

Enemy at the Gate: Evolution of Twitter User's Polarization During National Crisis

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Abstract—Social networks are effective platforms to study the real-life behavior of users. In this paper, we study users' political polarization during the times of crisis and its relation to nationalism. To this purpose, we focus on the reaction of Indian and Pakistani Twitter users during February 2019 crisis and the ensuing Indian General Elections in 2019. We show that a national crisis affects the polarization and discourse in both countries. Also, we show that user activities increase during a national crisis, and political discourse strengthens while polarization decreases on critical days. Finally, we highlight the links between this crisis and the Indian elections and show how the political parties discussed the crisis in their campaigns.

Index Terms—Social Networks, Polarization, Computational Politics, Nationalism

I. INTRODUCTION

Social media, although having proved to be effective in communication that is independent of borders and effectively bringing people together on many issues, still faces massive problem of polarization [1]. Polarized opinions, on large scales, can be exploited to affect free-speech in the democratic process [2] or even to suppress facts [3]. In particular, crises fueled by nationalistic stance can lead to disorders in society, act as a catalyst for individuals' motives at the time of crisis, and be contingent on war [4].

In February 2019, tensions escalated between India and Pakistan, leading to a military stand-off between the two countries. The situation reached its peak between February 26th and March 1st in 2019, with a series of strikes and skirmishes at the border. In this paper, we analyze Twitter users in India and Pakistan to understand the evolution of polarization and the apparition of nationalistic stances in both countries during a national crisis, right before the national elections in India. We compare the publishing characteristics of users over three contiguous periods: pre-crisis, during the crisis, and post-crisis. We look at the users' activity patterns to find correlations across these three time-frames. We focus on the retweeting behavior of users during the crisis period and show that inter- and intra-party retweeting pattern exists on both sides. The motivation for our polarization study is based on the nationalist stance during the times of crisis. To the best of our knowledge, this is the first work on polarization in times of national crisis among South Asian users, including both pre and post-crisis analysis. This work aims to understand show that such crisis effects OSN users' discourse towards

significant national events such as election as such discourse can also affect the users' voting choice [5]. We ask the following questions:

- **RQ1:** How do users' online activities differ between the pre-crisis, during-crisis and post-crisis periods?
- **RQ2:** How do polarized groups evolve during the crisis?
- **RQ3:** How did this event affect the 2019 Indian Elections' political discourse for the active polarized users?

II. RELATED WORK

In recent years, polarization has received significant attention in relation with political situations [6]. There exist only a few studies on South Asian users regarding the polarization in social media [7], [8]. Some other work focus on the usage of social media for political parties [9], election prediction [7], [10]. The most common method to study and measure polarization is based on the retweets networks as these networks are more polarized than global networks [11], [12]. While retweet networks can predict the political homophily, the content analysis can highlight the communities based on similar discussions [13].

Some studies show that users' activities are highly related to the groups they form on social media [11], [14]. Lalani et al. [15] examined the relationship between politicians in power and influencers that they follow on Twitter, such as celebrities and media accounts. The authors found that the media accounts highly engaged with politicians who follow them and share the same ideology, whereas celebrities do not have such alignment with politicians. Other than interaction based topological connections, textual data can also highlight the polarization and stance of the users. As such Hagen et al. [16] investigate emoji usages between two groups of actors, those who support the while nationalism ideology and those who oppose it in the United States. The authors present the notable differences in emoji use in the two groups. [17] treats such polarization as stance detection problem and shows the dimensional reduction methods on retweet networks can give better results than the networks than hashtags network.

III. DATASET

We collect data based on the trending hashtags related to the Indo-Pakistani crisis in February 2019. In total we gathered the 34 individual and paired hashtags¹. From the

¹<https://tinyurl.com/asonam-hashtags>

collected dataset, we isolate politicians and official accounts related to government and armed forces as main accounts. We expand our dataset by collecting followers/following networks of users in our dataset and the users they have retweeted. We collect the network of users in chronological order as the followers who have recently started following the main accounts are potentially politically-involved users. As we will analyze the polarization and political discourse during the crisis period, the Indian General Elections for Indian users, this will give us the set of politically active users. For all users, we collect the 500 most recent messages (tweets or retweets). The dataset contains 30.75 million tweets from 487,458 users, with an average of 3.4 million tweets per month for the first three months of 2019, from the 1st of January 2019 to the 31st of March 2019. As not all users provide their location information, we only select the users who have provided this information and map them accordingly using city lists from both countries. We ignore the users living in cities or provinces that exist within both countries, such as the Punjab province or Hyderabad city.

IV. METHODOLOGY AND OBSERVATIONS

India and Pakistan both have dozens of registered political parties in each country. We consider these parties in reference with the governments and oppositions in each country at the time of crisis. Due to our data collection method, we may have collected tweets from users who are not from the observed countries. As such, we only consider users who are identified as Indian or Pakistani in the dataset. In the first part of our analysis, we look at all users identified as Indian or Pakistani. We then examine the retweeters for the governments and opposition parties from each country to perform political discourse analysis. To study the polarization, we focus on the users' retweet patterns and retweet networks. To analyze the political discourse, we use hashtag co-occurrence graphs. We employ the above methods to analyze the users' behavior over three time periods: pre-crisis, during-crisis, and post-crisis. We consider various time granularities ranging from a single day to an aggregated week or a month, depending on the experiments [5], [18].

A. User Activity and Correlation

To answer RQ1, we focus on the identified Indian and Pakistani users' activity patterns – likes, replies, and retweets – in terms of frequency and volume. Intuitively, we assume that such users would become more active, and average number of likes, replies, and retweets by users would increase significantly compared to pre-crisis times. Our results confirm this intuition. Besides, we also shed light on the activity correlation between Indian and Pakistani users. Figure 1 shows the retweets, likes, and replies over time between January and March. Users activities increased during the crisis (14-28 Feb). A second peak around March 15, corresponds to the Indian elections. We analyze this period in more detail in Section IV-D. Another significant observation is the correlation between Indian and Pakistani user activity. In general, user

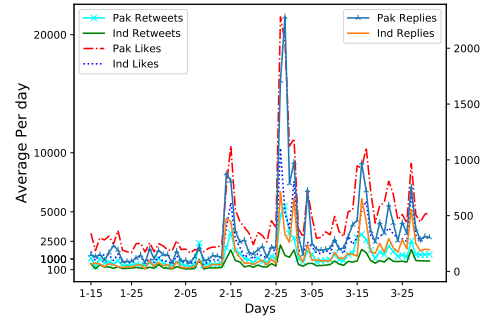


Fig. 1: Retweets, Likes, and Replies during three months. For all three parameters, we observe a peak after February 26, following the Balakot airstrike. The second peak around March 15 corresponds to the Indian elections.

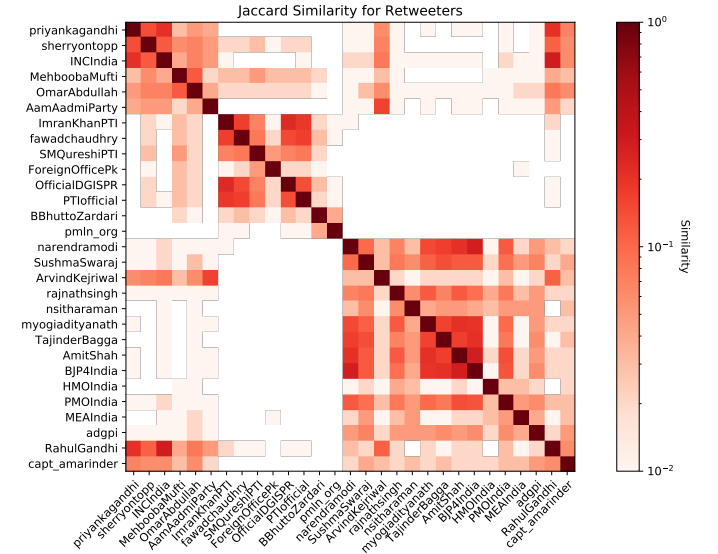


Fig. 2: Jaccard Similarity between the retweeters of the political and government entities. Partisan users maintain polarization.

engagement follows visibly similar patterns. We conduct the Chi-Square test to verify the dependence between the interaction patterns over three months. The Chi-Square test shows no statistical independence between Pakistani and Indian users' activity over the course of each month ($p < 0.05$).

B. Retweet Polarization

In this section, we analyse retweet patterns to observe the polarization. First of all, we compare the common retweeters among different political accounts. We focus on the retweeting behavior of users over five weeks centered around the crisis (from the first week of February to the first week of March). We measure the Jaccard Similarity of retweeters of any two different accounts as ratio of number of shared retweeters between the two accounts to the total number of retweeters in both accounts and show the results in Figure 2. We use a logarithmic scale for the representation and consider

the Jaccard similarity values below 0.01 to be insignificant. Users maintain polarization by retweeting content from like-minded individuals or organizations. However, users retweeting government accounts such as the account of ministries are less polarized than users retweeting the personal accounts of politicians from the ruling parties.

Two Way Polarization: In the five weeks, users exhibit two kinds of polarization. First is based on a purely partisan basis (such as the high number of retweets between leader and party accounts). At the same time, the second one concerns multiple parties united with a common goal (for instance, opposition parties). Both types of polarization are prominent for users on both sides of the border, as shown in Figure 2. The ruling parties in both countries have exclusive set of retweeters, in contrast the opposition parties share higher ratio of retweeters.

C. Polarization Evolution

To answer how the pre-existing groups evolve during the time of crisis, we use the method proposed by [19]. We construct the retweet network for each day in January, February, and March to better understand the polarization among users for both countries, giving us a total of 180 retweet networks. We use the Giant Component(GC) of retweet networks.

For each retweet network, we initially label a subset of users with a political score of -1, and 1 based on the two political sides. We use -1 for the parties in government and government accounts. The parties in the opposition are assigned 1. Hence our political spectrum is in the range [-1,1]. We manually label 171 most retweeted accounts from both countries for their political ideology by visiting their twitter profiles. We then measure the polarization influence of these users on the rest of the users. For a given node, the political score is calculated based on the average score of all the users that a specific user has retweeted. We repeat this process for each node until every node has converged to a score. We then use the probability distribution from [19] on this score to model the opinion distribution in the whole network.

Figure 3. shows the polarization in retweet network for both India and Pakistan in February. All the graphs present two arcs centered at both extremes of the x-axis. The higher the polarization, the deeper the curve is around 0 on the x-axis and vice-versa. Our results show that polarization noticeably decreased during our keys dates: Feb(14,26,27) and Mar (1). These are the days where significant events happened, and people engaged in less polarized discussions. It is interesting to note that the initial attack on February 14 had little influence on the polarization in Pakistan.

D. Political Discourse and Elections

The Indian General Elections were held in April 2019. To look at the political discourse right before the elections, we select two major parties in India: Indian National Congress (INC) and Bharatiya Jannata Party (BJP). We choose two Twitter accounts for each party: the personal account of the party's leader and the official account of the party. For each party we filter out the users who have exclusively retweeted

the BJP accounts or INC accounts, rest of the analysis in this section is based on this set of users only. Primarily, we want to see if this crisis had any effect during the election period. As such, we focus on the usage of hashtags during March 2019. Earlier literature suggests that the use of hashtags and co-occurrences of hashtags in a tweet boosts the reach of both the tweets and the hashtags [20], [21]. Due to the diversity of languages used by South Asian users, topic detection on a tweet text is not possible in the scope of this work. Hence we use the hashtag co-occurrence graph to highlight the political discourse. As users have been using similar hashtags regardless of the language they use to tweet, such hashtags overcome the language heterogeneity problem.

We perform a preprocessing step before the construction of the graph to merge similar occurrences of hashtags, e.g., some hashtags have been used with different spellings such as "surigicalstrike" and "surgicalstrikes". We also merge hashtags that refer to the same entity such as "Jammu and Kashmir", "Kashmir", or "generalelection2019" and "indiangeneralelection2019". For INC set we have 612 hashtags while for BJP we have 1,328 hashtags. To analyze the topics on political discourse, we construct the hashtag co-occurrence graphs for March 2019 for each set of users. For the set of selected users, we combine all co-occurring hashtags in pairs for all the hashtags occurring in their tweets. For each pair present in the given tweet, we add hashtags as nodes in the graph and add an edge between them. For every repetition of the pair in the data, we increase the edge weight by one. We apply statistical measures on nodes and edges to find the importance of relevant hashtags in the network. We use the Louvain method for community detection on the our graph along with Eigenvector Centrality (EC) and Clustering Coefficient(CC) to highlight the significance hashtags [22]. We use *Gephi* to visualise the network with *Force Layout*. In our visualization, the size of a node shows the Eigenvector Centrality for the node. That is, the bigger the size of the node, the higher the EC. The same color nodes belong the same community as detected by the Louvain method. This approach will give us information about the hashtags and hence the topics that are frequently used together and give the general discourse outline by placing co-occurring hashtags closer and by relative usage.

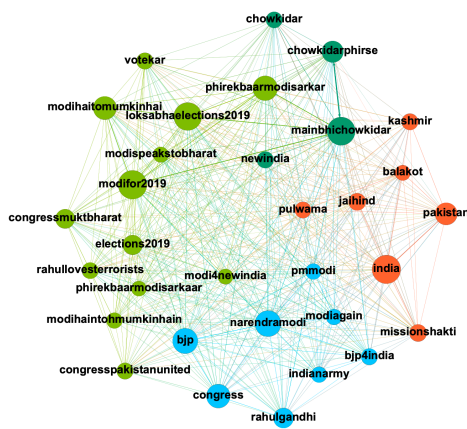
Figure 4 shows the results for both the INC and the BJP of India. The results highlight several aspects of the discourse. In terms of RQ3, we observe a) the presence of Kashmir-related discourse; and b) co-occurrences of Kashmir-related hashtags with election campaign hashtags is more common in BJP discourse than that for INC. The data also highlights how this situation is used in political campaigns, especially by the ruling party BJP. Both parties were using scams and scandals to counter each other's narratives. However, the BJP intensified linking INC leaders with Pakistani leaders and using hashtags like #rahulloverrorists and #congressispakistan.

E. Discussion

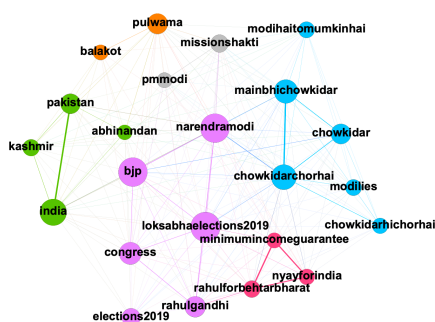
We now review our findings through our initial research questions. This study answers the following points:



Fig. 3: Polarization Influence Measure in February for both countries. The important days are highlighted in Red. The polarization influence reduced on the day after terrorist attack in India while Pakistan has normal polarization. However, during the airstrike days both countries have less polarized discourse.



(a) BJP: The political campaign is stronger, still mentioning the Kashmir crisis, also adding hashtags against INC and linking INC leaders with Pakistan. Avg CC = 0.52



(b) INC: Discourse is on political campaigns, mainly focusing on Modi. The Pulwama issue is still discussed. Avg. CC = 0.49

Fig. 4: Analysis for BJP and INC political discourse in March. The Kashmir issue is visible in both political discourse. .

- **RQ1:** All observed parameters (tweets, retweets, likes, replies) peak during the crisis. Post-crisis, users' activity drops to a level significantly higher than pre-crisis.

- **RQ2:** We show the polarization evolution for three months and show that polarized groups were involved in the discussions during the critical days during the crisis. User polarization is twofold: users tend to retweet the particular party leaders and their coalition political parties while the government accounts are less polarized.
- **RQ3:** This event has a significant effect on political discourse. We show that users mentioned the Kashmir issues in election campaign tweets. This situation was used by BJP in its political campaign against INC.

In summary, we show that the national crisis affects the polarization and the political discourse of users, and observe the signs of national stance reinforcement in political campaigns. This crisis led from a more polarized discourse in January to a less polarized discourse during the crisis days where users tend to exchange and interact more with opposing opinion people. The hashtag observation shows that users tend to use hashtags related to their nations. Use of hashtags such as #nationfirst, #JaiHind (Bless India) #Pakistanzindabad (Long Live Pakistan), and hashtags praising the armed forces on both sides are prominent. Our analysis highlights the engagement discourse around the crisis and shows that polarized groups tend to engage in discussions. However, more work is needed to analyze the exact political discourse during the crisis.

In terms of the democratic process, previous studies associate Twitter presence and tweet volumes with election-winning. We can see from the March discourse in India that the BJP party influences polarization and eventually won the elections in April 2019. These markers that can be further explored in linking election results and political discourse.

This analysis also highlights the political campaigns of two parties in India. Based on the history between the two countries, discussing the other country during the election seems quite intuitive. However, the data shows that the BJP election campaign focused on showing INC leaders as Pakistan friends, giving credits to Prime Minister Modi for the strikes, and calling him a man of action. The use of hashtags in favor of Narendra Modi is higher than for INC leaders and other parties in India. One potential reason could be significant

online support for his work as Prime Minister during the crisis. Hashtag communities are another key observation. In Figure 4a, we observe three clusters supporting BJP for the April 2019 election, with notable differences between the topics. For instance, the blue cluster focuses on the personalities and political parties, the dark green focuses on Modi's catch phrase "chowkidar" while the light green encompasses the anti-congress sentiment. Finally, the last cluster (red) deals with the February 2019 crisis. This cluster is much more prominent than for INC. The INC network is less focused. Some hashtags refer to the BJP's campaign. We do not focus on the causal for that behavior, but a future study on such usage could provide more details whether the crisis had made those user support the other political party ideology.

V. CONCLUSION

In this paper, we highlight Twitter users' social media activities and polarization in a time of a crisis between India and Pakistan. Users display similar behaviors in terms of tweets, retweets, likes, and replies in both countries. During the crisis, user activity peaks before decreasing to a level higher than before the crisis. The number of people who retweet political entities then keeps growing. In India, such growth may be the result of the upcoming election. However, in Pakistan, this increase could be due to a more active involvement during the crisis. Users from different parties tend to interact more with each other almost immediately after key events of the crisis, leading to a decrease in polarization. However, polarization returns in just a few days. We finally highlight the crisis as a significant part of the Indian Elections discourse for the leading party and expose the diversity of topics in the discourse of the opposition party. We noticed that opposition political parties share each other's content, while the leading party tends to retweet its own content across multiple accounts (party members, government officials). This study is the first one to link national crisis and election discourse for South Asian users, a widely understudied population.

Many other exciting directions deserve further research. First of all, we want to explore the evolution of the users and the echo chambers' formation in more detail. As we observed that the political discourse was less polarized during the crisis dates, we wish to further analyze the content of the messages at that time. During our study, we noticed that users also tend to share third party media links. We will aim to relate media polarity with user profiles. Finally, the correlation of such crises with future events such as elections could also be explored and would be helpful for election prediction studies.

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