

Social Network Viral Marketing Tool For Victory In Tariff War

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ABSTRACT

Social networks are densely connected graphs with the most influential nodes enjoying important and central locations. The nodes connected with influential nodes often get updates of their activities and get influenced by them. The research explores the effect of the most connected nodes in the viral spread of 4 major Indian telecom operator related information in a crucial period immediately before a significant tariff hike. Central nodes and subgraphs have been identified in the tweet datasets of the 4 operators which help in understanding viral information propagation. Their degree or the number of connections with other nodes makes them an important source of information. The social network viral information spread is of high importance for brand promoters to understand the behavior of social network users in highly competitive environments.

Keywords: -connectedness, online social networks, telecom, viral marketing

I. INTRODUCTION

The exponentially increasing demand and outreach of social media networks have created a number of research domains to apply the wisdom of the crowds in day to day decision making[1]. The vast amount of content posted on social networks needs to be classified and analyzed empirically to validate its usefulness for society. Popular social networks like Facebook, YouTube, Wikipedia, Instagram, Twitter, Flickr, etc. currently have one of the highest user engagements as per the number of monthly connected users[2]. All of these social network services offer similar features in distinct formats. Also termed as websites that facilitate the building of a network of contacts in order to exchange various types of content online, "social network media websites offer a user-friendly platform for interaction to initiate and grow beyond personal level communications.

Numerous social networks surround us and fascinate us with their size, complexity and the amount of information they contain. Their analysis helps us to understand and utilize them for the betterment of human life. Degree (both indegree and outdegree) represents a basic connectedness measure of a node in a network. Long chains of edges form when nodes interact with them. The nodes can be filtered on the basis of their ties with other nodes and their location in the parent graph. Degree, centrality measures and community structure can be visualized to learn more about the networks. Connections between the nodes form long chains of online word of mouth. Even large networks have a smaller degree of separation and follow the power-law degree distribution[3]. Within a few hops, one can traverse the lengths and breadths of the network. On social network platforms due to the multiplicity of relationships among nodes, the spread of information is viral in nature[4].

The research proposed discusses the connectedness property of social networks which enables them to absorb and handle enormous data and make them a successful tool for businesses. The experiment explores the spread of online word of mouth for Indian sector telecom operator Bharat Sanchar Nigam Limited (BSNL), Reliance Jio, Vodafone and Bharti Airtel hashtag from 1st November 2019 to 30th November 2019 through their

top 3 central nodes in the network. The Indian telecom market is the second-largest in the world with 1173 million wireless or mobile subscribers [5]. Due to one of the lowest tariffs in the world and a large population, there is always a competition among all the telecom players to retain the subscribers and add new ones. The telecom tariffs in the Indian market are set to sharply increase on 1st December 2019 and all major telecom players are applying their best strategies on social media platforms like Twitter to retain their customers and also attract new customers. The tweets corresponding to the hashtags of the operators represent the collection of sentiments of individuals and the chains correspond to the spread of word posted on the network.

II. RELATED WORK

Thousands and even millions of nodes forming large networks are ubiquitous in different scientific domains [6]. Identifying communities in large networks is a challenging task as many parameters defining communities exist. Communities are subgraphs within a graph in which the constituent nodes are more densely connected as compared to the rest of the graph. Research studies state that the most reliable nodes or users of any given network are those users who are friends with a maximum number of other users belonging to the same network. These reliable or influential nodes tend to be placed at the core of the network graph while others spread away from the gravity center of the network. It frames a postulate that the amount of information traversing through a particular node is inversely proportionate to the distance of the node from the core of the network. This model suits the marketing strategies, if the node has been targeted for a brand or a service, its connections are likely to be affected by these strategies. As a result, the rapidly growing social media platform has become the first choice of brand promoters for communicating with customers [7].

Viral information spread is finding importance in the next generation smart cities [8]. Top influencer nodes once identified can help in increasing the general public's participation in smart city evolution. The research discussed basic methods of community detection based on graph clustering. The rate of information spread is directly proportional to the degree of a node and its location-based centrality in the network. Based on the combined input from the general public, authorities can plan for the features of the smart city.

Social network analysis can help brands in preventing churn prediction by providing real-time feedback of customer sentiments [9], [10]. In the highly competitive era of marketing and information, customers not only keep a close watch on the associated product but also its competitors. They collect the product and brand-related information from various platforms like social networks in the form of reviews and ratings and thus get influenced to stick to a particular brand or shun it. The reviews they read are displayed to them in the form of notifications from the post by their connections. Central nodes that have a high degree occupy an important location in the graph and spread their message to a large number of nodes. Brands target these central or highly connected nodes to create positive sentiment about them.

The telecom sector is a special market segment that has high interaction with the general public. Most of their business and revenue depends on continuous acceptance by the public. When subscribers have an option to port out of a particular operator and join some other operator, it becomes important for the operators to monitor user opinions on a real-time basis[11]–[13]. As soon as a dissatisfied subscriber willing to churn out posts about his decision on social networks, his connections get this update information. The influence of the information initiator becomes a contributor to the connected node's decision to churn out. The information propagation throughout the network is through the chain of connected edges of online word of mouth.

III. EXPERIMENTAL FRAMEWORK

Tweets for the hashtags of the major Indian telecom operators namely Bharat Sanchar Nigam Limited (BSNL), Reliance Jio, Vodafone and Bharti Airtel were mined using Python to create 4 datasets. The datasets contain user activity in response to the aggressive campaigns launched by the telecom operators to spread information related to upcoming tariffs. The top 3 central nodes from each dataset were selected for their role in viral information propagation. Figure 1 shows the directed graph of #bsnl tweets. Dark regions in the graph depict a large number of connections of the influential nodes.

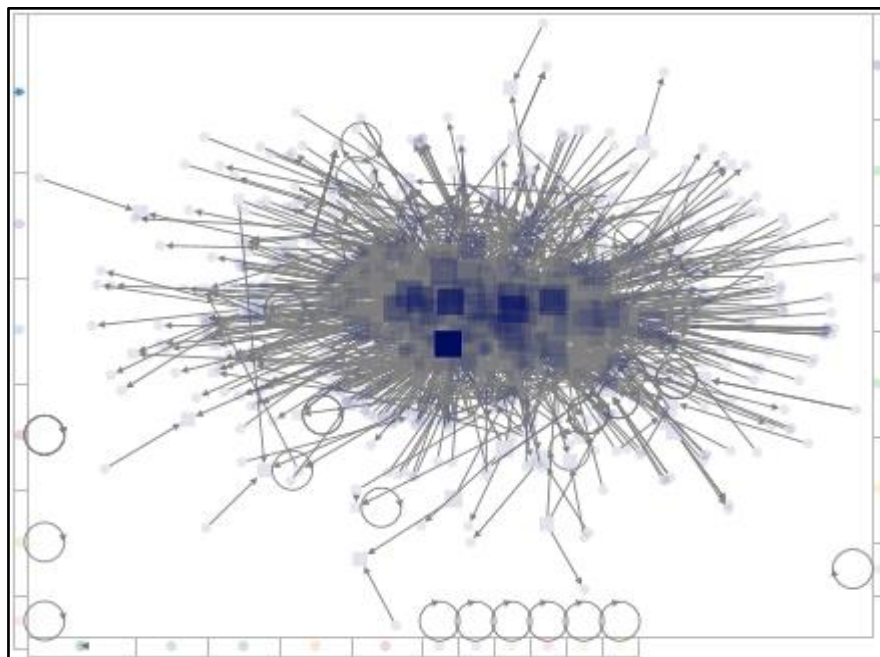


Figure 1Directed graph of information flow for the #bsnl dataset network.

The influential nodes through their high connectivity form their subgraphs in the main graph. The nodes in subgraphs have more connections among themselves compared to the rest of the graph. Figure 2 shows 8 subgraphs within the #bsnl dataset graph. Figure 3 shows the dense interactions among the individual subgraphs of the main network.

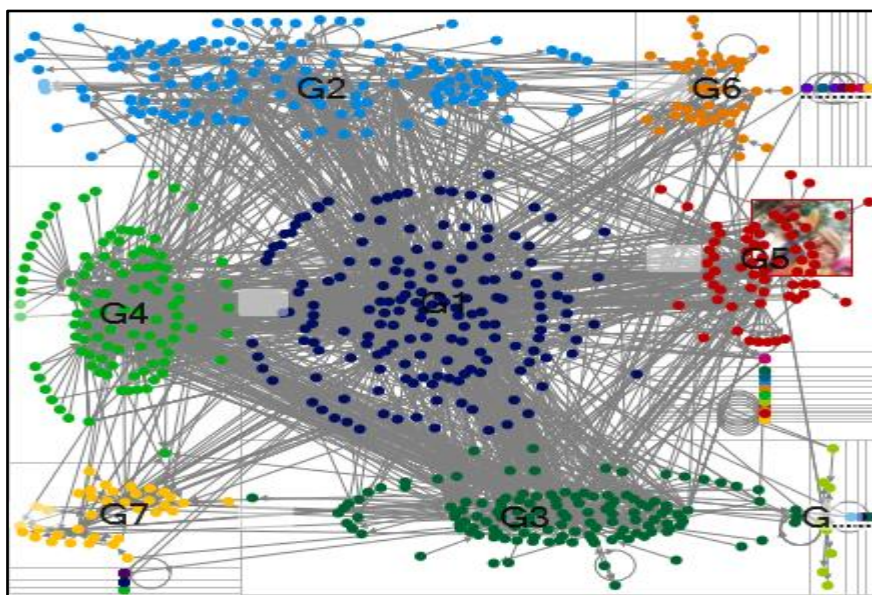


Figure 2 Connected subgraphs identified in the #bsnl dataset network.

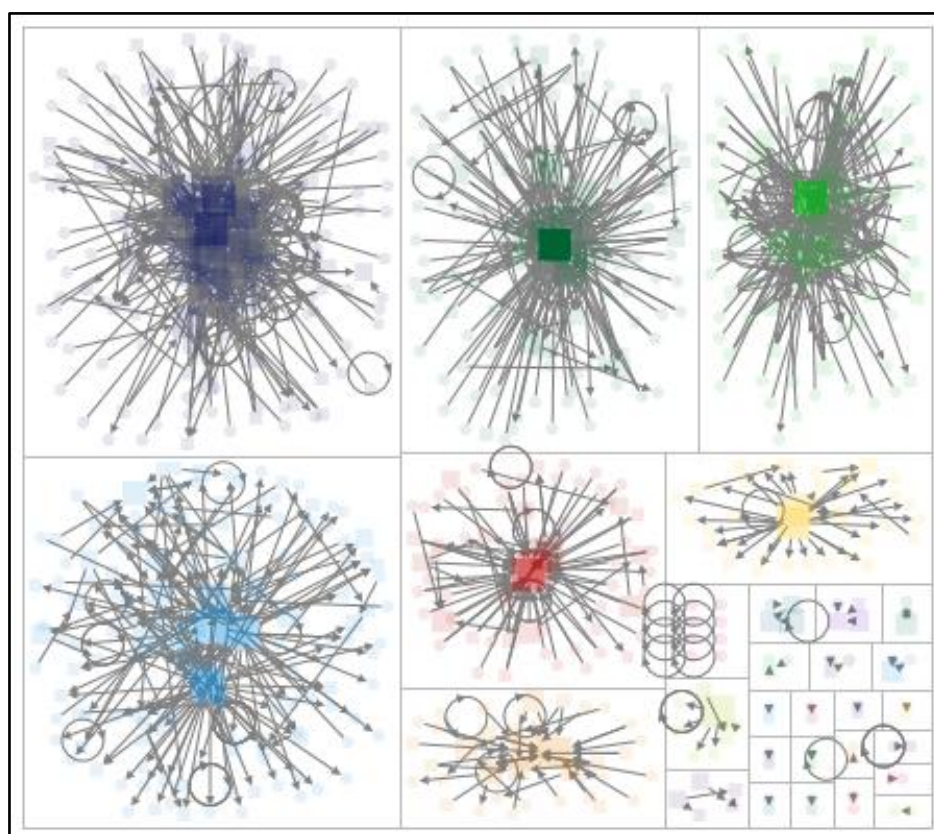


Figure 3 Interactions among the individual subgraphs in the #bsnl dataset network.

The degree measure values of the top 3 influential nodes have been mentioned in table 1. A higher value of degree means the information posted by the influential or the source nodes is reaching a large number of connected nodes. Table 2 shows the number of retweets corresponding to these top influential nodes in the research duration.

Table 1. Degree of top 3 influential nodes

# (hashtag)	Node Rank	Degree
#airtelindia	1	214
	2	198
	3	146
#bsnl	1	101
	2	82
	3	94
#reliancejio	1	243
	2	206
	3	174
#vodafonein	1	144
	2	132
	3	106
Total		1840

Table 2. Change in the number of retweets in November 2019

# (hashtag)	Node Rank	Retweets		Change
		1 st Nov 2019	30 th Nov 2019	
#airtelindia	1	89	142	59.6
	2	70	98	40.0
	3	53	89	67.9
#bsnl	1	84	104	23.8
	2	74	92	24.3
	3	55	68	23.6
#reliancejio	1	157	262	66.9
	2	144	214	48.6
	3	149	247	65.8
#vodafonein	1	65	74	13.8
	2	51	56	9.8
	3	32	49	53.1
Total		1023	1495	46.1

VII. CONCLUSION

There has been a significant increment of 46.1% in the number of retweets at the end of the month compared to the starting of the month. This is primarily the result of the viral spread of information by the centrally located influential nodes. The notification received by the connected nodes as soon as the comment is posted by the central node serves as a stimulus for the connected nodes. In the vital month of November 2019, the telecom tariffs were expected to rise sharply and the general public was searching for inputs from others as to which operator will suit them from 1st December 2019. The highly connected nodes posted operator related data and got a good response from other nodes. Thus social network-based marketing can help the brands to spread their word at a fast pace compared to other communication media.

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