 (KTB): The Police, Crime, Sentencing, and Courts Bill (PCSC) introduced new police powers and reviewed the present rules around crime and protests in England and Wales. The activists opposed the law due to its ability to impose conditions on any protest deemed disruptive to the local community, leading to upto 10 years of jail. The punishable conditions included disruption of public properties, and statues, along with restricting access in and out of parliament [15].

Since each protest is unique in its goals, we propose an unsupervised cluster-based framework to identify the different narratives of the protest. The primary motivation for using cluster-based analysis is to leverage the semantic difference between clustered texts and identify fine-grained separation between clusters as different narratives in a protest. We also focus on a comparative study of narratives in protests under study to examine converging narratives across the different protests. Using a clustering-based framework, we bridge the gap of unified narrative detection in social media protests and identify converging narratives across different protests. Broadly, we ask the following research questions:

RQ 1: What are the different narratives present in a protest?

RQ 2: What are the most prominent narratives present within a protest?

RQ3: Are there any converging narratives across protests?

The succeeding sections of the paper are organized as follows. We discuss the related work in Section II. Next, we discuss the Data and Methods in Section III, followed by Results in Section IV and the Conclusion in Section V.

II. Related work

The early work on social media protests focused on how a protest can reach critical mass for collective mobilization through network analysis of participants [6], [17]. The analysis of textual features for understanding the sentiment of protest tweets shows the prevalence of negative sentiment [18] and specific psycho-linguistic lexicons over the others [19]. A study of tweeting activity during a protest shows that social media activists plan the protest and share relevant tweets with a future date and time of offline protest conduct (call-to-action) to gain critical mass [20], [21]. The call-to-action tweets have helped successfully predict future protests [22]–[24].

More recently, researchers have focused on advocates [25] and extreme users [26]–[29] who tend to spread the content of one particular side over the other, leading to the formation of echo chambers and biased opinions [30], [31]. Moreover, the politicians use social media to create a "us vs. them" narrative leading to marginalization and polarization among the public at large [32]. While some protests are accompanied by offline gatherings, which may turn violent [5], [9], [33], others are sustained on the online platform only [8], [34]. The use of collective action to conduct recent anti-government protests has shown how hashtag activism has helped reach mass mobilizaiton [9], [33].

Social media protests often tend to bring social justice and help marginalized social groups [35]. On the other hand, posts shared during protest activity shed light on the people's will and hardships [18]. Protest tweets have been used to study and reduce online prejudice around certain social groups [36]. The study of anti-vaccine infodemic helped to understand the human perception around the topic [37]. With twitter achieving the center position for most of the modern online activism and protests, manipulation of the campaigns has emerged as another topic of interest among various research [38]–[40]. The study of social media-mediated protests have been done concerning protest prediction [1], protest participation [6], and study of protest growth [17].

Our work builds on the previous literature on the ingredients present in the protests, including grievance [9], call-to-action [6], [10], and reporting of on-ground activity [5]. However, to the best of our knowledge, we are the first to propose an unsupervised tweet clustering-based framework to identify the presence and relative abundance of all the narratives in an online protest.

III. Data and Method

This section discusses the dataset and method for discovering the narrative clusters in the protest tweets.

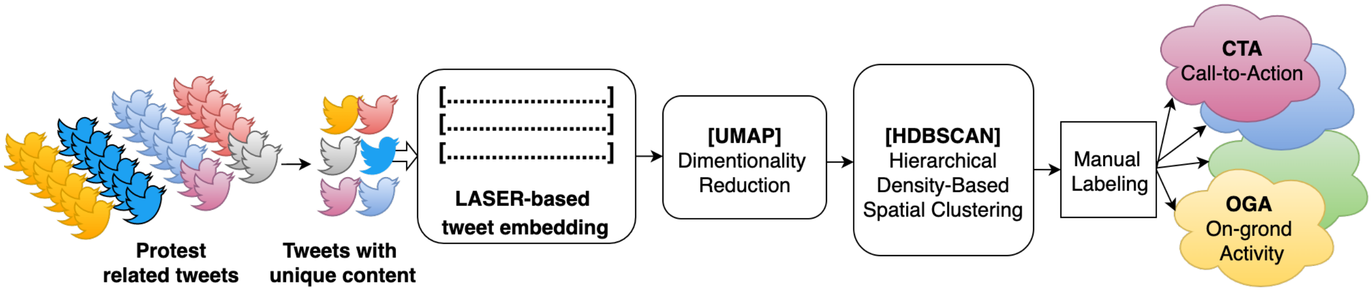


Fig. 2: Framework to identify dominant narratives amid social media protest. The different color of tweet represents different narrative tweets present in the dataset.

A. Data

As a starting point of data collection, we used the trending hashtags in the debate. We used the Twitter API [2] to collect tweets and incrementally include the relevant hashtags through snowball sampling. The statistics of the collected data are present in Table I.

TABLE I: Statistics of the collected data used for the analysis of campaign narratives. Abbr; CAA: Citizenship Amendment Act, FP: Farmers Protest, KTB: Kill the Bill protest.

Protest	Start date	End date	#Tweets	#Users
CAA	Dec 07, 2019	Feb 27, 2020	11,350,276	931,175
FP	Mar 31, 2021	Aug 13, 2021	1,509,703	160,286
KTB	Jan 14, 2022	Jan 26, 2022	280,549	73,666

The collection for CAA and KTB coincides with the initial months of the protest. The collection of FP tweets was done during a much later stage. The reason for the timestamps for data collection is arbitrary.

Pre-processing: After we collect the initial tweets, as shown in Table I, we follow the following pre-processing steps to ensure good quality of data: a) remove the mentions and URLs and emojis b) case-folding, where we lowercase the tweets c) remove tweets with less than 10 words d) split the hashtags at the capital letters.

As shown in Table I, the initial data collected for CAA was 11,350,276 from 931,175 users. Among the total tweets, the original tweets were 1,543,805, while Retweets/Quoted tweets were 9,806,471. After the first pre-processing step, the CAA tweet count was 11,302,023. The initial data collected for FP was 1,509,703 tweets, with 199,626 original tweets and 1,310,077 retweets. The first step of pre-processing reduced the FP tweet count to 1,500,022. The initial tweets collected for the study of KTB were 280,549, produced by 73,666 users. The data constituted 40,798 original tweets and 239,751 retweets / quoted tweets. After pre-processing step, the total number of tweets for KTB was 278,065.

[2]https://developer.twitter.com/en/docs/twitter-api/v1/tweets/curate-a-collection/overview

B. Method:

The narratives in an online campaign tend to be topic-driven [8], [41]; therefore, a fixed set of labels may not always fit a given protest. Hence, we propose an unsupervised framework for identifying significant narratives of a protest, as shown in Figure 2. Our framework is inspired by the unsupervised user-based stance detection framework proposed recently [42], [43]. Instead of user-based detection, we follow a tweet-based approach to identify the prominent narratives present in a social media protest.

Active tweet identification: We use a two-step process to consider a rich and unique instance of tweets around a protest. First, we use string matching to identify duplicate tweets in an online protest. We remove the hashtags and mentions to conduct string matching on the tweet text. While using most retweeted tweets is one of the approaches to identify duplicates, we also wanted to include the use of the same text tweeted by two or more users. The practice of tweeting the same text instead of retweeting has recently gained much traction in the global south recently [38]. Secondly, we use the tweets whose occurrence (duplicates) exceeds a particular threshold. The threshold adopted is based on the size of the data, and manual intervention, where we recheck the cluster outputs with different threshold values.

Tweet representation: To identify the most active tweets for CAA, we choose the threshold for semantic similarity as 30. With 30 as the threshold, tweets identified as duplicates were 36,109 unique tweets, which account for total 7,878,996 tweets/retweets in our dataset. For FP, we choose the threshold as 30 based on the manual analysis of clusters. With the threshold as 30 for FP, we obtained 7,553 unique tweets that constituted 112,186 total tweet/retweet in the FP dataset. The threshold for KTB was set to 5, with total tweets considered for analysis after threshold selection being 278,065 tweets. The unique tweets considered for clustering are found to be 3,821 tweets.

Once we have identified the most active tweets, we first represent the tweets in the embedding space using BiLSTM encoder based universal language agnostic sentence embedding (LASER) [44], which has proven to give best performance for retaining linguistic information among various sentence embeddings [45]. The other motivation for using LASER is that it offers a benefit over limited resource language and code-switching texts. Given India's rich linguistic diversity, building models that cover as many languages as possible for a protest/campaign study becomes essential. LASER uses Moses tool [3] for pre-processing a sentence. After pre-processing, the sentence representation is 1024 dimensional.

Tweet projection: We then project each tweet onto a two-dimensional plane using Uniform Manifold Approximation and Projection (UMAP) algorithm [46]. UMAP attempts to project the similar elements closer to each other while dissimilar elements are projected far away. The performance of UMAP has shown better projection than other techniques, including t-distributed Stochastic Neighbor Embedding (t-SNE) [47].

Clustering: We cluster the projected tweet vectors using hierarchical density-based clustering (HDBSCAN) [48]. HDBSCAN finds clusters of varying densities. We also tried using other clustering algorithms, including Meanshift [49] and DBSCAN [50]. However, HDBSCAN gave us the best clustering performance, determined by manual evaluation. We used prominence score to analyze and validate our manual labeling of different narratives qualitatively.

IV. Results

RQ1: Narratives present in a protest

Per RQ 1, we examine the clusters formed in each campaign using our framework. We leverage the semantic difference in the clusters to identify plausible narratives in the campaign. We have not reported the tweets clustered as noise for brevity. For annotation of protest clusters into different narratives, we leverage the previous literature on protest studies in different parts of the world [5], [9], [10].

CAA: With the duplicate threshold set as 30, the number of unique tweets for clustering was $36,109$. As shown in Figure 3a, 6 clusters of tweets were formed for CAA. For analysis of narratives, we manually annotate randomly selected two sets of 10 sample tweets from each cluster. Table II shows the 4 different narratives clusters in the campaign with highest engagement. The other two clusters belonged to personal grievances and location-specific tweets. In terms of engagement (i.e., tweet/retweet activity), the largest cluster showed skepticism towards the Act. On manual intervention, we found that skepticism was present in both tweets that opposed the Act and who opposed the protesters. The second dominant narrative for CAA was the Questioning cluster, where the tweets posed questions to the Act, politicians, and protesters for violent actions. The other two important narrative clusters included call-to-action and on-ground activities clusters. The example tweets for the 4 major narratives are presented in Table II.

FP: The duplicate threshold to give the best clustering result for FP is 30. Unlike CAA, with the same framework for narrative clustering, we found 20 clusters for FP. However, we focused on the top 4 clusters for further analysis, constituting more than 500 unique tweet text each. As shown in Table II, the most dominant narrative in FP was call-to-action, with $6,287$ (CTA-AP) and 845 (CTA-AP) unique tweets respectively . While the cluster (denoted as CTA) called for participation in support of farmers, the cluster CTA-AP (i.e., Call to action against politicians) contained tweets against the ruling government for their proposal of the bill.

KTB: The duplicate threshold for KTB was set to 5, as the data collected for the protest was small. With duplicate threshold as 5, KTB had $203,355$ total engagements, with $5,601$ original tweets and $197,754$ retweets. The UK protest on the policing formed 2 clusters using our framework as shown in Figure 3c. Among the two clusters, more engagement was around call-to-action. Table II shows the example of tweets from both on-ground activities and call-to-action for the protest.

RQ2: Prominent narratives in a protests

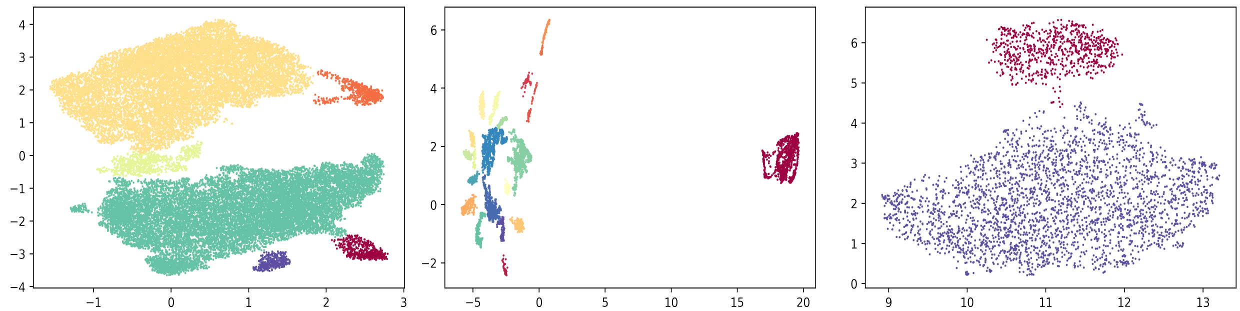
From the analysis of the clusters in the protests, we found that the protests might show specific clusters unique to the protest. There also exist narratives that are common across all protests. We found the presence of call-to-action (CTA) and reporting of on-ground activities (OGA) forming two persistent clusters in all the protests under study. The other common narrative across protests is grievances or personal complaints [9]. While grievances play a vital role in contentious politics, they are highly subjective in nature [51]. Therefore, it becomes challenging to deduce meaningful narrative clusters for the grievances across the protests.

However, our proposed framework was able to form clusters with deductible characteristics for call-to-action and on-ground reporting of activities with similar features across the protests under study. The skepticism and questioning in CAA reveal the contention in the online social media about the Act. On the contrary, the FP protest was more in harmony with opposing the bill, with narratives formed majorly towards CTA and OGA. The call-to-action narrative in FP was further differentiated into CTA against the bill (CTA) and CTA against the current ruling government (CTA-AP). The KTB protest also formed two clusters for CTA and OGA narratives, respectively.

RQ3: Converging narratives across protests

The converging narratives across protests were call-to-action (CTA) and on-ground activities (OGA). With the help of Prominence score Pr in Equation 1, we found the

[3]http://www2.statmt.org/moses/



(a) #CAA (b) #FP (c) #KTB

Fig. 3: Clusters of narratives for CAA, FP and KTB respectively.

TABLE II: Main narratives present in the protests under study.

Protest	**Narrative**	**Unique Tweets**	**#Tweets**	**#Users**	**Example**
CAA	Questioning	13,380	2,387,533	278,184	The police showed patience and did not shoot. Who fired at 56 policemen in Lucknow? Those who are saying that they do not have any paper, are they who are the end? Listen to the story of Pakistani Hindu.
	Skepticism	15,274	3,911,679	466,139	Thousands on the street in support of CAA! I was not expecting this from Bhubaneshwar
	CTA	865	154,926	72,415	What ever way is there we oppose poisonous #CAA Rangoli is our tool
	OGA	647	98,221	48,276	The demonstration was held today at the Valluvar Fort in Chennai on behalf of the Tamil National Party and the Tamil National Alliance. Urged to withdraw the Citizenship Act
FP	CTA	6,287	13,734	464	Through violence, haarsh weather, beatings, & amp; Deaths of OurThers and Sisters, We Stand Tall And Adud! We Will Not Back Up Down Till Farm Laws ARE Repealed. #300deathsatProtest The war continues ... the war continues ...
	CTA-AP	845	26,897	9,470	We want humanity in our country We want a government who serve for nation/people not for corporations No more BJP
	OGA	683	66,660	2,538	Watch- On #HolikaDahan, Farmers in Rajasthan #BurnFarmLawsOnHoli amidst slogans for 300+ who have died in #FarmersProtest.
KTB	OGA	742	20,557	9,431	Don't worry we are no longer being gaslighted @BorisJohnson @Conservatives @sajidjavid no trial needed you are as bad as each others. Lie after lie after lie #BorisJohnsonMustGo #ToriesDevoidOfShame #ToriesUnfitToGovern
	CTA	2,958	178,499	56,079	The government are stripping away our fundamental rights with the #PolicingBill. It would: - Ban noisy protests - Criminalise the GRT community - Increase stop search powers - Jail protest organisers for up to 10 years. Join us at protests tomorrow to #KillTheBill

most prominent terms, emojis, hashtags, and mentions in each narrative cluster. The Prominence score also helped validate the cluster narratives identified through manual annotations. Table IV shows the engagement around the prominent narratives in the protests under study.

Since the collection of protest data for CAA and KTB was done during the initial months of the protest, while the data collection for FP was done during a later stage, the analysis shows that the narratives for CTA stayed strong throughout the protest and not just start of the protest. While FP and KTB have tweets divided into OGA and CTA, we find the dominant narratives in CAA as Questioning and Skepticism. It can be catered to the fact that CAA led to a vibrant discourse in the country.

TABLE III: Prominence score for CAA

Protest	Narrative	Top terms	Emoji	Top hashtags	Top Mentions
CAA	OGA	Assam, struggle, reality, curfew, Tripura, Punjab, Chennai, Northeast	📣, 💐, 😥, 🤦‍♂️, 🖤, 🚩, ✌️, 👈, 👉, 👇, ❓, ❗, 😡, 👍, ⁉️	#assam,#curfew, #tripura, #section144, #uttarpradesh, #keralagovt	*@nishantchat*, *@naqvimukhtar*, *@abbas_nighat*, *@prashantjourno*, *@sanjaykumar_ind*
	CTA	initiative, require, showcase, stronger, trending, bhaktriot, trending, we	👇, 🍿, 🌹, 👀, 🔃, ☠️, 🤦‍♂️, 🙏, ✊, 👈, 🐖, 🕉️, 🔱, 🏹, 🍷	#jaishriram, #jaihind, #protestisplanned, #jihadists, #solidaritypledge	*@republicpoll*, *@jyotithakur81*, *@satpalsattibjp*, *@manojkureel*, *@mrsgandhi*, *@kushwahpooja19*
FP	OGA	wife, missing, arrest, bathinda, arrested, hospital, hindutva, survived, gazipur, toolkit, rajasthan	👉, 🖤, ✊🏿, ✊, 💔, 🎥, ⚠️, 🕉️, 💵, 🤟, 👆, 👍, 💚, 🎞️	#taliban, #toolkit, #pakistan, #freeranjitsingh, #lahore, #bangladesh	*@themsbf*, *@imrankhanpti*, *@cnn*, *@sikhpa*, *@anilvijminister*, *@potus*
	CTA-AP	boycottbjp_4farmers, boycotting, satisfaction, socialism, nazi, meal, child	😥, 🙏, ✍️, ✨, 🔥, 🤙, 💪, 🌾, 👇	#boycottbjp_4farmers, #23marchwithfarmers, #wholootedbanks	*@sushant_says*, *@rakeshtikaitbku*, *@lambaalka*, *@ramnsekhonramn*, *@vishallochab6*
	CTA	modisansad, kisansansad, strengthen, shipping, appreciating, represent	➡️, 🚜, 🧑‍🌾, 🌾, 🐖, ✊, 🙏	#myfarmer_mypride, #boycottbjp_4farmers, #modi, #india	*@narendramodi*, *@rakeshtikaitbku*, *@navjammu*, *@drarchanainc*, *@whoneerajkumar*
KTB	OGA	toriesdevoidofshame, toriespartiedwhilepeopledied, toriesunfittogovern, borisjohnsonout, sue	🔥, 🤦‍♀️, 🤷‍♀️, 🐷, 🤬, 😷, 😤	#toriesdevoidofshame, #toriesoutnow, #toriesunfittogovern, #toriespartiedwhilepeopledied, #borisjohnsonout	*@borisjohnson*, *@rishisunak*, *@conservatives*, *@scottories*, *@trussliz*
	CTA	draconian, peers, amendments, manchester, votes, protesters, noise, saturday, activists	📢, ‼️, ⚠️, 🖤, 👀, 🎥	#killthebill, #policingbill, #pcscbill, #protestisnotacrime, #righttoprotest, #nationalityandbordersbill	*@natalieben*, *@greenjennyjones*, *@killthebill*$_1$, *@labourlordsuk*, *@thegreenparty*

TABLE IV: Total engagement in the narrative common across protests in our study.For FP, we report a consolidated result for CTA and CTA-AP.

Protest	Narrative	Total Tweets	Tweet	Retweet
CAA	CTA	154,926	2,926	152,000
	OGA	98,221	1,580	96,641
FP	CTA	40,631	925	39,706
	OGA	66,660	879	65,781
KTB	CTA	178,499	4,546	173,953
	OGA	20,557	868	19,689

However, FP and KTB were predominantly single-sided protests, where users were mainly tweeting against the bill.

A. Qualitative analysis of clusters:

This section sheds light on the framework's performance. We focus on the semantic difference between clusters as a measure of cluster quality [42], [43]. We identify the most prominent term in each cluster to show how each narrative uniquely talks about the same issue in a different context. To suit our need, we generalize the prominence score used in the literature [43] for more than two cases. The *prominence score* uses valence score and term frequencies to distinguish cluster narratives.

For each term t, we capture the degree of its occurrence in a set of tweets from cluster i, i.e., tf_i, as compared to all other clusters tf_j (where j ranges from $Cluster_1$ to $Cluster_n$). The *prominence score* of a term t is defined as a product of its valence score and its term frequency as follows:

$$V(t,i) = \log(tf_{t,i}) * (2 * \frac{\frac{tf_i}{total_i}}{\sum_{j=1}^{n} \frac{tf_j}{total_j}} - 1) \quad (1)$$

Using the Prominence score Pr, we compute the top terms, emojis, hashtags, and mentions for each narrative cluster. We present the result of the Pr score for each protest in Table III, and discuss the result for each protest in detail below:

CAA: Table III shows that the top terms for OGA include state and location information. It gives evidence of users sharing location-specific on-ground activity on social media. We exclude the prominent terms that included the various forms of CAA (e.g., Citizenship, CAB, Bill) due to their redundancy through all the narratives. The top hashtags also include states in India (i.e., Assam, Uttar Pradesh, etc.). Since the offline protest broke in different states, the top terms and top hashtags show prominence of states in the cluster. The top emojis used in OGA were index-pointing fingers, loudspeaker, red flag, and black heart. The top mention in OGA included news editors, reporters, and ministers. The top terms for CTA included words like initiative, showcase, trending, and notion of 'we', among others. The top hashtags also had a call-to-action context, including a pledge to solidarity (#solidaritypledge). Most of the top accounts under CTA are currently suspended by Twitter. At the same time, others included political party leaders. In CAA, we found that the OGA narrative more prominently mentioned news channel personnel, while common people were mentioned mostly in CTA.

FP: The top terms for the OGA narrative for FP included terms like arrest, missing, and locations, which were in line with the on-ground activity narrative. The most prominent emojis include black heart, broken heart, video camera, and money. The OGA narrative's prominent mention included NGO handles, politicians, and news outlets. The top terms and hashtags for CTA included terms like appreciation and farmer's pride. CTA-AP included terms like nazi and socialism. The context-specific emojis of crops, farmers, and tractors were commonly used in CTA and CTA-AP. Prominent mentions in CTA-AP were of Bollywood actors, farmer's unions, and activists. CTA mentioned the prime minister among other activist accounts and a few suspended accounts.

KTB: The top prominent terms and hashtags for OGA in the KTB protest included narratives of shame against the Prime Minister and reporting of deaths. The emojis used included anger, face, facepalm, and fire. The mentions in OGA included the Prime minister's handle, members of parliament, and other politicians. While the CTA cluster top terms and hashtags included words like peers, places, and calling out activists, the top mentions included members of the green party and activists' handles.

V. Conclusion

In this work, we propose an unsupervised framework to identify the different narrative clusters in a social media protest. Catering to the fact that protests are composed of certain narratives discussed in previous literature, we leverage clustering algorithms to cluster protest narratives. We used the anti-government policy bill-related tweets in India and the United Kingdom and deciphered the most prominent and common narratives within and across the protests. The proposed Prominence score validation for narratives is qualitatively consistent in all protests under study. We found that call-to-action and on-ground activities as converging narratives across protests. In a protest that led to discourse, we found narratives that show skepticism and questioning tweets. However, we can conclude that the protests that contain majorly on-ground reporting and call-to-action are single-sided anti-government protests. With the help of the prominence score, we found a pattern of emojis commonly used in protest-related tweets. The mentions in the protests provide evidence that OGA has more verified accounts tagged, while the CTA mentions more of the general public, some of whom were suspended.

References

[1] R. Korolov, D. Lu, J. Wang, G. Zhou, C. Bonial, C. Voss, L. Kaplan, W. Wallace, J. Han, and H. Ji, "On predicting social unrest using social media," in *2016 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM)*. IEEE, 2016, pp. 89–95.

[2] M. De Choudhury, S. Jhaver, B. Sugar, and I. Weber, "Social media participation in an activist movement for racial equality," in *Proceedings of the... International AAAI Conference on Weblogs and Social Media. International AAAI Conference on Weblogs and Social Media*, vol. 2016. NIH Public Access, 2016, p. 92.

[3] A. Field, G. Bhat, and Y. Tsvetkov, "Contextual affective analysis: A case study of people portrayals in online #metoo stories," *Proceedings of the International AAAI Conference on Web and Social Media*, vol. 13, pp. 158–169, Jul. 2019. [Online]. Available: https://www.aaai.org/ojs/index.php/ICWSM/article/view/3358

[4] R. Wang and A. Zhou, "Hashtag activism and connective action: A case study of# hongkongpolicebrutality," *Telematics and Informatics*, vol. 61, p. 101600, 2021.

[5] G. Lotan, E. Graeff, M. Ananny, D. Gaffney, I. Pearce *et al.*, "The Arab Spring| the revolutions were tweeted: Information flows during the 2011 Tunisian and Egyptian revolutions," *International journal of communication*, vol. 5, p. 31, 2011.

[6] S. González-Bailón, J. Borge-Holthoefer, A. Rivero, and Y. Moreno, "The dynamics of protest recruitment through an online network," *Scientific Reports*, vol. 1, pp. 1–7, 2011.

[7] R. Wang and K.-H. Chu, "Networked publics and the organizing of collective action on Twitter: Examining the #Freebassel campaign," *Convergence*, vol. 25, no. 3, pp. 393–408, 2019.

[8] K. Neha, T. Mohan, A. B. Buduru, and P. Kumaraguru, "Truth and travesty intertwined: a case study of# ssr counterpublic campaign," in *Proceedings of the 2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, 2021, pp. 643–648.

[9] A. Sinpeng, "Hashtag activism: social media and the #freeyouth protests in thailand," *Critical Asian Studies*, vol. 53, no. 2, pp. 192–205, 2021. [Online]. Available: https://doi.org/10.1080/14672715.2021.1882866

[10] A. Rogers, O. Kovaleva, and A. Rumshisky, "Calls to action on social media: Potential for censorship and social impact," *EMNLP-IJCNLP 2019*, p. 36, 2019.

[11] O. Varol, E. Ferrara, C. L. Ogan, F. Menczer, and A. Flammini, "Evolution of online user behavior during a social upheaval," in *Proceedings of the 2014 ACM conference on Web science*, 2014, pp. 81–90.

[12] J. DeFronzo and J. Gill, *Social problems and social movements.* Rowman & Littlefield, 2019.

[13] E. W. desk, "Farmers end year-long protest: A timeline of how it unfolded," 2021. [Online]. Available: https://indianexpress.com/article/india/one-year-of-farm-laws-timeline-7511961/

[14] V. S. Damini Nath, "After a heated debate, Rajya Sabha clears Citizenship (Amendment) Bill," *The Hindu*, 2019.
[15] T. B. I. W. desk, "What are the Kill the Bill protests?" *The Big Issue*, 2022.
[16] A. Chandrachud, "Secularism and the citizenship amendment act," *Indian Law Review*, vol. 4, no. 2, pp. 138–162, 2020. [Online]. Available: https://doi.org/10.1080/24730580.2020.1757927
[17] P. Barberá, N. Wang, R. Bonneau, J. T. Jost, J. Nagler, J. Tucker, and S. González-Bailón, "The critical periphery in the growth of social protests," *PLoS ONE*, vol. 10, no. 11, 11 2015.
[18] J. M. Costa, R. Rotabi, E. L. Murnane, and T. Choudhury, "It is not only about grievances: Emotional dynamics in social media during the brazilian protests," pp. 594–597, 2015.
[19] M. De Choudhury, S. Jhaver, B. Sugar, and I. Weber, "Social Media Participation in an Activist Movement for Racial Equality," Tech. Rep., 2016. [Online]. Available: http://www.wired.com/2015/10/how-black-lives-matter-uses-
[20] S. Muthiah, B. Huang, J. Arredondo, D. Mares, L. Getoor, G. Katz, and N. Ramakrishnan, "Planned protest modeling in news and social media," *Proceedings of the National Conference on Artificial Intelligence*, vol. 5, pp. 3920–3927, 2015.
[21] U. Yaqub, S. A. Chun, V. Atluri, and J. Vaidya, "Analysis of political discourse on twitter in the context of the 2016 US presidential elections," *Government Information Quarterly*, vol. 34, no. 4, pp. 613–626, 12 2017.
[22] S. Muthiah, P. Butler, R. P. Khandpur, P. Saraf, N. Self, A. Rozovskaya, L. Zhao, J. Cadena, C. T. Lu, A. Vullikanti, A. Marathe, K. Summers, G. Katz, A. Doyle, J. Arredondo, D. K. Gupta, D. Mares, and N. Ramakrishnan, "EMBERS at 4 years: Experiences operating an open source indicators forecasting system," *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, vol. 13-17-Augu, pp. 205–214, 2016.
[23] B. J. Goode, S. Krishnan, M. Roan, and N. Ramakrishnan, "Pricing a protest: Forecasting the dynamics of civil unrest activity in social media," *PLoS ONE*, vol. 10, no. 10, pp. 1–25, 2015.
[24] G. Korkmaz, J. Cadena, C. J. Kuhlman, A. Marathe, A. Vullikanti, and N. Ramakrishnan, "Multi-source models for civil unrest forecasting," *Social Network Analysis and Mining*, vol. 6, no. 1, pp. 1–25, 2016.
[25] S. Ranganath, X. Hu, J. Tang, and H. Liu, "Understanding and identifying advocates for political campaigns on social media," *WSDM 2016 - Proceedings of the 9th ACM International Conference on Web Search and Data Mining*, pp. 43–52, 2016.
[26] X. Zheng, "Social Network of Extreme Tweeters : A Case Study," 2016.
[27] E. Spiro and Y.-Y. Ahn, Eds., *Predicting Online Extremism,Content Adopters, and Interaction Reciprocity*, ser. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2016, vol. 10047. [Online]. Available: http://link.springer.com/10.1007/978-3-319-47874-6
[28] S. Dash, D. Mishra, G. Shekhawat, and J. Pal, "Divided We Rule: Influencer Polarization on Twitter During Political Crises in India," 5 2021. [Online]. Available: http://arxiv.org/abs/2105.08361
[29] S. Horawalavithana, K. W. Ng, and A. Iamnitchi, "Drivers of Polarized Discussions on Twitter during Venezuela Political Crisis," in *ACM International Conference Proceeding Series*. Association for Computing Machinery, 6 2021, pp. 205–214.
[30] A. Ingrams, "Connective action and the echo chamber of ideology: Testing a model of social media use and attitudes toward the role of government," *Journal of Information Technology and Politics*, vol. 14, no. 1, pp. 1–15, 1 2017.
[31] K. Garimella, G. De Francisci Morales, A. Gionis, and M. Mathioudakis, "Political discourse on social media: Echo chambers, gatekeepers, and the price of bipartisanship," *The Web Conference 2018 - Proceedings of the World Wide Web Conference, WWW 2018*, vol. 2, pp. 913–922, 2018.
[32] N. Karkın, N. Yavuz, İ. Parlak, and Ö. Ö. İkiz, "Twitter use by politicians during social uprisings: An analysis of gezi park protests in turkey," in *Proceedings of the 16th Annual International Conference on Digital Government Research*, 2015, pp. 20–28.
[33] R. Wang and A. Zhou, "Hashtag activism and connective action: A case study of #HongKongPoliceBrutality," *Telematics and Informatics*, vol. 61, 8 2021.
[34] T. Mitra, S. Counts, and J. W. Pennebaker, "Understanding anti-vaccination attitudes in social media," in *Tenth International AAAI Conference on Web and Social Media*, 2016.
[35] A. Khatua, E. Cambria, K. Ghosh, N. Chaki, and A. Khatua, "Tweeting in support of LGBT? A deep learning approach," in *ACM International Conference Proceeding Series*. Association for Computing Machinery, 1 2019, pp. 342–345.
[36] K. Wei, Y. R. Lin, and M. Yan, "Examining Protest as An Intervention to Reduce Online Prejudice: A Case Study of Prejudice Against Immigrants," in *The Web Conference 2020 - Proceedings of the World Wide Web Conference, WWW 2020*. Association for Computing Machinery, Inc, 4 2020, pp. 2443–2454.
[37] F. Germani and N. Biller-Andorno, "The anti-vaccination infodemic on social media: A behavioral analysis," *PLoS ONE*, vol. 16, no. 3 March, pp. 1–14, 2021. [Online]. Available: http://dx.doi.org/10.1371/journal.pone.0247642
[38] M. Jakesch, K. Garimella, D. Eckles, and M. Naaman, "Trend alert: A cross-platform organization manipulated twitter trends in the indian general election," *Proc. ACM Hum.-Comput. Interact.*, vol. 5, no. CSCW2, oct 2021. [Online]. Available: https://doi.org/10.1145/3479523
[39] A. Badawy, K. Lerman, and E. Ferrara, "Who Falls for Online Political Manipulation?" [Online]. Available: https://doi.org/10.1145/3308560.
[40] L. Luceri, A. Badawy, A. Deb, and E. Ferrara, "Red bots do it better: Comparative analysis of social bot partisan behavior," in *The Web Conference 2019 - Companion of the World Wide Web Conference, WWW 2019*. Association for Computing Machinery, Inc, 5 2019, pp. 1007–1012.
[41] A. Panda, R. Kommiya Mothilal, M. Choudhury, K. Bali, and J. Pal, "Topical focus of political campaigns and its impact: Findings from politicians' hashtag use during the 2019 indian elections," *Proceedings of the ACM on Human-Computer Interaction*, vol. 4, no. CSCW1, pp. 1–14, 2020.
[42] K. Darwish, P. Stefanov, M. J. Aupetit, and P. Nakov, "Unsupervised User Stance Detection on Twitter," 2019. [Online]. Available: http://arxiv.org/abs/1904.02000
[43] A. Rashed, M. Kutlu, K. Darwish, T. Elsayed, and C. Bayrak, "Embeddings-Based Clustering for Target Specific Stances: The Case of a Polarized Turkey," 5 2020. [Online]. Available: http://arxiv.org/abs/2005.09649
[44] M. Artetxe and H. Schwenk, "Massively multilingual sentence embeddings for zero-shot cross-lingual transfer and beyond," *Transactions of the Association for Computational Linguistics*, vol. 7, pp. 597–610, 2019.
[45] K. Krasnowska-Kieraś and A. Wróblewska, "Empirical linguistic study of sentence embeddings," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019, pp. 5729–5739.
[46] L. McInnes, J. Healy, and J. Melville, "Umap: Uniform manifold approximation and projection for dimension reduction," *arXiv preprint arXiv:1802.03426*, 2018.
[47] L. Van der Maaten and G. Hinton, "Visualizing data using t-sne." *Journal of machine learning research*, vol. 9, no. 11, 2008.
[48] L. McInnes and J. Healy, "Accelerated hierarchical density based clustering," in *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*. IEEE, 2017, pp. 33–42.
[49] D. Comaniciu and P. Meer, "Mean shift: A robust approach toward feature space analysis," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 24, no. 5, pp. 603–619, 2002.
[50] E. Schubert, J. Sander, M. Ester, H. P. Kriegel, and X. Xu, "Dbscan revisited, revisited: why and how you should (still) use dbscan," *ACM Transactions on Database Systems (TODS)*, vol. 42, no. 3, pp. 1–21, 2017.
[51] E. Simmons, "Grievances do matter in mobilization," *Theory and Society*, vol. 43, no. 5, pp. 513–546, 2014.